STRATÉGIES D'INTÉGRATION DU PROCESSUS DE CADENASSAGE/DÉCADENASSAGE EN PRODUCTION MANUFACTURIÈRE INTELLIGENTE : VERS LA SANTÉ, SÉCURITÉ ET ENVIRONNEMENT (SSE) 4.0

par

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Stratégies d'intégration du processus de cadenassage/décadenassage en production manufacturière intelligente : vers la santé, sécurité et environnement (SSE) 4.0

Victor Delpla

RÉSUMÉ

Cette thèse explore des stratégies d'intégration des procédures de cadenassage/décadenassage (Lockout-Tagout / LOTO) dans un environnement manufacturier intelligent, visant à améliorer la santé, la sécurité et l'environnement dans le cadre de la transition vers l'Industrie 4.0. Le LOTO est une procédure de sécurité utilisée pour garantir que les machines soient correctement arrêtées et ne puissent pas être redémarrées avant la fin des travaux de maintenance. L'objectif principal est d'apporter des solutions concrètes aux défis rencontrés dans l'industrie manufacturière pour la planification, la préparation et l'exécution des procédures LOTO.

Une politique conjointe de production, maintenance et LOTO opérationnel a été proposée, avec le développement d'un modèle sur la théorie du contrôle optimale stochastique et utilisant les équations de Hamilton-Jacobi-Bellman. Les résultats montrent une réduction significative des coûts de production grâce à l'inclusion du LOTO opérationnel. De plus, un outil de gestion de la production et de la maintenance de gestion a été obtenu.

L'assistance à la rédaction des procédures LOTO a été abordée avec l'utilisation de l'apprentissage machine et de l'apprentissage profond. Des algorithmes de classification multi-tâches ont été employés pour prédire les dispositifs à verrouiller à partir des noms de machines. Le temps nécessaire à l'élaboration des procédures LOTO diminue, mais cette assistance de rédaction se restreint aux machines simples. Les machines complexes nécessitent encore une intervention humaine en raison de la criticité du LOTO.

La fusion des procédures LOTO a été automatisée à l'aide d'un modèle d'optimisation en programmation non-linéaire en nombres entiers multi-objectifs, planifiant les trajets des équipes de maintenance en fonction des machines à verrouiller. L'utilisation d'algorithmes de résolution de problème de routage de véhicules a permis de réduire les déplacements des travailleurs et le temps de verrouillage de plus de 30%.

Des stratégies de LOTO intelligentes adaptées à l'environnement manufacturier ont également été développées. La première approche, basée sur la position géographique des dispositifs, permet aux équipes de se répartir géographiquement les dispositifs à verrouiller, maximisant l'utilisation des ressources humaines et réduisant le temps de verrouillage de 20%. La seconde approche est une approche dynamique du LOTO, où les procédures s'adaptent en temps réel aux imprévus, réduisant le temps de verrouillage de 30% dans les scénarios les plus difficiles.

Les technologies intelligentes, dans le contexte de l'Industrie 4.0, telles que l'Internet des Objets et l'Intelligence Artificielle peuvent considérablement améliorer les procédures LOTO en augmentant l'efficacité des opérations. Une réduction significative des temps de cadenassage, une meilleure gestion des ressources humaines et une amélioration de la continuité de la production sont possibles avec les stratégies proposées. Les résultats ont été développés et validés avec des études de cas réels provenant des partenaires industriels.

Mots-clés : Cadenassage/Décadenassage ; Santé, Sécurité et Environnement (SSE) ; Programmation dynamique stochastique ; Optimisation multi-objectif ; Simulation à évènements discrets ; Apprentissage machine ; Apprentissage profond

Integration strategies for lockout/tagout processes in intelligent manufacturing: towards health, safety and environment (HSE) 4.0

Victor Delpla

ABSTRACT

This thesis explores strategies for integrating Lockout-Tagout (LOTO) procedures into an intelligent manufacturing environment, aiming to enhance health, safety, and environmental conditions during the transition to Industry 4.0. LOTO is a safety procedure used to ensure that machines are properly shut off and cannot be restarted before maintenance work is completed. The primary objective is to provide concrete solutions to the challenges faced in the manufacturing industry regarding the planning, preparation, and execution of LOTO procedures.

A joint policy for production, maintenance, and operational LOTO has been proposed, with the development of a model based on the stochastic optimal control theory and using Hamilton-Jacobi-Bellman equations. The results show a significant reduction in production costs due to the inclusion of operational LOTO. Additionally, a management tool for production and maintenance has been developed.

The assistance in drafting LOTO procedures was addressed using machine learning and deep learning. Multi-task classification algorithms were employed to predict the devices to lock out based on machine names. The time required to develop LOTO procedures decreases, but this drafting assistance is limited to simple machines. Complex machines still require human intervention due to the criticality of LOTO.

The fusion of LOTO procedures was automated using a multi-objective mixed-integer non-linear programming optimization model, planning the routes of maintenance teams based on the machines to lock out. Using vehicle routing problem-solving algorithms reduced worker travel and locking time by more than 30%.

Intelligent LOTO strategies adapted to the manufacturing environment were also developed. The first approach, based on the geographical position of devices, allows teams to geographically distribute the devices to lock out, maximizing human resource utilization and reducing locking time by 20%. The second approach is a dynamic LOTO approach, where procedures adapt in real-time to unforeseen events, reducing locking time by 30% in the most challenging scenarios.

Intelligent technologies, in the context of Industry 4.0, such as the Internet of Things and Artificial Intelligence, can significantly improve LOTO procedures by increasing the efficiency of operations. A significant reduction in lockout times, better management of human resources, and improved production continuity are possible with the proposed strategies. The results have been developed and validated with real case studies from industrial partners.

Keywords: Lockout/tagout; Environment, Health and Safety and (EHS); Stochastic dynamic programming; Multi-objective optimization; Discrete-event simulation; Machine learning; Deep learning

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LISTE DES ABRÉVIATIONS, SIGLES ET ACRONYMES

LOTO	Cadenassage/Décadenassage
SSE	Santé, Sécurité et Environnement
MINLP	Programmation Non-Linéaire en Nombres Entiers
AI	Intelligence Artificielle
ML	Apprentissage Machine
KNN	K-plus proches voisins
RF	Forêt Aléatoire
DL	Apprentissage Profond
ANN	Réseau de Neurones Artificiels
IoT	Internet-des-Objets
DES	Simulation à évènements discrets

INTRODUCTION

Le cadenassage/décadenassage, plus couramment nommé sous son appellation anglophone Lockout/Tagout (LOTO), est une procédure cruciale pour garantir la sécurité des travailleurs lors de la maintenance et de la réparation des équipements industriels. En 1989, l'Occupational Safety and Health Administration (OSHA) a établi la norme 29 CFR 1910.147, qui impose aux employeurs de mettre en place des programmes de contrôle des énergies dangereuses comprenant des dispositifs de verrouillage et d'étiquetage. Au Québec, le règlement ROHS (2017) exige également des révisions périodiques des procédures de cadenassage.

La mise en œuvre efficace des procédures LOTO est essentielle pour prévenir les accidents dus à la libération d'énergie dangereuse, tels que l'électrocution, les brûlures et les amputations. Cela implique l'isolation et la désactivation des sources d'énergie, l'utilisation de dispositifs de verrouillage pour empêcher le démarrage involontaire des machines et la formation des employés sur les méthodes de contrôle de l'énergie. Chaque étape doit être minutieusement documentée et inclure des instructions spécifiques pour chaque type de machine ou d'équipement.

Malgré l'importance de ces procédures, leur mise en œuvre reste souvent manuelle et repose largement sur la connaissance des opérateurs. Les récents progrès technologiques offrent cependant de nouvelles opportunités pour améliorer ces procédures. L'intégration des technologies de l'Industrie 4.0, telles que l'Internet des Objets (IoT), l'intelligence artificielle (IA) et l'apprentissage machine (ML), peut transformer les procédures LOTO, les rendant plus efficaces et sécurisées.

Cette thèse explore les stratégies optimales d'intégration des procédures LOTO dans un environnement manufacturier intelligent, en mettant l'accent sur l'amélioration de la sécurité, de la santé et de l'environnement (SSE) dans le cadre de la transition vers la SSE 4.0. Elle propose une approche multidimensionnelle combinant l'optimisation conjointe de la production, de la maintenance et des procédures LOTO, l'automatisation de la rédaction des fiches LOTO à l'aide de techniques d'apprentissage machine, et le développement de procédures LOTO intelligentes basées sur la géolocalisation et l'adaptabilité dynamique.

Ce projet de recherche est soutenu par des partenaires industriels, tels que CONFORMiT et Cascades Inc., et vise à apporter des solutions concrètes aux défis rencontrés dans l'industrie. Les résultats attendus permettront non seulement d'améliorer la sécurité des travailleurs, mais aussi d'optimiser les opérations de maintenance et de production, contribuant ainsi à la compétitivité des entreprises manufacturières dans le cadre de l'Industrie 4.0.

Cette thèse est structurée en six chapitres. Le Chapitre 1 présente une revue de la littérature sur les procédures LOTO, les enjeux de la sécurité au travail et les perspectives de développement du LOTO avec les avancées récentes en termes de technologies. Le Chapitre 2 détaille les objectifs de recherche et la méthodologie adoptée. Le Chapitre 3 propose une politique d’optimisation conjointe de production, de maintenance et du LOTO. Le Chapitre 4 propose une approche prédictive pour l'automatisation de la rédaction des procédures LOTO à l'aide de l'apprentissage machine et l’apprentissage profond. Le Chapitre 5 développe un modèle de fusion de procédures LOTO et propose une approche intelligente de cadenassage basée sur la géolocalisation des dispositifs énergétiques. Enfin, le Chapitre 6 développe une approche dynamique du LOTO, plus flexible selon les imprévus. La thèse se termine par une conclusion qui synthétise les résultats obtenus et propose des recommandations pour les recherches futures.

CHAPITRE 1

REVUE DE LITTÉRATURE

1.1 Introduction

Avec l'avènement de l'Industrie 4.0, les systèmes de production évoluent vers des environnements plus connectés et automatisés. Les technologies de l'industrie 4.0, telles que les systèmes cyber-physiques, les capteurs intelligents et l'analyse des données en temps réel, offrent des opportunités significatives pour améliorer la sécurité des travailleurs (Converso et al., 2023). Ces technologies peuvent permettre une meilleure surveillance, une gestion dynamique des risques, et une optimisation des processus de maintenance, renforçant ainsi la sécurité tout en maintenant l'efficacité opérationnelle (Hadjadji et al., 2023).

Cette revue de littérature se concentre sur les différentes approches et études concernant les procédures LOTO et leur intégration dans les systèmes de production modernes. Nous examinerons les recherches sur la mise en œuvre des procédures LOTO, les enjeux de la sécurité au travail, et les innovations technologiques qui peuvent améliorer ces pratiques. La littérature existante aborde largement les méthodes traditionnelles de LOTO, mais explore également les possibilités offertes par les nouvelles technologies, telles que l'IoT et l'IA, pour optimiser la sécurité et l'efficacité des interventions de maintenance.

En examinant ces études, nous mettrons en lumière les défis actuels et les opportunités futures pour intégrer de manière plus efficace les procédures LOTO dans l’industrie manufacturière.

1.2 Le Cadenassage/Décadenassage

La mise en place d'une procédure LOTO implique plusieurs étapes clés, comme l'identification des sources d'énergie dangereuses, l'isolement des énergies, et l'utilisation de dispositifs de verrouillage et d'étiquetage. Chaque étape doit être documentée et inclure des instructions spécifiques pour chaque type de machine ou d'équipement. Par exemple, il est crucial de vérifier et de neutraliser toutes les sources d'énergie stockée, telles que l'énergie hydraulique, pneumatique, ou thermique, avant de commencer les travaux de maintenance.

Les dispositifs de verrouillage empêchent physiquement l'utilisation des machines, tandis que les étiquettes servent d'avertissements visuels indiquant que l'équipement ne doit pas être utilisé. Les employeurs doivent veiller à ce que ces dispositifs soient correctement appliqués et régulièrement inspectés pour garantir leur efficacité. De plus, les employés doivent être formés à reconnaître les sources d'énergie spécifiques et à utiliser les méthodes appropriées pour leur contrôle (OSHA, 2024).

Une procédure LOTO est un processus structuré visant à garantir la sécurité des travailleurs lors de la maintenance et de la réparation des machines. Par la suite, on nommera un membre du personnel qui exécute une procédure, cadenasseur (l’usage du masculin sera utilisé dans un souci d’allégement du texte). Voici les principales composantes d'une procédure LOTO, basée sur les recommandations de l'OSHA et les meilleures pratiques en vigueur :

1) *Préparation et planification :*

- Identification des sources d'énergie : identifier toutes les sources d'énergie (électrique, mécanique, hydraulique, pneumatique, chimique, thermique) associées aux machines ou équipements.
- Élaboration de procédures spécifiques : développer des procédures détaillées pour chaque type de machine ou d'équipement, incluant des instructions pour l'isolement et la neutralisation des sources d'énergie. Les procédures se trouvent sous la forme de fiche de cadenassage comme sur la Figure 1.1. Ces fiches indiquent les différentes consignes et étapes à suivre pour sécuriser la machine.

[redacted]

FICHE DE CADENASSAGE

[redacted]

[redacted] Transformateur du panneau S-T2HS1	Titre de la procédure **[1] CADENASSAGE COMPLET**

Emplacement: Bloc W, sous-sol, sous-station électrique 00W03

Approuvé - 2018-11-20

Préparation, avis et arrêt de l'équipement

N°	Typ. Disp.	No Dispositif	Description / Emplacement	Instruction	CAD / TEM
1	**AVISER** les employés affectés que l'équipement / la machine va être cadenassé(e).				
2	**ARRÊTER** l'équipement / la machine en suivant les procédures normales d'opération.				

Cadenassage, contrôle et vérification

N°	Typ. Disp.	No Dispositif / Énergie	Description / Emplacement	Instruction	Mecanismes		Pos. Ope.	CAD / TEM	EZ / DEC
1		[redacted] 600 Volts	Disjoncteur du transfo [redacted] et du panneau [redacted] sous-sol, sous-station électrique [redacted], panneau [redacted]	**OUVRIR "OFF"** et **CADENASSER** le disjoncteur.			Fermé (On)		
2	**VÉRIFIER** qu'il n'y a plus de **TENSION** sur les lieux des travaux avec un détecteur de tension sans contact approprié à la tension nominale du circuit.								
3	**EFFECTUER** un *ESSAI DE DÉMARRAGE* à l'aide des boutons de commande. Aucun mouvement ne doit être détecté. Attention aux interverrouillages (interlock) entre les équipements.								

Décadenassage et remise en service

N°	Typ. Disp.	No dispositif	Description / Emplacement	Instruction	Pos. Ope.	DEC / TEM
1	**VÉRIFIER** l'équipement et l'aire de travail pour s'assurer que seul le personnel autorisé demeure sur place et que tout le personnel ait quitté la zone dangereuse, que les outils et les articles non essentiels ont été enlevés et que les dispositifs de sécurité sont en place.					
2	**ENLEVER** les mécanismes de cadenassage des dispositifs d'isolation en suivant les instructions d'isolation en ordre inverse, placer les dispositifs d'isolation à leur position normale d'opération et vérifier que la zone de travail est nettoyée.					
3	**AVISER** tout le personnel pouvant être affecté par la remise en état de service de l'équipement que les mécanismes de cadenassage ont été enlevés et que l'équipement est prêt à être utilisé.					

Figure 1.1 Fiche de cadenassage typique

2) *Isolement de l'énergie :*

- Désactivation des équipements : éteindre les équipements en suivant les procédures spécifiques pour chaque type de machine.
- Isolation des sources d'énergie : utiliser des dispositifs de verrouillage pour isoler physiquement les sources d'énergie. Les dispositifs de verrouillage peuvent inclure des cadenas, des couvercles de valves, des verrous de disjoncteurs, des chaînes, etc.

3) Application des dispositifs de verrouillage et d'étiquetage :

- Verrouillage : apposer des dispositifs de verrouillage sur les sources d'énergie pour empêcher toute remise en marche des machines.
- Étiquetage : attacher des étiquettes d'avertissement indiquant que l'équipement est en cours de maintenance et ne doit pas être mis en marche. Les étiquettes doivent inclure des informations sur l'identité de la personne qui a appliqué le verrouillage et la date.

4) Vérification et neutralisation de l'énergie stockée :

- Vérification de l'isolement : vérifier que toutes les sources d'énergie ont été correctement isolées en testant les commandes de la machine.
- Neutralisation de l'énergie résiduelle : s'assurer que toute énergie stockée ou résiduelle (comme l'énergie dans les ressorts, les systèmes hydrauliques ou pneumatiques) est dissipée ou isolée.

5) Formation et communication :

- Formation des employés : former tous les employés sur les procédures LOTO, y compris les dangers liés aux sources d'énergie et les méthodes de contrôle appropriées.
- Communication : informer tous les employés concernés des travaux de maintenance en cours et des procédures LOTO appliquées.

6) Surveillance et révision :

- Inspection des procédures : effectuer des inspections régulières pour s'assurer que les procédures LOTO sont correctement suivies.
- Mise à jour des procédures : réviser et mettre à jour les procédures LOTO en fonction des changements dans les équipements ou les méthodes de travail.

Ces composantes sont essentielles pour garantir la sécurité des travailleurs et prévenir les accidents liés à la libération inattendue d'énergie dangereuse. On peut aussi représenter les procédures LOTO le long de trois phases : l'intégration à la planification manufacturière

(Badiane et al., 2016), la préparation des procédures LOTO (Dudgeon, 2014), et l'exécution de la procédure LOTO dans l'environnement manufacturier (Illankoon et al., 2019). Chaque groupe correspond à une phase du LOTO à différents échelons de l'usine. D'une vision considérant le LOTO comme un élément faisant partis d'un ensemble de processus et de décisions au niveau de l'usine, en passant par l'élaboration des procédures LOTO en tant que telles, à leur application concrète comme la pose de cadenas, chacun de des niveaux impliquent une ou plusieurs composantes. La Figure 1.2 montre les regroupements de ces composantes parmi ces phases.

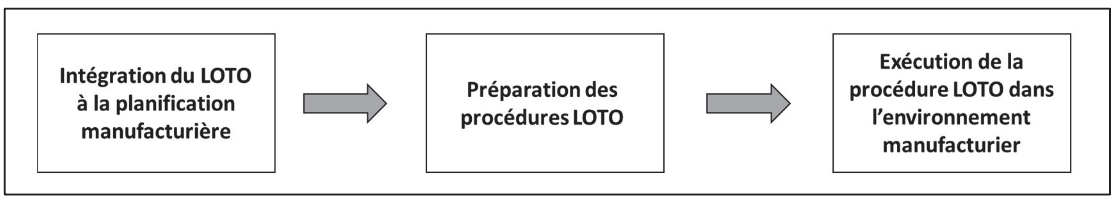

Figure 1.2 Les phases du LOTO

1.3 Enjeux des procédures LOTO et de la sécurité du travail dans le contexte manufacturier actuel

En 2021, 5,486 travailleurs ont été mortellement blessés aux États-Unis, dont 705 par « contact avec des objets et du matériel » et 798 par « exposition à des substances ou à des environnements nocifs » (U.S. Bureau of Labor Statistics, 2021). Les équipements industriels et les substances qui peuvent y circuler représentent une source majeure de blessures pour les travailleurs de certaines professions, notamment ceux impliqués dans l'installation, l'entretien et la réparation des machines, qui sont particulièrement exposés à des risques de décès par blessure (Bulzacchelli et al., 2008). Face à ces dangers, le LOTO reste aujourd'hui un des moyens les plus sûrs et à privilégier pour réduire les accidents, et ainsi indirectement contribuer à la réduction des coûts, à l'amélioration de la productivité et à l'efficacité opérationnelle accrue (Ravanbakhsh, 2024).

Une partie conséquente de la recherche sur les procédures LOTO se concentre sur les circonstances des accidents survenant malgré la mise en place de ces procédures et l'installation de mécanismes de verrouillage des équipements. Par exemple, l'accès aux zones dangereuses autour des machines doit également suivre de nombreuses recommandations, notamment l'accès alternatif à ces zones lorsque le LOTO ne peut être effectué, par exemple pour détecter des dysfonctionnements nécessitant l'observation de la machine en fonctionnement (Chinniah, Aucourt et Bourbonnière, 2015). L'efficacité de différents mécanismes de verrouillage de valves dans le cadre du LOTO et des recommandations pour améliorer ces mécanismes a par exemple été réalisée (Sotoodeh, 2024). Les pratiques LOTO pour des équipements spécifiques sont aussi étudiées et améliorées comme pour des batteries électriques (Rosewater, 2023). Les comportements des travailleurs lors des accidents ont aussi été étudiés afin de déterminer les causes comportementales. Dans le cas des électrocutions, une plus grande éducation des travailleurs lors du LOTO pourrait permettre d'éviter la majorité des accidents (Majano et Brenner, 2023). La recherche scientifique a aussi montré que des audits réguliers des processus LOTO et une évaluation régulière des travailleurs sur le sujet a un grand impact sur la réduction du nombre d'accidents impliquant des énergies (Rochman, 2023).

Une procédure LOTO ne se limite pas à l'installation d'un mécanisme. Elle exige une vérification minutieuse après sa mise en œuvre. La documentation joue un rôle essentiel dans cette procédure. Décrire les incidents survenus lors de l'installation des mécanismes LOTO permet de développer des protocoles visant à renforcer la sécurité et le contrôle du LOTO (Dewi, 2019). Cette documentation doit inclure les outils requis, les sources d'énergie dangereuses, et les étapes de déconnexion et d'étiquetage nécessaires pour garantir la sécurité des équipements (Burlet-Vienney et al., 2009). Les mécanismes LOTO présentent souvent des risques pour les travailleurs, car ils diffèrent selon les sources d'énergie, peuvent être inadaptés (Kumar et Tauseef, 2021a). Par conséquent, la supervision et la formation des opérateurs sont cruciales pour assurer une application correcte de la procédure LOTO dans une usine (Karimi et al., 2018). Enfin, il est possible de cadenasser partiellement les machines afin de maintenir la continuité de la production, c'est le LOTO opérationnel. Cela consiste à verrouiller et déverrouiller certaines énergies de manière sélective (Karimi et al., 2019).

Les procédures LOTO ont été étudiées pour leur mise en œuvre tant au niveau des mécanismes que de la documentation. Cette mise en place de procédures qui indique les mécanismes à verrouiller est très dépendant de l’humain et ne fait pas usage de nouvelles technologies. Ces dernières peuvent néanmoins tenir un rôle majeur dans la SSE de demain (Illankoon, 2020).

1.4 La SSE à l’heure de l’Industrie 4.0 et de l’Industrie 5.0

La gestion de la SSE est une approche organisée pour gérer les structures organisationnelles, les responsabilités, les politiques et les procédures de sécurité nécessaires. Il s'agit des dispositions prises par une organisation pour promouvoir une solide culture de sûreté et atteindre de bonnes performances en matière de sûreté. Elle est liée à la prise de décision, à la planification, à l'organisation et au contrôle pour atteindre les objectifs de sécurité. Elle utilise des principes, des méthodes et des moyens de sécurité pour analyser et étudier divers facteurs dangereux, et adopte en outre des mesures efficaces en termes de technologie, d'organisation et de gestion, pour résoudre et éliminer ces facteurs et prévenir les incidents.

Les composantes de la gestion de la sécurité comprennent la politique de sécurité et la formation à la sécurité (Amyotte et al., 2007). La politique de sécurité couvre les ressources et les responsabilités en matière de sécurité, l'identification et l'atténuation des risques, les normes et procédures et la conception de systèmes basés sur les facteurs humains. La formation à la sécurité concerne la surveillance des performances de sécurité, le signalement et les enquêtes sur les incidents, l'audit, l'amélioration continue et la gestion du changement. La gestion de la sécurité affecte positivement les performances de sécurité (taux d'accidents), la compétitivité de l'entreprise et la performance économique (Blanco-Novoa et al., 2018).

L'Industrie 4.0, également connue sous le nom de quatrième révolution industrielle, représente une transformation profonde des processus industriels grâce à l'automatisation, la numérisation et l'utilisation des données pour améliorer l'efficacité et la qualité de la production (Da Silva et al., 2020). Cette révolution englobe des technologies avancées telles que l'intelligence artificielle (IA), l'Internet des objets (IoT), le cloud computing et les systèmes cyber-physiques, qui forment ensemble la base des usines intelligentes (Udvaros et al., 2023). L'intégration de ces technologies s'étend au-delà de la fabrication à toute la chaîne de valeur, des fournisseurs aux clients, favorisant des produits et des processus innovants (Zalozhnev et Ginz, 2023).

Les tendances récentes en matière de gestion de la Sécurité, Santé et Environnement (SSE) dans l'industrie sont largement influencées par les avancées technologiques. L'intégration des technologies révèle l'importance croissante de ces outils pour améliorer la gestion SSE, permettant un suivi intelligent du personnel et aidant à détecter précocement les dangers sur le lieu de travail, créant ainsi un environnement plus sûr grâce à une collecte de données agile et automatisée (Tawfeeq, Thiruchelvam et Abidin, 2024).

L'intelligence artificielle (IA) joue également un rôle crucial dans la gestion SSE, avec un assistant IA capable de fournir des réponses instantanées à diverses questions réglementaires. Cet outil utilise les dernières technologies de traitement du langage naturel pour extraire des données réglementaires à jour, le rendant ainsi beaucoup plus efficace que les moteurs de recherche traditionnels (Hojageldiyev, 2018). L'IA joue un rôle de plus en plus important la gestion des risques en matière de santé et de sécurité au travail dans les secteurs à haut risque tels que la construction, les mines et le pétrole et gaz. Des capteurs peuvent être attachés aux équipements de protection individuelle ou aux équipements pour permettre la collecte de données. Ces données vont être analysées par l'IA et fournir des retours aux travailleurs pour des comportements appropriés aux situation en temps réels, y compris pendant les opérations LOTO (Tang, 2024).

Dans le cadre de l'Industrie 4.0, de nouveaux défis et innovations en matière de sécurité sont explorés, soulignant l'importance des modèles de sécurité pour identifier les problèmes liés à la mise en œuvre et à l'évaluation des systèmes de sécurité industrielle. Des algorithmes d'apprentissage machine sont utilisés pour classifier les risques industriels (Di Nardo et al., 2023).

Le développement récent de technologies comme l'Internet des objets (IoT), les systèmes cyber-physiques (CPS), le cloud computing et les capteurs intelligents a initié de nombreuses applications à la gestion de la sécurité. Une étude a révélé que diverses technologies d'automatisation sont adoptées dans les usines intelligentes pour une meilleure gestion de la sécurité (Podgórski et al., 2017). De plus, l'importance de développer des robots soucieux de la sécurité, capables de reconnaître les actions susceptibles de blesser les travailleurs, est soulignée (Beetz et al., 2015). Les technologies de l'information et les communications sans fil jouent un rôle crucial dans la détection continue et efficace des dangers sur le lieu de travail (Gisbert et al., 2014). En outre, l'IoT est examiné pour son potentiel à améliorer les processus de sécurité et l'efficacité des sites de travail. Bien que les données et les analyses en temps réel améliorent la productivité organisationnelle et la conformité, l'accent est mis sur l'amélioration de la sécurité des travailleurs individuels plutôt que sur une réorganisation complète de la SSE au niveau organisationnel (Stinson, 2022).

De plus, l'utilisation des équipements de protection individuelle (EPI) (Shpilevoy et al., 2013) intelligents est mise en avant pour améliorer la sécurité du personnel. Ces EPI, équipés de technologies sans fil et de textiles intelligents, augmentent la sécurité individuelle sans nécessairement transformer les structures SSE au sein des organisations (Ledda et Palomba, 2020).

Plus récemment, la transition vers l'Industrie 4.0 est complétée par l'émergence de l'Industrie 5.0, qui se concentre sur la création d'un environnement industriel centré sur l'humain et durable (Gródek-Szostak et al., 2023). En effet, l'Industrie 5.0 marque une évolution par rapport à l'Industrie 4.0 en intégrant des technologies émergentes telles que l'intelligence artificielle, l'internet des objets (IoT), la réalité virtuelle et les cobots, tout en plaçant l'humain au centre de ce processus (Delbari et Hof, 2024). La réalité virtuelle peut aussi jouer un rôle très important pour former des électriciens à faire aux dangers, y compris en les formant à réaliser les opérations de cadenassage (Stefan et al., 2024). L'objectif est de créer des systèmes résilients et durables qui respectent les limites de la planète et améliorent le bien-être des travailleurs dans l'industrie manufacturière (Mert, Akkaya et Andreea, 2023). En Croatie, une étude a révélé que bien que la sensibilisation à l'Industrie 5.0 soit faible, il existe une ouverture accrue vers l'intégration des éléments verts plutôt que numériques dans les activités logistiques (Trstenjak et al., 2023). En Europe, l'Industrie 5.0 est perçue comme un complément à l'Industrie 4.0, visant à rendre l'industrie plus durable et centrée sur l'humain (Gródek-Szostak et al., 2023). Une analyse bibliométrique a montré une augmentation significative des publications et des citations sur l'Industrie 5.0, soulignant l'intérêt croissant pour ce domaine et l'importance de facteurs tels que la durabilité et la résilience (Madsen, Berg et Di Nardo, 2023). En Indonésie, l'Industrie 5.0 impacte l'économie en intégrant des technologies avancées pour améliorer l'efficacité des systèmes de production, bien que des défis subsistent en termes d'infrastructure numérique et de compétences de la main-d'œuvre (Nugroho, Amarco et Yasin, 2023).

Cette nouvelle révolution industrielle place la sécurité, la santé et l'environnement (SSE) au cœur de ses préoccupations, en améliorant les conditions de travail et en réduisant les risques professionnels (Kim et al., 2024). Par exemple, une étude propose un modèle stratégique pour déployer des politiques de sécurité et de santé au travail alignées sur les objectifs de développement durable de l'ONU, soulignant l'importance d'une approche intégrée pour gérer les risques dans les systèmes sociotechniques complexes (Ávila-Gutiérrez, Suarez-Fernandez de Miranda et Aguayo-González, 2022). De plus, l'Industrie 5.0 favorise la coopération entre les humains et les machines intelligentes, ce qui non seulement augmente l'efficacité et la productivité, mais améliore également la sécurité en éliminant les tâches dangereuses pour les travailleurs (Mert, Akkaya et Andreea, 2023). En outre, l'accent mis sur la durabilité environnementale, avec des technologies visant à réduire les déchets et à optimiser la gestion des ressources, montre un engagement fort envers la protection de l'environnement (Agote Garrido, Martín-Gómez et Lama-Ruiz, 2023).

Ainsi ces études proposent l'utilisation de nouvelles technologies pour améliorer les pratiques de gestion SSE dans le cadre de l’Industrie 4.0 et plus récemment de l’Industrie 5.0. Cependant, ces technologies visent principalement à renforcer la sécurité des travailleurs individuellement plutôt qu'à modifier en profondeur l'organisation SSE. Par la suite, nous allons donc ainsi voir comment il est possible d’intégrer la gestion du LOTO plus en profondeur dans la gestion des systèmes manufacturiers.

1.5 Intégration des procédures LOTO aux politiques de production et de maintenance

Les problématiques liées au LOTO vont bien au-delà des simples questions de sécurité et d'isolation des énergies. Elles concernent également l'élaboration de procédures claires et précises, ainsi que la bonne interaction entre l'opérateur et la machine en maintenance. Dans les milieux manufacturiers, les entreprises cherchent à réduire leurs coûts pour maximiser leurs profits. Les opérations de maintenance se déroulent entre les périodes de production, avec des demandes clients variables, des pannes aléatoires, des niveaux de stocks fluctuants et des fournisseurs dont la fiabilité n'est pas toujours parfaite. Les machines opèrent donc dans un environnement complexe où la prise en compte de tous ces aspects permettrait d'optimiser les politiques de production et de maintenance, mais aussi de LOTO.

De nombreux auteurs se sont appuyés sur les travaux pionniers de Rishel (1975) pour aborder les problèmes de planification de la production dans les systèmes de fabrication. Ces auteurs ont utilisé un modèle où les défaillances et les réparations sont représentées par un processus de Markov homogène. Cependant, cette approche rencontre une difficulté majeure : le manque de méthodes numériques efficaces pour résoudre les équations de Hamilton-Jacobi-Bellman (HJB) qui en découlent (Gershwin, 1994). La planification de la production et de la maintenance est un sujet récurrent dans la littérature, car ces deux aspects sont intrinsèquement liés et leur optimisation conjointe peut améliorer significativement les performances de fabrication. Par exemple, Zied, Sofiene et Nidhal (2014) ont analysé un plan de production optimal et un calendrier de maintenance préventive en tenant compte d'une demande de produits aléatoire à satisfaire avec un niveau de service requis. L’aspect qualité a aussi été considéré dans ces plans de maintenance. Nourelfath, Nahas et Ben-Daya (2016) ont exploré l'intégration de la maintenance préventive et de la planification de la production dans le contexte de la production défectueuse, proposant une inspection et une maintenance préventive périodiques pour remettre à neuf la machine en fonction du niveau de maintenance effectué.

Plus récemment, une autre approche d'optimisation basée sur la simulation pour le contrôle conjoint de la production, de la maintenance préventive et du plan d'échantillonnage de la qualité a été proposée (Rivera-Gómez et al., 2020). Les aléas météorologiques, très variables et difficile à prévoir, ont aussi pu être considérés dans des approches probabilistes de planification de la production et de la maintenance pour répondre aux défis et aux incertitudes uniques des parcs éoliens en mer (Papadopoulos, Coit et Aziz Ezzat, 2024), soulignant les efforts de la recherche pour fournir des modèles de plus en plus robustes. Des modèles d’optimisation conjointe pour des systèmes de productions flexibles avec des changements à haute-fréquence de produits fabriqués ont aussi été conçue en s'appuyant sur des algorithmes méta-heuristiques hybrides. Ces algorithmes mêlent algorithmie génétique, optimisation par colonies de fourmis ou la recherche de voisinage variable (Wang et al., 2024). Pour les machines ayant un rendement aléatoire et des délais de maintenance variables, il est possible de formuler le problème dans un cadre de processus de décision markovien. Des plans de maintenance conditionnelle peuvent être déterminés après avoir trouvé un optimal par méthode d'apprentissage par renforcement (Zhang et al., 2024). Des modèles plus précis pour simuler la détérioration des machines ont été proposée et intégrer dans des problèmes d'optimisation. Ces problèmes de planification des activités de maintenance en fonction de l'état réel de la machine peuvent être maintenant résolu dans des temps de calculs raisonnables (Briskorn, Gönsch et Thiemeyer, 2024).

Comme le révèlent les articles présentés, les chercheurs ont examiné l'interaction entre la production et la maintenance sous divers angles. Toutefois, l'impact du LOTO sur ces aspects de l'industrie manufacturière a été largement ignoré à part dans quelques rares travaux. Le premier de ces travaux a exploré le contrôle de la production pour un système de fabrication sujet à des défaillances et des réparations aléatoires. L'objectif était de déterminer les taux de production, de maintenance préventive considérant le LOTO pour minimiser les coûts d'exploitation, les coûts de pénurie, les coûts d'inventaire, ainsi que les coûts de maintenance et de réparation (Charlot, Kenné et Nadeau, 2007). Ces fondations ont été approfondies, augmentant la complexité du système de fabrication étudié. Une analyse a été menée sur la planification optimale de la production et de la maintenance préventive avec LOTO pour un système de fabrication. Ce modèle considère simultanément les activités de maintenance préventive avec LOTO et les erreurs humaines (Emami-Mehrgani, Nadeau et Kenné, 2014). L'optimisation de la production nécessite une révision des politiques de maintenance des installations. Une stratégie de production intégrant le LOTO, tout en maximisant la disponibilité du système de fabrication et en minimisant les coûts, a été proposée (Badiane et al., 2016). De plus, une politique de contrôle optimale, prenant en compte le LOTO dans les opérations de maintenance corrective et les erreurs humaines, a été développée (Diop, Nadeau et Emami-Mehrgani, 2019).

Les différents articles cités présentent des politiques optimales de production, de maintenance et de LOTO conjointes. Les processus de LOTO sont ainsi intégrés dans l'ensemble de l'environnement manufacturier dans lesquels ils sont appliqués. Cette optimisation ayant pour but la minimisation des coûts, une telle approche de l'intégration du cadenassage dans les politiques de maintenance et de réparation a pour avantage d'encourager les industriels à mettre en place ce type de méthode tout en ayant moins de crainte de diminuer leurs profits.

Néanmoins, les aspects de cadenassage opérationnel, c'est-à-dire un cadenassage simplifié permettant la continuité de la production (Chinniah, Aucourt et Bourbonnière, 2015), ne sont pas considérés. Il s'agirait pourtant d'un moyen de diminuer les coûts liés au LOTO. Enfin, les systèmes manufacturiers étudiés sont relativement simples et ne considèrent que quelques machines dans quelques états possibles. Des modèles prenant en compte des contextes manufacturiers complexes ne pourraient pas être résolus dans des temps raisonnables avec les méthodes numériques utilisées. Il faudrait alors se tourner vers de nouvelles méthodes de résolution comme les méthodes de l'apprentissage machine. Enfin, aucun aspect de l'Industrie 4.0, des technologies avancées, des intelligences artificielles ou des interactions humain-machine n'est abordé dans ces articles. Or le LOTO ainsi que la sécurité du travail en général peuvent profiter de ces nouvelles technologies pour être plus performantes. Il serait ainsi pertinent d'étudier l'intérêt de ces technologies, en particulier les modèle d'apprentissage machine et d'apprentissage profond.

1.6 Intérêt de l'apprentissage machine et de l'apprentissage profond dans l'amélioration des procédures LOTO

Nous avons vu que le LOTO est un processus ancien, se basant sur la manutention des opérateurs et des mécanismes anciens comme de simples cadenas et des fiches papier. Les récentes avancées dans les domaines de l'intelligence artificielle (IA) et de l'apprentissage machine (Machine Learning - ML) ont affecté plusieurs domaines de recherche, conduisant à des améliorations qui n'auraient pas été possibles avec les techniques d'optimisation classiques. Parmi les secteurs où l'IA/ML permet une pléthore d'opportunités, l'industrie manufacturière peut s'attendre à des gains importants grâce à l'automatisation accrue des processus. Comme les autres domaines de l’industrie, ces nouvelles technologies pourront servir à améliorer le LOTO et la sécurité au travail. Ces améliorations sont rendues possibles grâce à l’amélioration des prédictions et quelques applications concrètes des IA et de ML.

Il existe d'importantes contributions dans le domaine de l'intelligence artificielle et de ses techniques telles que le raisonnement à base de cas (Baruque et al., 2010) et les algorithmes d'apprentissage automatique, afin de faire des prédictions, d'améliorer les résultats et de mieux généraliser les ensembles de données. Il est donc nécessaire de construire des modèles qui facilitent la prédiction et l'analyse pour prendre des décisions (Fyfe et Corchado Rodríguez, 2002).

Au cours des dernières décennies, l'IA et les techniques de ML ont transcendé une grande variété de domaines tels que les activités scientifiques, la santé (Glez-Peña et al., 2009), l'industrie et l'économie, et un grand nombre de travaux scientifiques ont été publiés sur ce sujet, révélant son importance (Alvarado-Pérez, Peluffo-Ordónez et Therón-Sánchez, 2015). En outre, comme montré sur la Figure 1.3 (Angelopoulos et al., 2019), les principaux types d'apprentissage machine se distinguent comme suit (Bonaccorso, 2018) :

- Le ML supervisé "suppose que les exemples d'apprentissage sont classifiés" (c'est-à-dire qu'il existe une relation d'apprentissage entre un ensemble de caractéristiques descriptives et une caractéristique cible),
- Le ML non supervisé "concerne l'analyse d'exemples non classifiés”.
- Le ML de renforcement utilise différents scénarios pour découvrir l'action la mieux récompensée dans un processus d'essais et d'erreurs en recueillant les réactions de l'environnement.
- L'apprentissage profond (Deep Learning – DL), souvent considéré comme un groupe distinct du ML, où plusieurs couches sont employées afin de construire un réseau de neurones artificiels, capable de prendre des décisions intelligentes en traitant de grandes quantités de données avec une grande complexité, sans aucune intervention humaine (Romero et al., 2016).

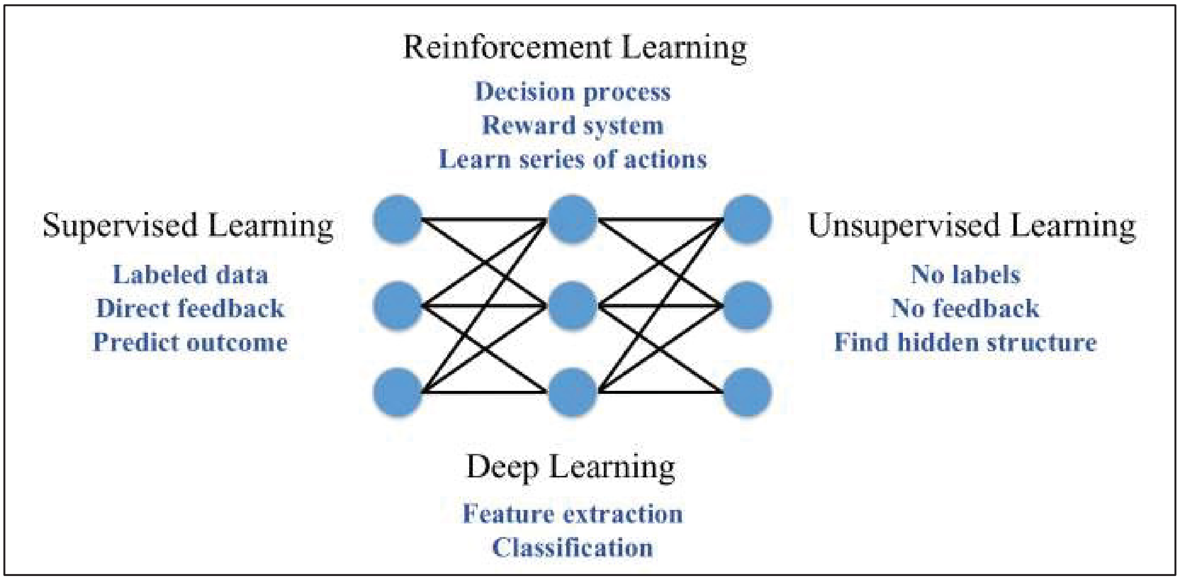

Figure 1.3 Les principaux types d'apprentissage machine
Tiré de Angelopoulos et al. (2019, p.3)

Dans un environnement réel actuel, un ensemble de données doit être obtenu avant que les techniques de ML puissent être appliquées (Corchado et al., 2005 & Yáñez, 2005). Elles passent ensuite par différentes phases, telles qu'un prétraitement, l'entraînement des données et l'application d'un modèle d'apprentissage et enfin une phase d'évaluation. À partir de la description faite dans (Zhou et al., 2017), un schéma des étapes du ML a été conçu. Dans la Figure 1.4, elles sont décrites dans l'ordre dans lequel elles sont réalisées. Le prétraitement des données est effectué afin de préparer les données brutes. À ce stade, les données sont non structurées, incomplètes et incohérentes, et elles sont transformées pour être utilisées comme entrées pour les algorithmes sélectionnés pour l'entraînement. Par la suite, les données de test seront utilisées pour entraîner le modèle développé, et les prédictions qui sont extraites du nouvel ensemble de données de test seront également obtenues.

Pour évaluer le modèle, les données d'estimation des erreurs et les résultats des tests statistiques sont analysés, ces analyses sont utilisées pour ajuster les paramètres des algorithmes appliqués et pour déterminer si l'utilisation d'autres algorithmes est nécessaire (Japkowicz et Shah, 2011). Ainsi, les méthodes de ML pour la classification, la formation et la prédiction fourniront les bases pour le développement d'algorithmes qui génèrent des modèles prédictifs adaptés aux organisations, dans le contexte de l'Industrie 4.0 (Candanedo et al., 2018).

Les algorithmes de ML offrent de nombreuses possibilités pour l'industrie manufacturière intelligente, comme le montrent de nombreuses recherches (Rai et al., 2021). Dans l'industrie manufacturière, le ML est utilisé pour des applications de sécurité telles que pour surveiller la dégradation des matériaux due à la corrosion (Hakimian, Pourrahimi et Hof, 2022), ainsi que la détection des fuites ou des incendies sur les équipements (Sankarasubramanian, 2023). Le ML permet également de déterminer et de quantifier les causes des risques d'accidents majeurs dans des industries comme le secteur pétrolier offshore (Zhen et al., 2023), et d'identifier des risques spécifiques tels que les chutes de travailleurs en hauteur (Zermane et al., 2023). Grâce à ces capacités, les algorithmes de ML peuvent être utilisés pour élaborer des politiques efficaces de prévention, de maintenance et de formation dans le secteur manufacturier.

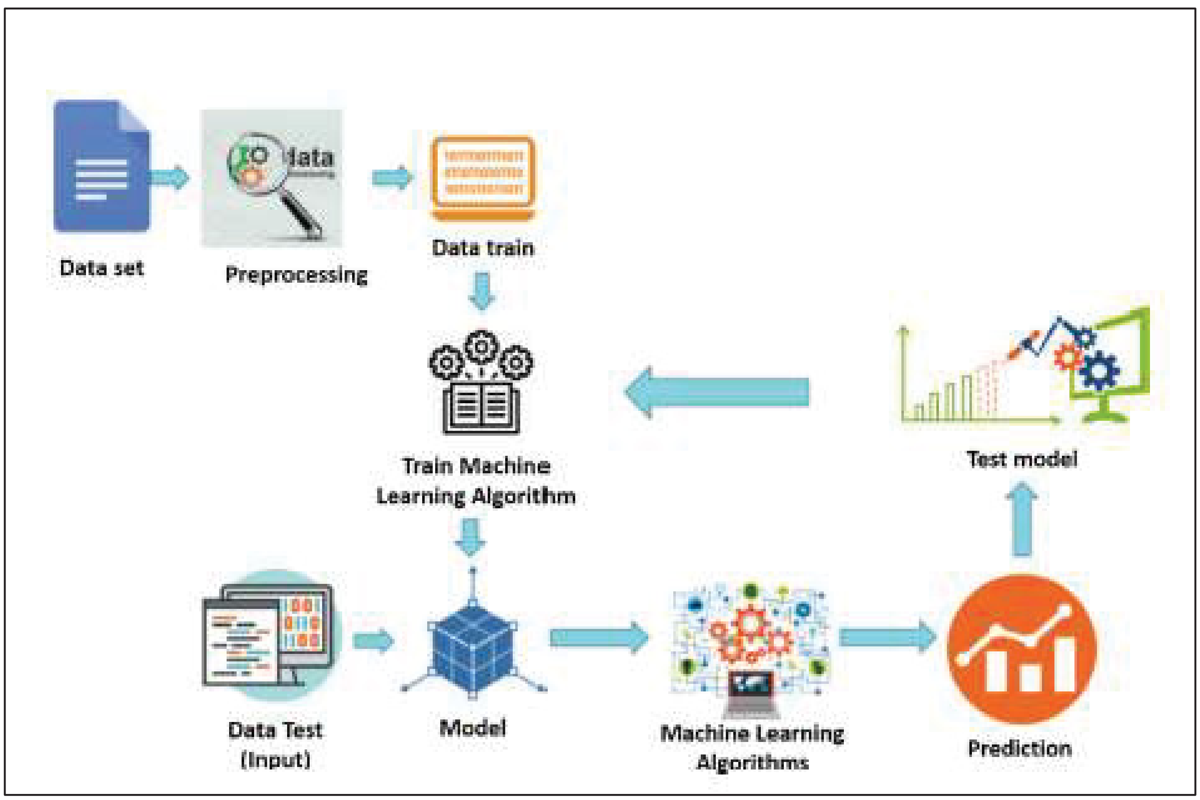

Figure 1.4 Étapes de l'apprentissage machine
Tiré de Candanedo et al. (2018, p.504)

Enfin le ML pourrait soutenir la rédaction et la validation des protocoles d'isolation énergétique pour l'arrêt des équipements avant la maintenance par l’analyse des fiches LOTO existantes, c'est-à-dire de documents techniques textuels. En analysant les fiches LOTO existantes, qui sont des documents techniques textuels, le ML pourrait identifier les informations clés et les organiser dans un format standardisé utilisable par toutes les entreprises manufacturières, facilitant ainsi une prise de décision coopérative et collaborative (Ittoo, Nguyen et van den Bosch, 2016). Le minage de texte, une technologie conçue pour résoudre ce problème (Jo, 2019a). En effet, cette technologie consiste à utiliser des algorithmes dit de traitement du langage naturel (NLP) qui peuvent traiter et un document textuel comme séparer les mots d’un texte ou comparer la similarité des mots d’un document avec ceux d’un dictionnaire (Qiu et al., 2020). Une fois ce traitement réaliser, il est possible de convertir le texte non structuré des documents originels en et des bases données structurées, gérable par les ML ou le DL.

Nous avons donc vu les différentes méthodes de ML et de DL, ainsi que de possibles applications pour les procédures LOTO. La rédaction des procédures, si chronophage en temps normal, pourrait être assister par ML et DL. Néanmoins, les intérêts de ces technologies se portent avant tout sur la préparation de la procédure en tant que texte, mais la réalité de l’environnement manufacturier n’est pas prise en compte. Il serait intéressant de se pencher vers les nouvelles méthodes de production intelligentes afin de voir lesquelles pourraient être applicables au LOTO.

1.7 Vers des procédures LOTO plus intelligentes inspiré de méthodes de production

Nous allons maintenant passer en revue la littérature sur les contrôles intelligents de la production sous différentes approches. Ces approches donnent des pistes de recherche intéressantes pour améliorer les procédures LOTO. Dans un premier temps, nous verrons comment différents aspects de la planification de la production peuvent être améliorés avec des méthodes intelligentes.

La planification de la production repose fortement sur les problèmes d'ordonnancement. Pour faire face aux imprévus et aux perturbations comme les variations de la demande, les pannes de machines et les pénuries de matières premières, diverses stratégies ont été développées (Berger et al., 2019). Par exemple, certains systèmes peuvent choisir de traiter une pièce avec un équipement disponible ou de réorganiser l'ordre de fabrication si l'équipement suivant est en panne (Lanza, Stricker et Moser, 2013). Ces ajustements peuvent être appliqués à un seul ou à plusieurs sites de production, ce qui aide à atténuer l'impact des perturbations sur la productivité et les retards. En outre, l'ordonnancement dynamique représente une approche encore plus réactive. En utilisant les données de fabrication en temps réel, il est possible de modifier le planning de production pour répondre précisément aux besoins en ressources pour chaque commande, tout en tenant compte des perturbations en cours (Xu et Chen, 2016). Cette méthode offre une flexibilité exceptionnelle, permettant aux systèmes de production de s'adapter rapidement aux changements et aux imprévus, garantissant ainsi une efficacité opérationnelle optimale.

Des modèles d'optimisation qui créent des plannings de production changeant selon l'état des ressources ont été développés. Les données en temps réels alimentent une simulation qui optimise l'utilisation des ressources (Zhou, Nie et Liu, 2024). Ces données en temps réels peuvent être récupérées par des CPS (Asadzadeh, 2015). D'autres modèles permettent de suivre le processus de fabrication en temps réels pour minimiser les temps d'attente et de préparation entre les stations (Lin et al., 2018). Des plans qui reprogramment uniquement les tâches en attente au moment où les perturbations sont détectées existent aussi (Mourtzis et Vlachou, 2018). Enfin, il existe aussi des modèles qui équilibrent la charge de travail et la capacité de chaque poste en fonction des délais de livraisons des commandes (Grundstein, Freitag et Scholz-Reiter, 2017). Les lignes de production des systèmes de production intelligents peuvent être aussi reconfigurables pour optimiser l'utilisation des ressources selon les commandes (Erol et al., 2016). Certaines modélisations de l'allocation des ressources permettent de reconfigurer les usines lorsque des perturbations au niveau des ressources internes ou externes apparaissent (Kubo et al., 2016).

Un autre aspect du contrôle intelligent de la production étudié dans la littérature est le soutien à la prise de décision. Ce soutien peut être effectué par un système autonome de répartition des commandes à l'aide de CPS et de l'apprentissage par renforcement (Kuhnle, Röhrig et Lanza, 2019). La décision dépend des taux de production et des éventuels retards. Dans les systèmes de production intelligents, la prise de décision est décentralisée et peut se faire localement en prenant en compte les disponibilités des ressources (Lachenmaier, Lasi et Kemper, 2017). Ces prises de décisions décentralisées peuvent être réalisées grâce à des CPS (Gräler et Pöhler, 2018). La simulation et la réalité virtuelle peuvent aussi aider la prise de décisions lorsqu'il y a des perturbations en permettant d'évaluer l'utilisation des ressources en capacités limitées (Wandt, Friedewald et Lödding, 2012).

Ainsi des technologies comme les CPS ou la réalité virtuelle sont des outils qui peuvent permettre de mettre en place des politiques de production plus intelligentes. Une analyse plus complète de l'impact des technologies de l'Industrie 4.0 peut être faite.

Tout d'abord, les CPS sont un des piliers du contrôle intelligent de la production afin de collecter les données des processus de production (Georgiadis et Michaloudis, 2012 ; Mourtzis et Vlachou, 2018). Les informations récoltées peuvent être les temps de cycle entre chaque station, les temps d'inactivités des équipements, l'état des ressources, le niveau de charge des machines (Biesinger et al., 2019). Les CPS peuvent être utilisés pour choisir le meilleur équipement. En effet, les travailleurs peuvent indiquer au CPS s'ils peuvent ou non réaliser la tâche prévue. Le CPS va alors réadapter la planification (Graessler et Poehler, 2017). Les CPS peuvent aussi jouer un rôle dès la phase de conception en déterminant les ressources nécessaires pour une tâche précise (Illmer et Vielhaber, 2018). Les CPS pourraient aussi avoir un rôle déterminant dans les simulations des processus de production en recueillant des informations sur les perturbations en temps réels (Lachenmaier, Lasi et Kemper, 2017).

L'Industrie 4.0 et les jumeaux numériques réunissent de nouvelles technologies qui augmentent la productivité de la fabrication (Amadi-Echendu et de Smidt, 2015). En effet, le contrôle des processus de production devient rapidement un élément clé des opérations de fabrication intelligente en évaluant les différents plans d'action et en changeant les paramètres alignés sur une mission (Cardillo Albarrán et al., 2021). Une autre technologie centrale de l'Industrie 4.0 qui se couple très bien aux CPS est l'IoT. Des produits intelligents qui échangent des informations avec les systèmes de production intelligents permettent de coordonner la production, l'approvisionnement et les livraisons des clients (Saif et al., 2019 ; Meyer, Wortmann et Szirbik, 2011). Par exemple, un produit capable de communiquer son numéro de commande pourrait avertir les travailleurs en cas de problèmes et de retard dans la production (Engelhardt et Reinhart, 2012). Ce même principe pourrait s'appliquer à des procédures LOTO.

L'IoT peut aussi permettre de surveiller les ressources des partenaires industriels d'une compagnie et d'informer cette dernière en temps réel de l'état de ces ressources (Shamsuzzoha et al., 2016). L'intégration des technologies de l'IoT pourrait considérablement améliorer ces procédures en permettant un verrouillage à distance et une surveillance accrue pendant les opérations de maintenance, comblant ainsi les lacunes laissées par les méthodes manuelles et permettant de réduire le trajet des cadenasseurs (Kumar et Tauseef, 2021b). Les innovations récentes brevetées offrent des solutions prometteuses, telles que les dispositifs LOTO électroniques contrôlés par l'IoT et ceux nécessitant plusieurs authentifications pour être déverrouillés, améliorant ainsi la sécurité globale (Douglass et al., 2020).

L'informatique en nuage est une autre technologie qui peut aider à la planification. En effet, elle offre de nouvelles possibilités aux entreprises pour utiliser des logiciels proposés en tant que service qui aident à la planification et au contrôle intelligent de la production (Erol et Sihn, 2017). De plus, la technologie cloud permet de surveiller chaque poste de fabrication en temps réel afin de coordonner les tâches (Helo, Phuong et Hao, 2019). Les plateformes cloud permettent aussi de coordonner différents fournisseurs avec une entreprise (Um, Choi et Stroud, 2014). La Big Data peut aussi offrir des possibilités pour planifier intelligemment la production. En effet, des modèles de simulation par événements discret (DES) peuvent être alimentés par des données sur le produit, les étapes de traitement, les niveaux de stock et les ressources disponibles en entrée du modèle (Li, Yi et Xing, 2023). Enfin, la réalité virtuelle peut aussi avoir ses utilités pour le contrôle intelligent de la production. Elle peut être utilisée pour évaluer la géométrie des pièces avant l'assemblage et ainsi permettre de valider les plans de production, y compris en simulant des perturbations (Wandt, Friedewald et Lödding, 2012).

Les systèmes multi-agents et les algorithmes de ML augmentent la précision des prédictions des temps d'exploitation (Talmale et Shrawankar, 2021b) et facilitent l'optimisation dynamique des plannings de production (Gao, Popowski et Boerkoel, 2020). Des modèles de planification de la production s'adaptant en temps réels aux temps d'attente des clients afin de conserver une satisfaction de leur part ont été développée. Cette approche se repose sur de la programmation dynamique stochastique (Mahes et al., 2024). La littérature scientifique s'intéresse maintenant à prédire les imprévus pour s'adapter dynamiquement aux adaptations que doit suivre la production. Des modèles prédictifs-réactifs (Takeda-Berger et Frazzon, 2024) et pro-actifs (Fathollahi-Fard, Woodward et Akhrif, 2024) réactifs cherchant à minimiser les temps globaux de production sont ainsi développés.

Les algorithmes de ML couplé à des approches basées sur des chaînes de Markov permettent maintenant de planifier la maintenance de manière opportuniste basée sur les évènements aléatoires et la prédiction des bris. Le but étant ici de minimiser les coûts de maintenance (Su et Wu, 2024). Cette planification dynamique de la production peut aussi utiliser des algorithmes de DL afin de prédire les événements aléatoires et ainsi réduire les incertitudes sur la production (Tseremoglou et Santos, 2024). La planification dynamique est renforcée par l'IoT qui permet la collecte des données de production. Ces données, une fois analysée, peuvent permettre de prédire les besoins et les ajustements des opérations en temps réel (Kwon et al., 2023). De même, dans une usine, l'utilisation de systèmes de collecte de données en temps réel via des plateformes de transmission sans fil permet de surveiller et de gérer la consommation d'énergie (Nouinou et al., 2023).

Ainsi, le LOTO pourrait lui aussi bénéficier de ces méthodes de planification dynamique et des technologies qui permettent la mise en place de celles-ci. Des opérations de verrouillage des dispositifs s'adaptant en temps réel permettraient de réduire le temps de sécurisation en fonction des évènements aléatoires se produisant dans l’usine. Néanmoins, le test de ces méthodes en conditions réelles est difficile car le LOTO, concernant la sécurité des travailleurs, est un élément critique pour lequel il est difficile des tester de nouvelles façons de faire (Illankoon, 2020).

Bien que les méthodes intelligentes soient largement appliquées à la planification de la production, elles ne sont pas encore couramment utilisées pour le LOTO. Cela s'explique par la nature critique de la sécurité du LOTO, qui impose des normes rigoureuses et des protocoles manuels pour garantir la sécurité des travailleurs. Cependant, l'intégration de technologies telle que l'IoT pourrait considérablement améliorer ces procédures en offrant un accès autorisé et une surveillance accrue pendant les opérations de maintenance, réduisant ainsi les risques d'erreurs humaines et augmentant la réactivité face aux imprévus. Par exemple, des dispositifs LOTO électroniques contrôlés par l'IoT, nécessitant plusieurs authentifications pour être déverrouillés, pourraient renforcer la sécurité globale. De plus, la collecte et l'analyse en temps réel des données de maintenance permettraient d'optimiser la planification et de mieux gérer les ressources nécessaires pour chaque intervention. Ces technologies permettraient une surveillance en temps réel, une gestion dynamique des ressources et une réponse rapide aux imprévus, ce qui comblerait les lacunes des méthodes manuelles actuelles. Par exemple, les dispositifs LOTO électroniques contrôlés par l'IoT pourraient autoriser un accès sécurisé et surveiller les opérations de maintenance, tandis que les algorithmes de ML pourraient optimiser la planification des tâches en fonction de l’avancement du LOTO. En appliquant ces méthodes intelligentes au LOTO, on pourrait non seulement améliorer l'efficacité des procédures de sécurité mais aussi anticiper et résoudre les problèmes plus rapidement, comblant ainsi les lacunes laissées par les méthodes traditionnelles.

1.8 Conclusion

L'examen de la littérature révèle plusieurs lacunes importantes dans les études actuelles concernant l'intégration des procédures LOTO et la gestion de la sécurité dans les systèmes de production modernes. Les études récentes se concentrent principalement sur l'adoption de nouvelles technologies pour la production, la maintenance, la planification dans le cadre de l'Industrie 4.0. Mais ces études négligent souvent l'intégration directe de ces technologies dans les systèmes de gestion de la sécurité, dont fait le partie le LOTO. Par exemple, bien que les technologies comme l'IoT et l'IA soient explorées pour améliorer la productivité et la qualité, leur application directe pour la sécurité n'est pas suffisamment développée. Par ailleurs, les aspects d'Industrie 4.0, des technologies avancées, de l'IA ou des interactions humain-machine ne sont pas suffisamment abordés. Ainsi, la documentation et la mise en œuvre des procédures LOTO reposent encore largement sur des méthodes manuelles et traditionnelles, sans faire usage des nouvelles technologies disponibles. Les méthodes de LOTO opérationnel, qui permettraient une continuité de la production tout en maintenant la sécurité, ne sont pas considérées, elles non plus.

Pour combler ces lacunes, plusieurs directions de recherche futures s'inscrivant dans les contextes d'Industrie 4.0 et Industrie 5.0 peuvent être envisagées. En effet, l'intégration de technologies avancées telles que l'IoT, l'IA, les CPS ou le ML dans les procédures LOTO semblent prometteuses. Ces technologies devraient permettre une amélioration du LOTO à tous ces niveaux (voir Figure 1.2) : une meilleure intégration aux politiques de production et de maintenance, une meilleure préparation des procédures, et une meilleure exécution.

La littérature existante traite peu de l'impact des procédures LOTO sur les politiques de production et de maintenance. La plupart des recherches se concentrent sur l'optimisation de la production et de la maintenance sans intégrer les processus LOTO, qui sont pourtant essentiels pour garantir la sécurité des opérations de maintenance. Explorer des stratégies optimales de production et de maintenance considérant le LOTO opérationnelle pour maximiser la disponibilité des systèmes semble essentiel dans une ère où les industriels cherchent à minimiser leurs coûts de production. Plus globalement, il faut développer une gestion des opérations manufacturières qui considère le LOTO non seulement comme une contrainte de sécurité, mais comme un élément à intégrer dans les politiques de production et de maintenance.

Au niveau de la préparation des procédures LOTO, il est crucial de développer des modèles mathématiques traitant de contextes manufacturiers complexes afin d'y appliquer des algorithmes de ML, de DL ou d'autres algorithmes d'optimisation. Ces algorithmes pourraient aider et automatiser la préparation du LOTO en amont des arrêts planifiés des installations industrielles pour de la maintenance.

Pour l'exécution du LOTO, l'IoT peut permettre d'optimiser la gestion des ressources matériels et humaines. En effet, l'utilisation de dispositifs LOTO électroniques contrôlés par l'IoT offre la possibilité de suivre l'avancement des verrouillages des dispositifs et pourrait permettre des verrouillages à distance. La planification dynamique joue aussi un rôle crucial pour le LOTO. Dans le cas de la production, celle-ci rend possible des ajustements rapides des plans en réponse à des environnements incertains Par exemple, L'ajout de machines ou de travailleurs au niveau des goulots d'étranglement temporaires créés par ces imprévus est une solution potentielle. Dans le cas du LOTO, les cadenasseurs pourraient alors réagir aux imprévus et adapté la procédure en conséquence. D'autres cadenasseurs pourraient venir aider là où l'exécution est ralenti. De plus, l'utilisation de la réalité virtuelle pour la formation des opérateurs au LOTO peut également aider à visualiser et à comprendre les impacts des différentes politiques de sécurité, permettant une meilleure réaction aux imprévus lors de l'exécution du LOTO.

En explorant ces différentes directions, la recherche future peut non seulement améliorer les pratiques actuelles de gestion de la sécurité. Des solutions innovantes pour améliorer le LOTO à tous ses niveaux, comblant ainsi les lacunes laissées par les méthodes traditionnelles, peuvent être proposées.

Dans la suite de cette thèse par articles, la problématique de recherche et la méthodologie qui sera suivi pour y répondre sera présentée au Chapitre 2. Des revues littératures plus spécifiques aux problèmes, méthodes, algorithmes, etc. abordés sera détaillé dans chaque articles publiés ou soumis à publication. Ces revues de littératures plus exclusives aux approches proposées dans les articles complèteront certains des aspects de cette revue générale de la littérature.

CHAPITRE 2

PROBLÉMATIQUE ET MÉTHODOLOGIE

2.1 Introduction

La revue de littérature a mis en évidence les lacunes de la littérature sur la procédure LOTO et son intégration à l'environnement manufacturier. Cette procédure utilise principalement des moyens anciens et traditionnelles et bénéficie peu des progrès technologiques récents. Ce projet de recherche visera à développer, valider et mettre en œuvre des approches et des stratégies intelligentes pour la gestion du LOTO dans des systèmes de fabrication avec les opérations de production et de maintenance à l'heure des technologies telles que l'analyse des données, l'IA et l'IoT. Au-delà de l'École de technologie supérieure, ce projet est une initiative d'acteurs industriels québécois importants tant au niveau de la sécurité que de l'industrie manufacturière. Une présentation préalable de ces compagnies est nécessaire pour bien saisir la pertinence de la problématique et des objectifs de recherche.

2.2 Partenaires industriels

CONFORMiT, le premier partenaire industriel du projet, est une entreprise québécoise située à Saguenay qui propose des solutions pour la gestion des procédures LOTO pour divers types d'industries. Initialement, CONFORMiT fournissait une expertise dans l'implémentation des programmes d'isolation d'énergie, de sécurité machine, d'analyse de risque, et d'entrée et de gestion d'espaces clos. Au fil des années, l'entreprise a mis au point une méthodologie précise de mise en œuvre de la formation, de l'analyse technique, de la conception, de la gestion des données et du changement. CONFORMiT offre des solutions de contrôle administratif qui peuvent permettre aux entreprises de gérer les risques critiques au sein de leurs opérations. Pour accomplir sa mission principale, la firme met à profit son expérience de consultation dans la conception de programmes de sécurité selon des normes telles que ANSI, CSA et OSHA; la conception et l'apport de formations; l'identification et l'étiquetage des équipements; la gestion des entrées et sorties pour les espaces confinés; l'élaboration de procédures LOTO; et la conception de calendriers d'audit de conformité.

Parmi les clients de CONFORMiT se trouve Cascades Inc., le second partenaire industriel du projet. En 1964, Cascades Inc. a été fondée pour proposer des solutions en matière d'emballage, d'hygiène et de récupération. Cependant, la mise en place de tous ces produits vient avec un nombre d'unités d'exploitation de plus en plus important et, évidemment, un nombre croissant de machines de production. En effet, Cascades Inc. a des activités en Amérique du Nord, ce qui en fait un des plus gros acteurs mondiaux en termes de solution d'emballage, d'hygiène et de récupération. Étant une société québécoise avant tout, la compagnie a ouvert plusieurs dizaines d'unités d'exploitation à travers le Canada, et notamment à Kingsey Falls, où on peut retrouver quatre usines d'emballage spécialisé, une usine d'emballage carton-caisse et une usine de papiers tissus. Cet endroit est stratégique pour faire de la R&D et de l'innovation au Québec, puisqu'il regroupe plusieurs usines permettant d'avoir un bon échantillonnage des autres usines du monde. Ainsi, un tel lieu constitue une zone d'essai pour l'innovation.

Cascades reposant sur des chaînes de production linéaires pour opérer, il est nécessaire pour eux d'en faire l'entretien afin de ne pas avoir de bris impromptus. En effet, ces bris pourraient aussi bien endommager grièvement les autres machines, qu'interrompre pendant longtemps l'unité d'exploitation, ce qui serait critique dans les deux cas. De ce fait, Cascades opère une maintenance régulière sur sa chaîne de production, ce qui peut se chiffrer à 17 500 000 $ par année en temps de production perdue et main-d'œuvre pour les usines de Kingsey Falls. Le projet proposé ici aurait donc pour but de réduire ce montant, tout en conservant un cycle de maintenance adéquat pour assurer la pérennité des équipements, en en assurant une sécurité optimale pour leurs employés.

2.3 Problématique

La revue de la littérature ainsi que les nombreux échanges avec les partenaires industriels a permis dans un premier temps d'étudier les procédures LOTO actuelles dans les industries manufacturières pour comprendre les problèmes et les limites de ce processus, identifier les pistes améliorations et définir plus concrètement les différents objectifs de recherche.

La recherche sur les politiques de production, de maintenance et de LOTO a mis en évidence un manque d'intégration en général du cadenassage et la question du LOTO opérationnel n'a pas été abordé.

L'intégration globale du LOTO dans les politiques de maintenance et de production globale n'est pas le seul aspect du LOTO qui peut être amélioré. Une fois le cadenassage prévu, les fiches de cadenassage doivent être rédigées. Cette rédaction se fait manuellement, en se basant sur les connaissances des différents superviseurs et travailleurs des usines. De même, lorsque pour des raisons pratiques, on décide de regrouper des procédures LOTO entre elles, cette fusion demande un temps de travail conséquent.

Enfin, une fois que la procédure est prête, le cadenassage peut être réalisé. Son exécution se fait dans une environnement manufacturier complexe telle que les papeteries de Cascades Inc. Les dispositifs comme les valves, les disjoncteurs, les sectionneurs, etc. devant être verrouillés sont très nombreux, connectés entre eux et parfois difficile à trouver. Des imprévus pendant les opérations de cadenassage, comme le bris d'un dispositifs énergétiques, l'oubli d'un mécanisme de verrouillage, ou bien une grande difficulté à localiser un dispositif se trouvant en hauteur parmi une multitude de tuyaux dans un environnement sale. Le cadenasseur réalisant le cadenassage est seul face à cet environnement manufacturier complexe. Un autre problème est que lorsque des opérations LOTO ont lieu simultanément, elles sont considérées indépendamment au lieu d'un tout. Ainsi, lorsque plusieurs équipes de cadenasseurs réalisent le cadenassage, chaque équipe ne prend pas en compte les trajets des autres. Ce point ralenti grandement le temps nécessaire pour terminer le LOTO.

Une cartographie du LOTO actuel est réalisée sur la Figure 2.1, décrivant les limites actuelles des différentes phases du LOTO, comme elles sont définies sur la Figure 1.2. On y voit le manque d'intégration du LOTO aux politiques de production et de maintenance. La préparation des procédures LOTO y est aussi décrite, soulignant les différentes étapes et le temps nécessaires pour arriver à une procédure valide. Enfin, les interactions complexes entre les cadenasseurs et leur environnement y sont décrits, mettant en évidence les défis auxquels ils font face.

Ce travail cherchera à montrer que les différentes phases du LOTO peuvent être améliorés grâce à des politiques de gestions optimales des opérations et des outils technologiques s'inscrivant dans l'Industrie 4.0. Considérant, le contexte dans lequel s'inscrit cette recherche présenté et l'état actuel du LOTO réalisé, les récents progrès technologiques pourraient être un apport important pour le LOTO. Nous nous demanderons *comment les nouvelles technologies permettent des approches et stratégies intelligentes pour améliorer le LOTO dans un système manufacturier*.

Pour répondre à cette problématique et combler les lacunes de connaissances identifiées, quatre sous-objectifs ont été définit pour répondre à cette problématique.

2.4 Objectifs de recherche

Suite à l'analyse des procédures LOTO actuelles, cette thèse a pour objectif principal de proposer des approches et stratégies intelligentes pour optimiser les procédures LOTO. Des propositions pour des procédures LOTO futures sont faites et sont illustrées sur la Figure 2.2. On y voit un état futur possible, où les limites identifiées Figure 2.1 ne sont plus présentes, assurant ainsi une meilleure intégration du LOTO dans les systèmes manufacturiers. Différents sous-objectifs couvrant tous les aspects du LOTO au niveau de sa planification, de la préparation de la procédure et de son exécution sont présentés. Les différents sous-objectifs sont :

- Sous-objectif 1

  Le premier sous-objectif de cette recherche est de proposer une optimisation conjointe de « production – maintenance – cadenassage » dans la production manufacturière dans le contexte de l'environnement, de la santé et de la sécurité (SSE) et considérant un LOTO opérationnel.

- Sous-objectif 2

  Le deuxième sous-objectif est de proposer une approche pour assister la rédaction des procédures LOTO sur la base des fiches de LOTO existantes fournies par CONFORMiT. Cette approche permettra de réduire les temps de rédaction des procédures LOTO en utilisant des données de l'usine existantes.

- Sous-objectif 3

  Le troisième sous-objectif consiste à proposer un modèle de fusion de procédures LOTO, tester dans le cadre des usines de Cascades Inc, afin d'améliorer la préparation du cadenassage lors des arrêts planifiés et supprimer le temps nécessaire aux superviseurs pour les réaliser. Ce modèle de fusion prendra en compte l'environnement manufacturier réel comme la localisation des dispositifs et les interconnexions entre les valves.

- Sous-objectif 4

  Le quatrième sous-objectif est de développer des stratégies intelligentes pour l'exécution des procédures LOTO en prenant en compte les caractéristiques de l'environnement manufacturier et de la répartition des tâches de verrouillage. Ces caractéristiques sont la considération du travail de plusieurs équipes de cadenasseurs en parallèle, la position des dispositifs énergétiques, les interconnexions entre les valves et les évènements imprévus qui peuvent causés des retards dans l'exécution.

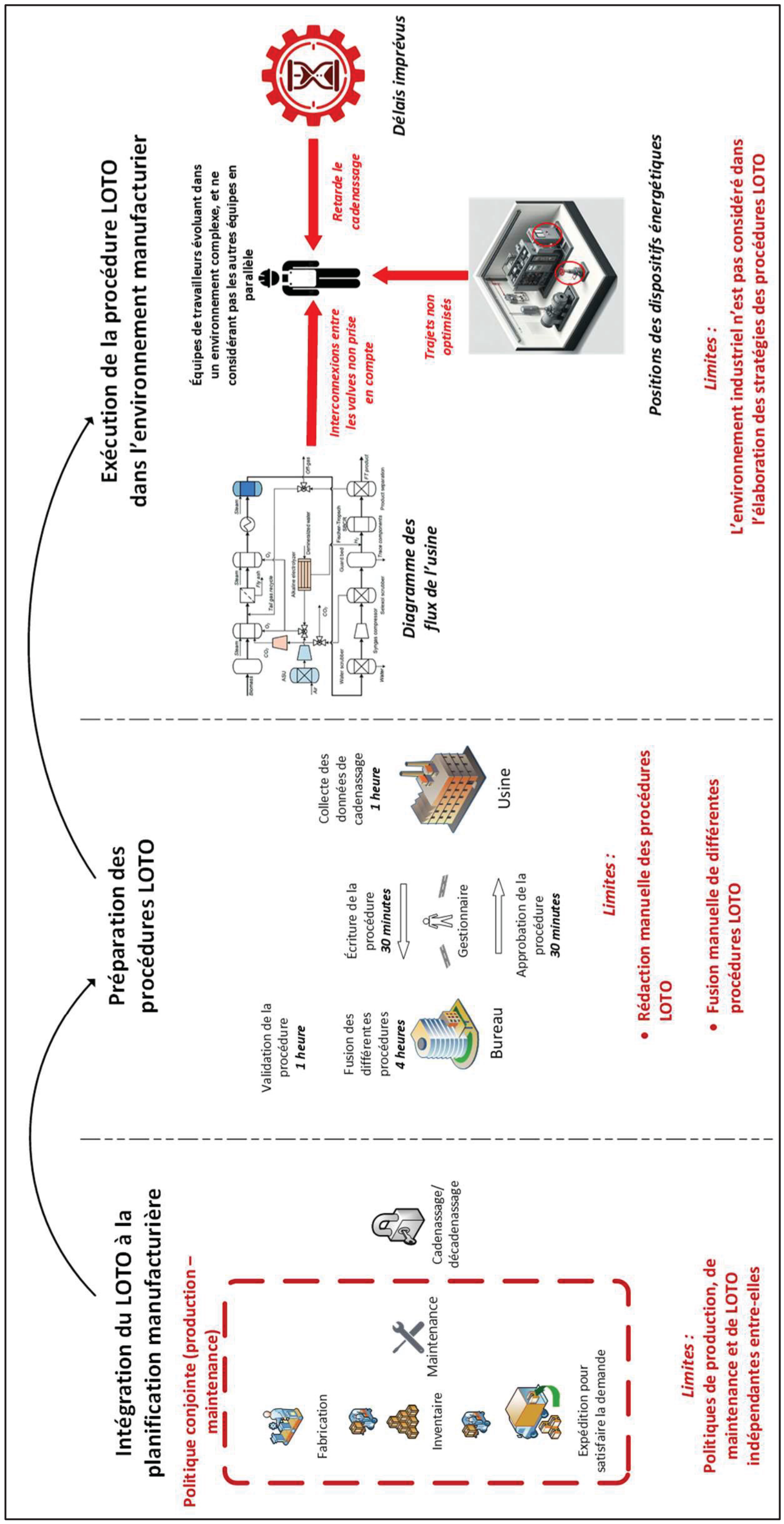

Figure 2.1 État actuel du LOTO et ses limites

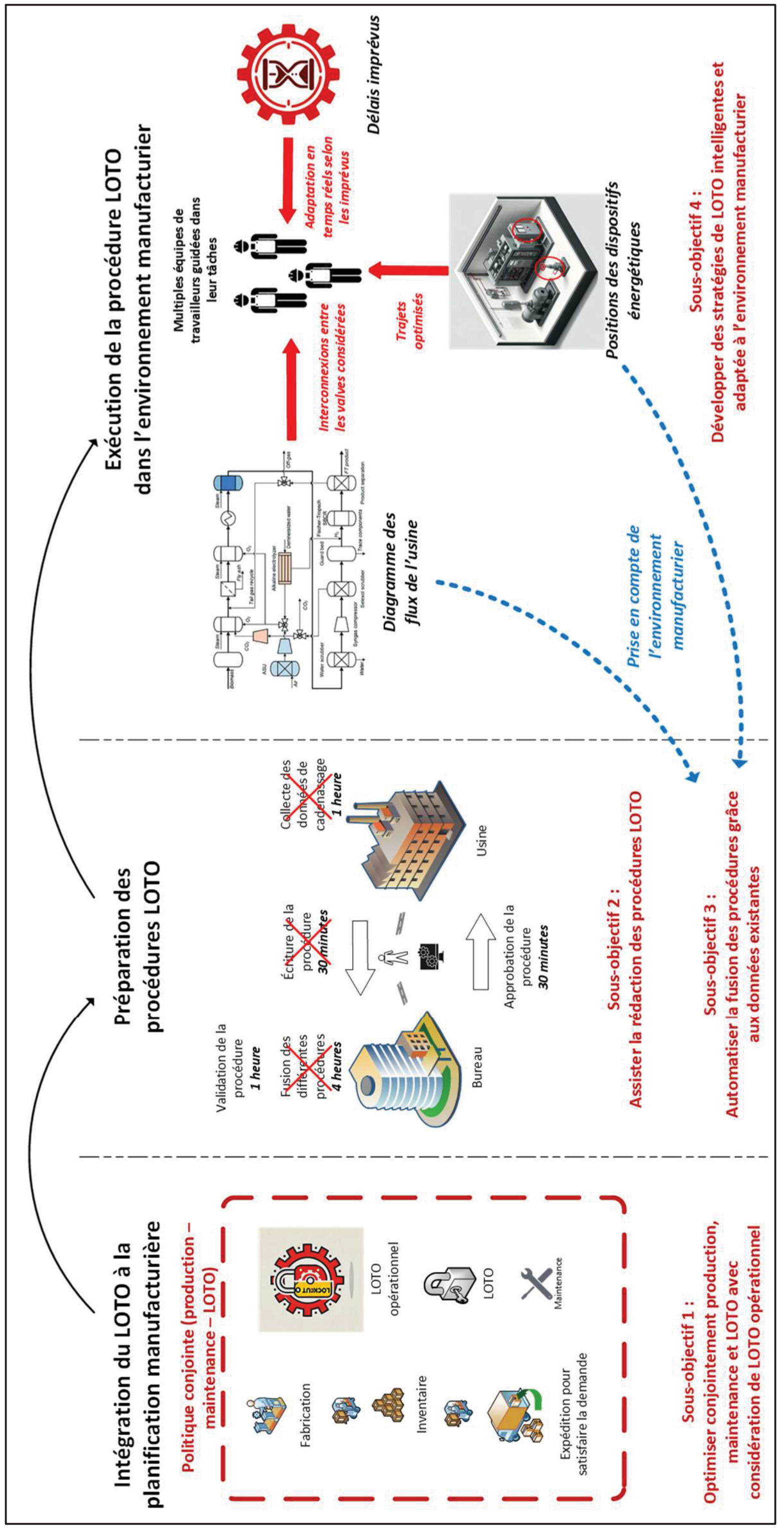

Figure 2.2 État futur du LOTO et sous-objectifs de recherches associés

2.5 Méthodologie

Afin de réaliser les différents objectifs énoncés précédemment, le travail de recherche peut être diviser en quatre étapes :

- Étude des procédures LOTO actuelles dans l'industrie manufacturière
- Optimisation conjointe de la production, de la maintenance et du LOTO opérationnel
- Assistance à la rédaction des procédures LOTO
- Fusion des procédures LOTO et approches intelligentes des procédures LOTO

Pour chacune de ces points, différents rendus seront attendus, principalement des articles de revue scientifique.

2.5.1 Étude des procédures LOTO actuelles dans l'industrie manufacturière

La première étape de la méthodologie nécessaire à ce travail de recherche est l'examen des procédures LOTO actuelles dans les industries manufacturières pour comprendre les problèmes de ce processus et identifier les améliorations et définir les objectifs de recherche. Les différentes étapes sont les suivantes :

- Analyser les procédures de sécurité (LOTO) par une revue de la littérature.
- Étudier des études de cas pratiques et effectuer une analyse approfondie des données et des informations recueillies pour formuler les problèmes et les limites des processus LOTO réels liés aux opérations de maintenance et au temps de production opérationnel.
- Établir des critères d'amélioration et d'optimisation ainsi que les contraintes associées à l'instrumentation des usines de fabrication et à la collecte de données sur la production.

Cette étape de la méthodologie est un prérequis à l'accomplissement des tous les objectifs de recherche définit à la Section 2.3.

2.5.2 Optimisation conjointe de la production, de la maintenance et du LOTO opérationnel

La deuxième étape principale de la méthodologie est l'accomplissement du premier sous-objectif définit qui est la proposition d'un modèle d'optimisation conjointe de la production, de la maintenance et du LOTO. Ce modèle constituera un modèle de base que l'on cherchera à améliorer progressivement en y intégrant des technologies intelligentes. Ce premier objectif s'apparente à la résolution d'un problème de programmation dynamique et de commande optimale stochastique. Les différentes étapes sont les suivantes :

- Réviser plus spécifiquement la littérature concernant le sujet.
- Identification de l'inertie des machines dans les industries du papier et minière et définition du LOTO opérationnel.
- Définition des variables décisionnelles dépendantes de la maintenance de la machine : taux de production et de taux d'envoi en maintenance préventive.
- Utilisation de la théorie du contrôle optimal stochastique pour formuler les conditions d'optimalité.
- Application des équations de Hamilton-Jacobi-Bellman (HJB) pour déterminer les conditions d'optimalité.
- Méthodes numériques pour résoudre ces conditions pour des cas industriels concrets.
- Présentation d'un exemple numérique pour valider l'approche développée.
- Analyse de sensibilité pour étudier le comportement du modèle en fonction de la variation de certains paramètres.
- Étude comparative de la politique développée dans l'article avec une politique plus restrictive de la littérature.
- Présentation des perspectives managériales dans l'industrie manufacturière avec les politiques de production optimales proposées.

La modélisation et la résolution de ce problème à donner lieu à des résultats préliminaires qui seront plus détaillés dans le Chapitre 3. Ce chapitre est un article publié dans l'*International Journal of Production Economics* (Delpla, Kenné et Hof, 2023).

Suite à ce travail, le sous-objectif 1 concernant le développement d'une politique conjointe de production, maintenance et LOTO opérationnel est atteint.

2.5.3 Assistance à la rédaction des procédures de LOTO

La troisième étape de la méthodologie est un travail se concentrant sur l'assistance à la rédaction des fiches de cadenassage. Afin d'aider les industriels à mettre en place rapidement les procédures LOTO, l'écriture de des fiches LOTO pourraient être assistée : à partir du nom des machines à sécuriser, ils pourraient être possible de déterminer les dispositifs à verrouiller. Il est dans un premier temps nécessaire de comprendre le but d'une fiche de LOTO, d'identifier les informations pertinentes à communiquer à l'opérateur et de déterminer les données qui seront utiles au modèle de prédiction. Nous utiliserons alors différents algorithmes de ML et DL pour atteindre notre objectif. Plus précisément, la démarche suivante sera suivie:

- Réviser la littérature spécifique concernant la prédiction de documents de sécurité et le minage de texte.
- Effectuer une analyse critique approfondie de la littérature sur les stratégies de ML et DL afin de déterminer quels types (par exemple, ML supervisé, ML non supervisé, ML de renforcement, DL) sont les meilleurs à adopter pour le problème.
- Récupérer les fiches de LOTO existantes dans les bases de données fournit par CONFORMiT.
- Traiter les fiches sous format PDF avec des algorithmes de minage de texte : récupération des entrées (nom procédure + nom de l'équipement + spécifications équipement) et des sorties (matériel requis + dispositif à verrouiller + contrôle des énergies) des modèles ML et DL.

- Définir les modèles de ML et DL satisfaisants permettant d'associer un nom d'équipement à une procédure.
- Tester et valider le modèle avec les données existantes fournies par CONFORMiT.

Pour atteindre cet objectif, ConformIT fournira toutes les données disponibles qu'elles possèdent déjà, en l'occurrence plusieurs milliers de fiches de LOTO appartenant à certains de leurs clients.

Cette étape est développée plus en longueur dans le Chapitre 4. Ce chapitre est un article publié dans l'*International Journal of Production Research* (Delpla et al., 2023). Cet article fait suite à un article de conférence publié et suivi d'une présentation à la conférence IFAC MIM 2022 à Nantes (Delpla et al., 2022).

Suite à ce travail, le sous-objectif 2 concernant la préparation des procédures LOTO, et plus précisément à l'assistance à la rédaction des procédures LOTO, sera complété.

2.5.4 Changement de paradigme du LOTO : vers une considération physique de l'environnement manufacturier et une meilleure répartition des tâches

La dernière étape de la méthodologie se concentre sur une refonte de la manière de préparer les opérations LOTO en amont des arrêts pour maintenance. Les procédures LOTO traditionnelles, bien qu'essentielles pour assurer la sécurité des travailleurs durant les opérations de maintenance industrielle, sont souvent limitées par leur nature statique, manuelle, ne prenant pas en compte l'environnement manufacturier et la parallélisation des tâches de verrouillage. Ces méthodes peuvent engendrer des inefficacités et augmenter les risques d'erreurs humaines, particulièrement dans les environnements industriels modernes caractérisés par une production à haut volume et une complexité accrue. De plus, lorsque plusieurs cadenassages sont réalisés, on les considère séparément, ce qui ne permet une optimisation globale de l'ensemble des opérations de cadenassage. Les équipes de cadenasseurs se retrouvent parfois à travailler dans des zones similaires de l'usine, plutôt que de se répartir les tâches géographiquement. De même, les cadenasseurs ne se soutiennent mutuellement pas lors d‘imprévus causant des retards. Ainsi, le but de cette partie est de développer des procédures LOTO plus intelligentes et dynamiques, intégrant des technologies avancées comme l'IoT, afin d'améliorer la répartition du travail entre les cadenasseurs et l'efficacité opérationnelle.

2.5.4.1 Fusion des procédures et approche géographique du LOTO

Une façon de simplifier et le LOTO et de le rendre plus efficace est le regroupement de plusieurs procédures entre elles. On parle de fusion. Comme décrit à la Section 2.2, ces fusions demandent une charge de travail de plusieurs heures de la part des superviseurs, ainsi qu’une bonne connaissance de leur usine. Automatiser ces tâches serait ainsi un moyen d’augmenter les performances du LOTO tout en déchargeant les superviseurs d’un tâches lourdes. En plus des fusions, une approche intelligente considérant le travail de plusieurs équipes en parallèle est proposée : l’approche géographique du LOTO.

La fusion des procédures et l'approche géographique du LOTO prennent en compte la disposition physique des équipements et des installations industrielles. La planification des procédures de verrouillage doit être optimisée en fonction de la localisation des dispositifs énergétiques pour minimiser les déplacements des équipes de cadenasseurs. En utilisant des modèles de programmation en nombres entiers, il est possible de déterminer les trajets optimaux et les dispositifs à verrouiller. Dans le cas de l’approche géographique, on y ajoute la coordination des équipes de maintenance de manière que chaque équipe puisse effectuer les verrouillages nécessaires sans interférer avec les autres, et en se répartissant les tâches selon leur localisation. Cette orientation géographique permet non seulement de réduire les temps de verrouillage, mais aussi d'améliorer la fluidité des opérations et de maximiser l'utilisation des ressources humaines.

Pour la fusion des procédures LOTO et l'approche géographique, la démarche suivante sera suivie :

- Réviser plus spécifiquement la littérature concernant les méthodes d'optimisation mathématiques, ainsi que les algorithmes de recherche de route optimale.
- Identifier les données clés à la modélisation du système manufacturiers et du LOTO.
- Modéliser mathématiquement les systèmes manufacturiers et le LOTO.
- Collecter les données sur le terrain d'un cas précis de machine. Cascades fournira l'accès à son usine de fabrication de carton d'emballage de Kingsley Fall.
- Programmer dans un langage adéquat et choisir des algorithmes de résolution adapté au problème d'optimisation.
- Tester et valider le modèle en le comparant à des cadenassages réaliser réellement chez Cascades Inc.
- Conclure quant à l'efficacité de la fusion automatique des procédures LOTO et de l'approche géographique.

Ces étapes sont développées plus en longueur dans les Chapitre 5. Ce chapitre est un article soumis dans une revue du domaine. Une affiche présentée à la TAPPICon 2024 à Cleveland, Ohio, a aussi traité de ces sujets. Cette affiche est visible dans l'Appendice I.

Grâce à ce travail, le sous-objectif 3 concernant la préparation des procédures LOTO, et plus précisément la fusion des procédures est abordé. L'approche géographique du LOTO se penchent sur le sous-objectif 4 traitant le développement de stratégies LOTO intelligentes et adaptée à l'environnement manufacturier et au travail de plusieurs équipe en parallèle.

2.5.4.2 Approche dynamique du LOTO

Une seconde approche intelligente est proposée pour l'exécution du LOTO lors des arrêts planifiés. Il s'agit de l'approche dynamique, une stratégie cherchant à minimiser l'impact des temps d'arrêt lors des opérations de cadenassage à cause d'imprévus. L'approche dynamique des procédures LOTO s'appuie sur l'intégration de systèmes de cadenas connectés pour ajuster les plannings de maintenance en temps réel. Lorsque des imprévus surviennent, comme des retards ou des pannes, ces systèmes peuvent redistribuer les tâches et réaffecter les ressources pour maintenir l'efficacité des opérations. Par exemple, si une équipe termine ses tâches de verrouillage plus rapidement que prévu, elle peut être redéployée pour aider une autre équipe en retard, minimisant ainsi les interruptions et les temps d'inactivité. Cette flexibilité est possible par l'utilisation de cadenas connectés par IoT, qui permettraient une surveillance continue et une adaptation instantanée aux conditions changeantes.

Pour l'approche dynamique, le caractère probabiliste des délais imprévus rend difficile une estimation déterministe de l'efficacité de la méthode. Les DES seront privilégiées pour tester l'approche. En effet, une vérification réelle étant complexe étant donné l'aspect critique du LOTO et l'absence de développement de connectés par IoT performants. La méthodologie sera la suivante, la démarche suivante sera suivie :

- Réviser plus spécifiquement la littérature concernant la planification dynamique et de la DES.
- Identifier les données clés à la simulation du système manufacturiers, du LOTO et des événements imprévus.
- Modéliser logiquement et mathématiquement les systèmes manufacturiers et le LOTO dynamique.
- Collecter les données sur le terrain d'un cas précis de machine. Cascades fournira l'accès à son usine de fabrication de carton d'emballage de Kingsley Fall.
- Concevoir le modèle de simulation sur un logiciel adapté à la DES.
- Tester et valider le modèle en le comparant à des cadenassages réaliser réellement chez Cascades Inc.
- Conclure sur l'efficacité de l'approche dynamique du LOTO et l'intérêt de développer des cadenas connectés par IoT.

Ce travail est approfondi dans le Chapitre 6, sous la forme d'un article soumis dans une revue du domaine. Cet article s'intéresse au sous-objectif 4 traitant le développement de stratégies LOTO intelligentes et adaptée à l'environnement manufacturier.

2.6 Conclusion

En conclusion, la revue de littérature et les échanges avec les partenaires industriels ont permis d'identifier les lacunes et les défis des procédures LOTO actuelles dans les industries manufacturières. La question principale de recherche qui ressort est comment les nouvelles technologies, s'inscrivant dans le cadre de l'Industrie 4.0, peuvent permettre de nouvelles approches et stratégies intelligentes pour améliorer le LOTO dans le milieu manufacturier.

Pour répondre à cette question, quatre sous-objectifs ont été définis, visant à optimiser conjointement la production, la maintenance et le cadenassage, à assister la rédaction des procédures LOTO, à fusionner les procédures et à développer des stratégies intelligentes pour leur exécution. Cette thèse proposera des solutions innovantes pour atteindre ces sous-objectifs. La Figure 2.3 présente les sous-objectifs énoncés ainsi que leur association aux différentes publications dans des revues scientifiques. Ces articles composent les différents chapitres suivants de cette thèse comme indiqué par la Figure 2.3.

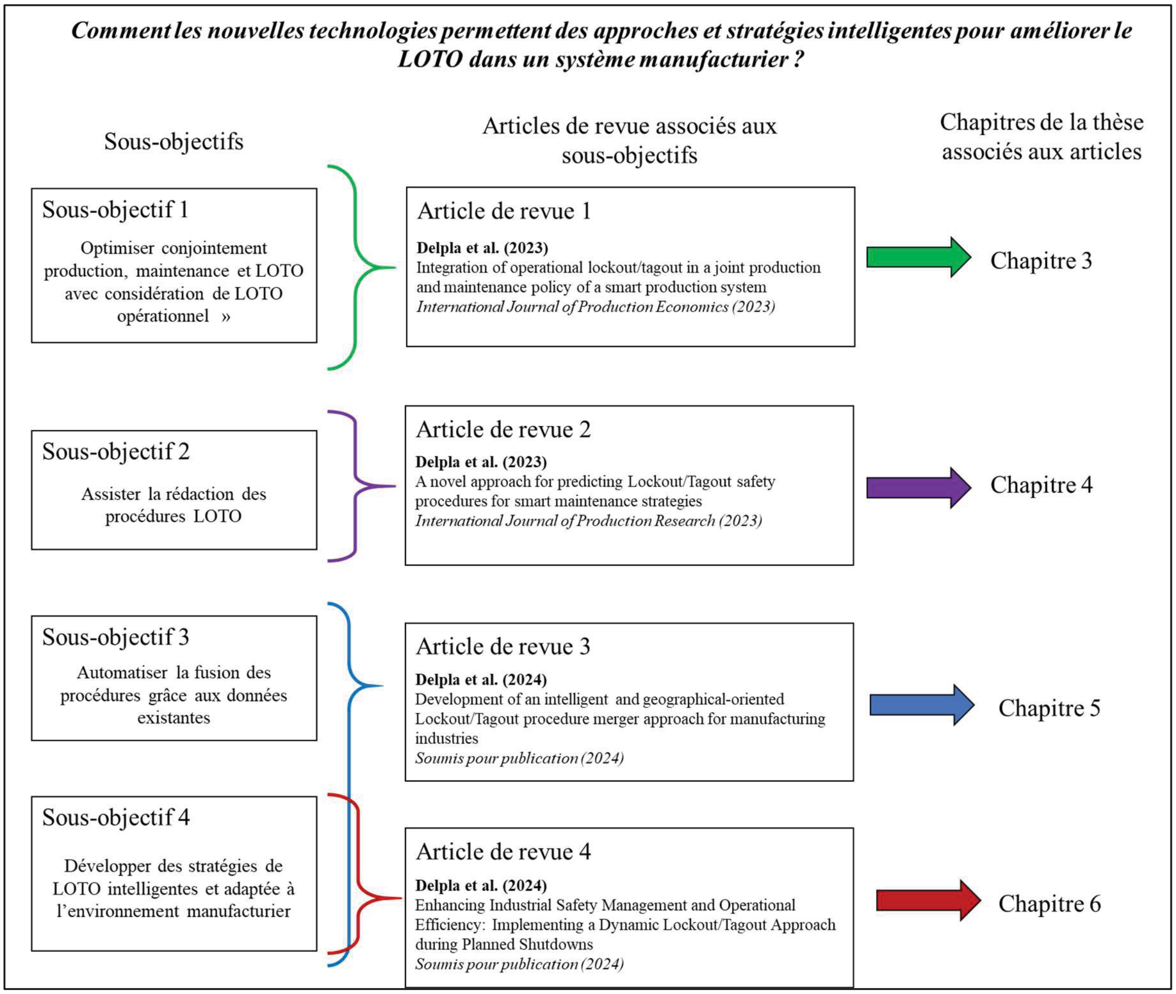

Figure 2.3 Contributions scientifiques, articles de revue et chapitres associés

CHAPITRE 3

INTEGRATION OF OPERATIONAL LOCKOUT/TAGOUT IN A JOINT PRODUCTION AND MAINTENANCE POLICY OF A SMART PRODUCTION SYSTEM

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Abstract

Accidents during maintenance operations are frequently occurring and sometimes even fatal. The lack of energy locking is one of the main factors of accidents during maintenance. The Lockout/Tagout (LOTO) process aims to ensure the safety of workers by providing a control of equipment energies before and after preventive or corrective maintenance activities. However, LOTO is often seen as an unnecessary delay that increases production costs. The objective of this work is to minimize production and inventory costs of finished products, while guaranteeing the safety of workers during maintenance activities by the implementation of operational LOTO actions, which allows for production continuity during the securing of energy sources. This work studies the problem of production and maintenance planning of a smart production system that deteriorates according to its age affecting its reliability and availability. The system under study consists of a production unit processing a single type of parts and exposed to random failures and repairs. The decision variables for this control problem are the machine age dependent production and preventive maintenance rates of the machine. The proposed model is based on the stochastic optimal control theory and the optimality conditions are obtained by the dynamic programming approach. Such conditions are of the Hamilton-Jacobi-Bellman (HJB) type and have been solved by numerical methods for concrete industrial case applications. The developed model is validated using a numerical example and a sensitivity analysis is conducted to study the behavior of the system related to the variations of some parameters. A comparative study shows that the proposed operational LOTO strategy performs better than a traditional LOTO strategy in optimizing maintenance operations and reducing incurred costs. This study proposes new managerial policies in terms of joint management of production, maintenance and safety.

Keywords: Production planning, Manufacturing systems, Optimal control, Maintenance, Occupational health and safety, Lockout/Tagout

3.1 Introduction

In the era of Industry 4.0, traditional production systems are transformed into smart production systems (SPS), to enable flexible, configurable and adaptable factories to meet the growing need for mass customization (Dotoli et al., 2019). Practically, current SPS are semi-autonomous operating systems. They have the ability to determine actions to improve production based on instructions set by the production manager. The resulting recommendations of the semi-autonomous SPS must also be validated by the production manager (Alavian et al., 2020). In fact, SPS can be regarded as collaborative manufacturing systems that respond to variations in demand, supply and equipment availability (Barnard Feeney, Frechette et Srinivasan, 2017). In order to meet increasing demand from customers and in a context of global competition, companies need to manufacture products in a cost-effective way. To achieve this goal, the availability of production equipment needs to be improved. Existing research has focused on optimizing machine utilization at the functional level by developing several maintenance strategies and it was highlighted that scheduling problems play a central role in production planning (Moeuf, 2021). Several approaches have sought to propose optimized planning changes in the occurrence of unforeseen events and disruptions such as changes in customer orders, machine breakdowns, and material shortages (Berger et al., 2019). Proposed solutions include adding of machines or workers at temporary bottlenecks created by these contingencies (Nonaka et al., 2015). Flexible and reconfigurable production systems that can be adapted to machine availability have also been proposed to deal with unexpected events causing production downtime (Lanza, Stricker et Peters, 2013). These scheduling changes could occur both at a single plant level as well as across multiple production sites around the world. This approach allows to mitigate the effect of disruptions on productivity and delivery schedules, both on national and global level. Dynamic scheduling that considers actual disturbances is another possibility. Retrieving manufacturing data in real time would allow for constant adjustment of the production schedule by accurately identifying the resources needed to satisfy an order (Xu et Chen, 2017).

These problems of optimal joint production and maintenance control of a production system have been discussed in the academic literature to address the challenges of increasing complexity and competitiveness. However, despite this extensive research, the management of the risks of adverse events during maintenance remains an issue and is still poorly explored and integrated into optimization policies. Production systems operate in a stochastic environment, with machines subject to random out-of-control failures. As manufacturing systems deteriorate, the number of failures and repairs increases. The availability of machines decreases and the number of occupational hazards due to maintenance operations rises, leading to mechanical accidents that are detrimental to human life and financial costs. The development and dissemination of manufacturing systems and work equipment regulations have created a decreasing trend in occupational accidents throughout the last century. Nevertheless, these significant company efforts to improve occupational health and safety (ROHS) are not sufficient and recent statistics on occupational accidents in the manufacturing industry show a global upward trend in recent years (Botti et al., 2020). Indeed, fatal occupational injuries caused 380,500 deaths worldwide in 2015, an 8% increase compared to 2010 (Hämäläinen, Takala et Kiat, 2017). Workers in machine installation, maintenance, and repair are at the highest risk of injury-related deaths (Rafindadi et al., 2020).

In fact, the challenge for manufacturers is to maintain an efficient production strategy in an unpredictable production environment, while respecting the safety rules for workers. The National Institute for Occupational Safety and Health (1983) established the first guidance for energy control during maintenance operations in North America in 1983. The procedures following these directives became required for industry when the Occupational Safety and

Health Administration (1989) enacted the Lockout/Tagout standard in 1989. This standard requires employers to set up an energy control plan for equipment lockout/tagout (LOTO), employee education and regular maintenance inspections. This method consists of locking a machine with a safety lock and specific mechanisms that control the energies of a machine (hydraulic, electrical, thermal, pneumatic) in order to discharge all the sources of energy to avoid a premature start of the equipment during maintenance. Nevertheless, production managers and workers mistakenly believe that the LOTO implementation time reduces productivity or performance (Kay et Schuster, 2018). As a result, LOTO is often omitted due to the fact that the related downtime is perceived as a barrier to productivity. In addition, LOTO operations have been rarely addressed in joint optimization problems, and existing policies need significant improvements.

Therefore, the objective of this article is to introduce a joint optimization model to control the production rate of a machine, which is subject to random failures depending on its age and repairs requiring LOTO procedures. The main contributions of this work are to reduce production costs and reduce machine downtime due to breakdowns, while ensuring worker safety by incorporating an operational LOTO policy. Operational LOTO policies allow production to continue (partially) while energy flows are secured. Given the difficulty of finding an analytic solution for this problem that can be used in industry, this paper presents an alternative procedure based on a numerical approach to find the optimal joint control policy. This article is organized as follows. Section 3.2 presents a review of the literature. Section 3.3 details the industrial context of this research and how an operational LOTO can be integrated into a maintenance policy. Section 3.4 introduces the notations and hypotheses of the study and describes the optimal control. The optimal conditions and the numerical approach to solve them are detailed in Section 3.5. Section 3.6 presents a numerical example with a sensitivity analysis whose purpose is to study the behavior of the model. Section 3.7 presents a comparative analysis of the policy developed in this article and a more restrictive one in the literature. Section 3.8 presents management perspectives in the manufacturing industry with optimal production policies proposed in this paper. Finally, Section 3.9 provides the conclusion of this work.

3.2 Literature review

The issues related to LOTO operations are not limited to safety, energy isolation, the development of a precise procedure and a good interaction between the operator and the machine being maintained. In fact, maintenance procedures are also part of a manufacturing environment where companies are looking to reduce their costs in order to maximize their profits in a sustainable manner. Maintenance operations occur between production periods, with varying customer demands, random breakdowns, and different stock levels or suppliers, whose reliability is not absolute. Hence, the manufacturing equipment evolves in a complex environment where only the consideration of all these aspects would allow to optimize the production and maintenance policies. In this section, we will review the literature on LOTO procedures and the optimization of production and maintenance policies.

3.2.1 Lockout/Tagout procedures

Much of the research on LOTO procedures concentrates on the circumstances of accidents that occur despite the applied LOTO procedure and the installation of mechanisms that lock out equipment. In Canada, the criteria for the application of OHS regulations are detailed in Canadian standards (Canadian Standards Association, 2013). For example, cleaning a mixer or conveyor and installing or removing electrical equipment are operations that regularly lead to injuries during the installation of LOTO mechanisms (Bulzacchelli et al., 2008). Access to hazardous areas around machines should also follow many recommendations, such as alternative access to these areas when LOTO cannot be performed, such as detecting malfunctions that require observation of the machine in operation (Chinniah, 2010). However, a LOTO system should not be viewed as simply installing a locking mechanism. The system must be checked after it is implemented. Describing incidents during the installation of LOTO mechanisms allows for procedures to be put in place to implement and control the LOTO more safely (Dewi, 2019). Documentations on a LOTO procedure should indicate the necessary tools, hazardous energies, and different steps of the LOTO actions to ensure proper equipment safety (Burlet-Vienney et al., 2009). LOTO mechanisms often pose a risk to workers because they are different for each energy source. They can be difficult to match to the power source and inspection of these devices is often visual (Kumar et al., 2018). Supervision and training of operators is also essential to ensure the LOTO procedure in a plant (Karimi et al., 2018). Operational LOTO, also known as partial LOTO (partial locking/unlocking of certain energies), can be used to ensure continuity in production. This type of operational LOTO could also reduce the risk of accidents during maintenance (Karimi et al., 2019).

From a managerial perspective, recent studies have addressed the issue of LOTO implementation in various industries in North America and the Middle East. Gauthier et al. (2021) examine the safety practices and needs of machinery designers and manufacturers in the province of Quebec, Canada. This study stresses out the need to improve safety practices to reduce risks faced by workers. Burlet-Vienney et al. (2021) provide an overview of safety in the construction industry in Quebec, with a focus on improving hazardous energy control on construction sites. Memarian et al. (2022) examine high-risk electrical tasks and contributing work factors in the electrical industry in Australia, highlighting the importance of appropriate training, experience, and procedures, as well as the correct use of personal protective equipment to reduce electrical risks. Finally, Almutairi, Albeladi et Elrashidi (2023) evaluate the health and safety hazards affecting workers at the Saline Water Conversion Corporation (SWCC) lathe workshop in Saudi Arabia. These studies emphasize the importance of awareness, training, and proper use of personal protective equipment in preventing workplace accidents and improving worker safety and health. However, the managerial aspect of LOTO implementation has been primarily studied only from the perspective of worker training to correctly apply established procedures, without rethinking LOTO planning. Although LOTO procedures have been studied for their implementation both in terms of mechanisms and documentation, the link between safety and maintenance efficiency is currently not well explored. However, these issues are of interest to industry as well as to advance the understanding of occupational safety and its integration into production planning (Narayan, 2012). Hence, LOTO is still an underdeveloped process and currently not well integrated into the various production and maintenance policies. The studies of these policies without LOTO consideration nevertheless provide valuable insights and can provide a basis for the development of LOTO integration into manufacturing policies. Finally, operational LOTO strategies have not been studied yet from a managerial implementation perspective.

3.2.2 Production and maintenance policies

Numerous researchers have addressed production planning issues in manufacturing systems on the basis of Rishel (1975). In his work, breakdowns and repairs are defined by a homogeneous Markov process. The major challenge of this approach is the low efficiency of numerical methods to solve this problem with stochastic process for more complex system, which can be characterized by the Hamilton-Jacobi-Bellman (HJB) equations (Gershwin, 1994). Production and maintenance planning have been studied frequently in the literature given that these two key aspects of manufacturing are connected and can be optimized together. For instance, a model for a manufacturing system that randomly changes from a controlled to an uncontrolled state after a production or maintenance period has been studied (Yedes, Chelbi et Rezg, 2012). A joint optimal production and preventive maintenance schedule, which were analyzed in conjunction with a random demand of products, including a given expected service level, were also proposed (Zied, Sofiene et Nidhal, 2014). The integration of preventive maintenance and production planning in a defective production context has also been studied. Here, throughout each cycle, the machine was inspected and preventive maintenance was conducted to remanufacture in proportion to the level of applied preventive maintenance (Nourelfath, Nahas et Ben-Daya, 2016). Another study discusses the development of a mathematical model to jointly address the production and maintenance policy problem. This system could split its production time between manufacturing, remanufacturing of returned parts, and maintenance (Polotski, Kenne et Gharbi, 2019). The connection between production and maintenance planning has also been studied. It has been shown that by reducing planning constraints and by reaching better rates of resource efficiency and availability, the synergy between production and maintenance could be improved (Glawar et al., 2019). The production lot volume, the inventory level, quality control sampling plan, and maintenance parameters can also be jointly optimized. Maintenance was performed when the proportion of defective parts reached a critical threshold (Bouslah, Gharbi et Pellerin, 2016). Other optimization methods have been explored in quality control and maintenance for a production system with inspected product shares (Lopes, 2018). An optimal production, repair, and preventive maintenance strategy for an unstable manufacturing system, in which the severity of failures and the quality of parts produced are affected by the fatigue of the production unit, has been proposed by Rivera-Gómez et al. (2018). Another approach based on simulation for the joint production, preventive maintenance and quality sampling plan control was proposed in the recent literature (Rivera-Gómez et al., 2020). A model for joint production, quality, and maintenance control of a manufacturing system, which is built on statistical control to supervise the system, was discussed by Abubakar, Nyoungue et Hajej (2020). As well, a production and maintenance strategy proposing an active sample policy that considers an increase in the failure rate to adjust the inspection level was modeled including a deterministic strategy (Zied, Sofiene et Nidhal, 2014). Rivera-Gómez et al. (2020) explored the age-based integration of production, random inspection, and maintenance planning for manufacturing equipement undergoing progressive degradation. In their study, the degradation of the production unit, characterized by the decrease in the conformity of the products, altered its reliability and the quality of the product. More recently, new joint production, maintenance and inspection control policies for failure-prone manufacturing systems have been developed in the literature. A comprehensive and thorough mathematical model was developed by Ait-El-Cadi et al. (2021) to capture the complex dynamic and stochastic behavior of a manufacturing system. The dynamics of the inventory was governed by a stochastic differential equation (e.g. by the Itô-Doeblin formula). Some models deal in particular with random demands. Production rates to meet these random demands while minimizing costs can be calculated using time-dependent second-order HJB equations with dynamic programming and stochastic computation (Ouaret, 2022). Existing manufacturing systems are characterized by stochastic demand, inventory, delivery and service level. Indeed, there is a significant correlation between these considerations. A statistical process control approach that helps to obtain an economical and dynamic maintenance planning is therefore a necessity to optimize management policies. Models integrating these four aspects under several constraints have been developed (Hajej et al., 2021). The lack of maintenance reliability was also considered in these policies (Abubakar, Zied et Nyoungue, 2022).

Recently, HJB equations have been employed to investigate the integration of preventive maintenance and silica exposure limits into the production planning of a granite processing unit to enhance the health and safety of workers (Dongmo Tambah, Kenné et Songmene, 2022). The results of this study demonstrate that the implementation of preventive measures such as regular equipment replacement and worker training has significantly reduced silica dust levels and improved the productivity of the unit. At the managerial level, the integration of production planning, adaptive quality control, and maintenance planning for continuous flow processes based on a reliability-oriented approach suggest that the use of this model can improve product quality, reduce downtime and maintenance costs, and increase production efficiency (Wan, Chen et Zhu, 2023). These articles highlight the importance of integrating maintenance, quality, and production planning to enhance the efficiency, productivity, and safety of industrial processes.

Following the discussed articles, the interaction between production and maintenance is widely studied from different points of view. Nevertheless, these studies have ignored the impact of LOTO in these policies especially from the managerial point of view for decision makers and planners in the industry. Therefore, this study reviews optimal joint production and maintenance policies considering LOTO strategies and subsequently propose a new joint policy incorporating LOTO operation.

3.2.3 Lockout/Tagout integration in production and maintenance policies

Different studies consider the integration of LOTO in their maintenance and production policies. One of the first studies dealing with such integration was proposed by Charlot, Kenné et Nadeau (2007). In their study, a production control problem for a manufacturing system exposed to random breakdowns was considered. Their objective was to determine the optimal production and preventive maintenance rates to minimize operating costs, shortage and inventory costs, and maintenance and repair costs. Emami-Mehrgani, Kenné et Nadeau (2013) continued this work by studying more complex manufacturing systems. They proposed an analytical model to jointly determine optimal production and workplace safety for a production system subject to random failure and repair with passively redundant machines. In subsequent work, Emami-Mehrgani, Nadeau et Kenné (2014) presented the analysis of an optimal production and preventive maintenance planning problem considering the LOTO and the human errors commonly. Their proposed model considered jointly preventive maintenance activities with LOTO and human error, instead of individual consideration of each action. Badiane et al. (2016) showed that production optimization requires a revision of facility maintenance policies. Their study proposed a production policy that included LOTO operations for the machines, maximizing manufacturing system availability and minimizing costs. Finally, Diop, Nadeau et Emami-Mehrgani (2019) developed an optimal control policy considering LOTO in corrective maintenance operations including human errors.

LOTO actions have been integrated into the production and maintenance policies of various manufacturing systems and under different assumptions. Nevertheless, none of these policies consider an operational LOTO.

3.2.4 Summary

This literature review presents the current state-of-the-art in development of optimal joint production, maintenance and LOTO policies. It can be concluded that LOTO procedures are an integral part of a practical operating manufacturing system, tagout actions and operational LOTO procedures were not considered so far. In particular, managerial insights that would better integrate operational LOTO for manufacturing decision makers have not yet been explored in the literature.

This work proposes a joint production, preventive maintenance and LOTO policy for a manufacturing system deteriorating in time and subject to failures. The proposed model is the first study in the scientific literature that clearly differentiates the different stages of energy security during maintenance, i.e., lockout/tagout, and incorporates an operational LOTO policy that guarantees production continuity during the equipment security stages. The studied problem will be characterized by the HJB equations typically used for this type of optimization problems. The major contribution of this paper is the development of a strategy for production managers to integrate operational LOTO approaches into their production policy.

Finally, Table 3.1 summarizes the key aspects addressed by the different articles that propose joint optimization policies, highlighting the different characteristics and objectives of each study. Following this literature review, the present joint optimization policy study is introduced in Table 3.1.

Table 3.1 Overview of the literature review on articles detailing joint optimization policies

	Production and maintenance policy	**Failure rate deterioration**	**Optimal control**	**Model considering stochastic process**	**Problem characterised by HJB equations**	**Lockout consideration in the policy**	**Failure and repair after lockout**	**Preventive maintenance after lockout**	**Distinction between maintenance and lockout**	**Tagout consideration in the policy**	**Operational LOTO consideration**
a) LOTO procedures											
CSA-Z460 (2013)							✓	✓			
Bulzacchelli et al. (2008)							✓	✓			
Chinniah (2010)							✓	✓			
Dewi (2019)							✓	✓			
Burlet-Vienney et al. (2012)							✓	✓			
Kumar et al. (2018)							✓	✓			
Karimi et al. (2018)							✓	✓			
Karimi et al. (2019)							✓	✓			✓
Narayan (2012)	✓						✓	✓			
Gauthier et al. (2021)							✓	✓			
Burlet-Vienney et al. (2021)							✓	✓			

Table 3.1(suite) Overview of the literature review on articles detailing joint optimization policies

	Production and maintenance policy	Failure rate deterioration	Optimal control	Model considering stochastic process	Problem characterised by HJB equations	Lockout consideration in the policy	Failure and repair after lockout	Preventive maintenance after lockout	Distinction between maintenance and lockout	Tagout consideration in the policy	Operational LOTO consideration
b) Production and maintenance policies											
Memarian et al. (2022)							✓	✓			
Almutairi et al. (2023)							✓	✓			
Yedes et al. (2012)	✓			✓							
Zied et al. (2014)c	✓	✓		✓							
Nourelfath et al. (2016)	✓		✓	✓							
Polotsky et al. (2019)	✓	✓		✓	✓						
Glawar et al. (2019)	✓										
Bouslah et al. (2016)	✓		✓	✓							
Lopes (2018)	✓			✓							
Rivera-Gomez et al. (2018)	✓		✓	✓	✓						
Rivera-Gomez et al. (2020)	✓	✓		✓	✓						
Abubakar et al. (2020)	✓		✓	✓	✓						
Ait-El-Cadi (2021)	✓	✓	✓	✓							
Ouaret (2022)	✓	✓	✓	✓	✓						
Hajej et al. (2022)	✓	✓	✓	✓							
Abubakar et al. (2022)	✓	✓	✓	✓							
Dongmo Tambah et al. (2022)	✓	✓	✓	✓	✓						
Wan et al. (2023)	✓	✓	✓								

Table 3.1 (suite) Overview of the literature review on articles detailing joint optimization policies

	Production and maintenance policy	Failure rate deterioration	Optimal control	Model considering stochastic process	Problem characterised by HJB equations	Lockout consideration in the policy	Failure and repair after lockout	Preventive maintenance after lockout	Distinction between maintenance and lockout	Tagout consideration in the policy	Operational LOTO consideration
c) LOTO integration											
Charlot et al. (2007)	✓	✓	✓	✓	✓	✓	✓				
Emani-Mehrgani et al. (2013)	✓	✓	✓	✓	✓	✓	✓	✓			
Emani-Mehrgani et al. (2014)	✓	✓	✓	✓	✓	✓	✓	✓			
Badiane et al. (2016)	✓	✓	✓	✓	✓	✓	✓	✓	✓		
Diop et al. (2019)	✓	✓	✓	✓	✓	✓	✓	✓			
This article	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3.3 Industrial context

LOTO is a method of controlling the energies that power a machine to eliminate the risk of any accidental restart or release of energy. Operational LOTO can be extremely useful for machines that have an inertia to stop or restart as in the mining, paper or textile industry (Karimi et al., 2019). This will be the case for machines in the paper industry or the mining industry, as in the present industrial context case study. Indeed, when considering this kind of machine, production can continue at lower production rates while workers start to install the various energy locking mechanisms.

Operational LOTO is a simplified lockout to ensure continuity of production. Thus, when the machine is in operational LOTO, it can continue to produce at a lower rate than during standard operation. However, the production will not be terminated as is the case during maintenance. Full LOTO or even maintenance operations can then begin while continuing to produce parts. Figure 3.1.a illustrates the sequence of operations for a maintenance policy with full LOTO procedures only. Figure 3.1.b shows the sequence of operations with an operational lockout: manufacturing can continue during part of the energy LOTO procedure.

In this study, we consider a manufacturing company, which operates a machine of a manufacturing unit producing one type of parts, such as tissue paper or mining products. The particularity of this type of machine is its possession of a certain inertia before being completely locked in terms of energy. The engineering management wishes to develop a joint optimal strategy for production planning, maintenance and LOTO to minimize costs while satisfying the demand. The management also wants to implement an operational LOTO procedure during the preventive maintenance of the machine. An SPS is proposed to help production managers to adjust production, maintenance, and operational LOTO policies based on real-time changes in different variables such as machine age, inventory level, demand, or different costs associated with each operation. This SPS can be considered semi-autonomous, i.e. the production manager defines the objective to be achieved, here the aim is to minimize production costs. After proposing joint policy recommendations by the SPS, the production manager will ultimately decide final policy actions. This section presents the developed SPS configuration (see Figure. 3.2) and the notations used throughout this article, as well as the considered assumptions and the problem formulation. Therefore, operational LOTO procedures are considered for the joint control policies in this study, which is developed further in the following sections.

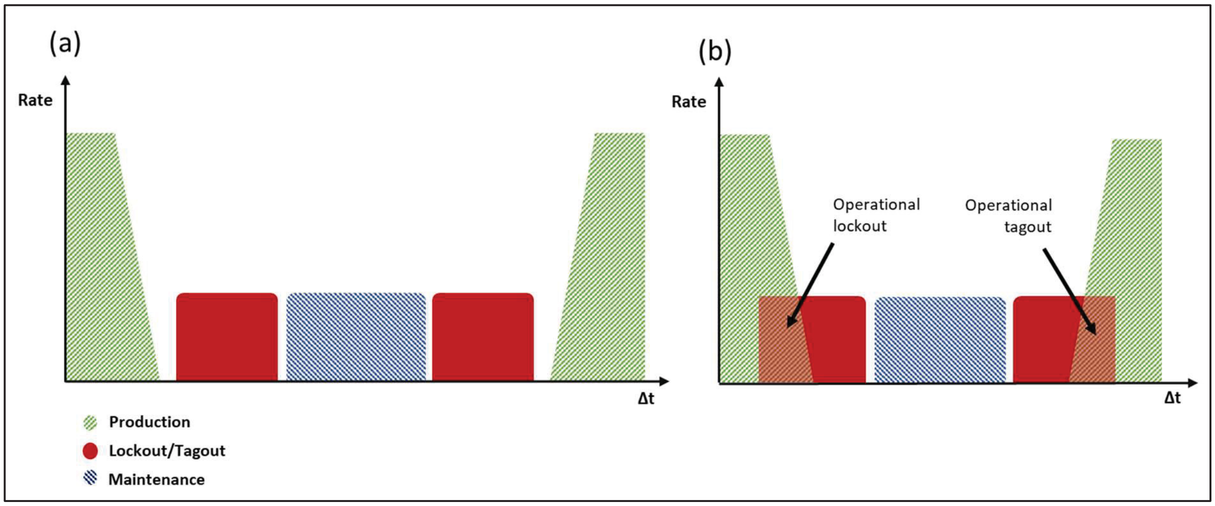

Figure 3.1 Sequence of operations. (a) without operational LOTO, (b) with operational LOTO

3.4 Problem statement

Notations

The following notations are used in this article:

d:	demand rate
x:	inventory level
c_α:	cost incurred for the operation on the machine at mode α
c^+:	holding cost per unit of item per unit of time
c^- :	backlog cost per unit of item per unit of time
$u(.)$:	production rate of the machine
$u_{max}(\alpha)$:	maximum production rate of the machine to produce at mode α
$\omega(.)$:	preventive maintenance rate of the machine
ω_{max}:	maximum preventive maintenance rate of the machine
ω_{min}:	minimum preventive maintenance rate of the machine
$q_{\alpha\beta}$:	transition rate from mode α to mode β
ρ:	discount rate
π_α:	limiting probabilities at mode α

3.4.1 Assumptions

This study considers the assumptions as described below.

- The raw material is available at anytime for production.
- The maximum production rate is known.
- Manufacturing, maintenance and LOTO costs are known.
- The demand rate is known and constant.
- The model is a continuous time model.
- The preventive maintenance is perfectly done: the machine is refreshed to as-good-as new (Polotski, Kenne et Gharbi, 2019) conditions.
- The repairs made at the time of the failure are minimal: the machine's deterioration level in as-bad-as-old (ABAO) conditions.
- The mean preventive maintenance time is shorter than the mean repair time.

3.4.2 Problem formulation

In this study, we consider an operational LOTO policy to plan the production and maintenance of a smart production system, which deteriorates according to its age, affecting its reliability and availability. The considered SPS configuration is illustrated in Figure 3.2.

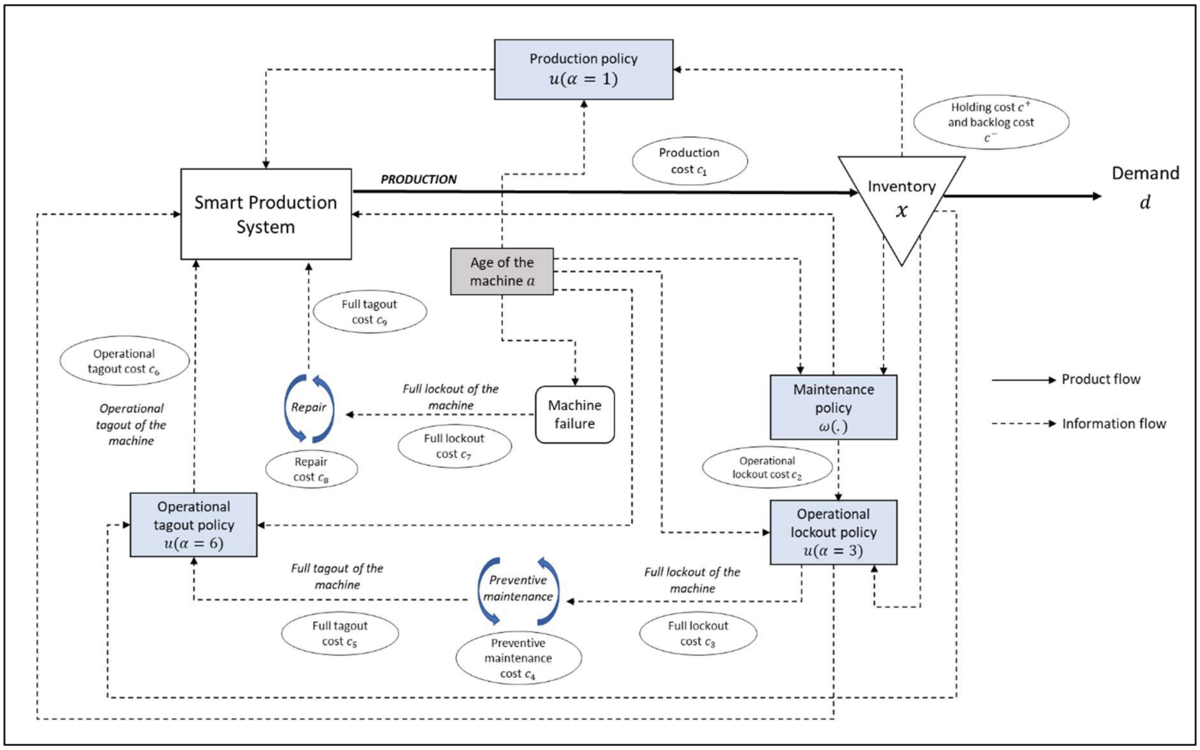

Figure 3.2 Smart Production System under study throughout the presented work, which includes joint production, maintenance and LOTO policies

When the machine is in operation, it can run up to a maximum production rate. When it is completely locked out or in maintenance, it can not produce anymore. When it is in operational lockout, it can produce at an intermediate production rate. Figure 3.3 illustrates this production system based on the machine's status.

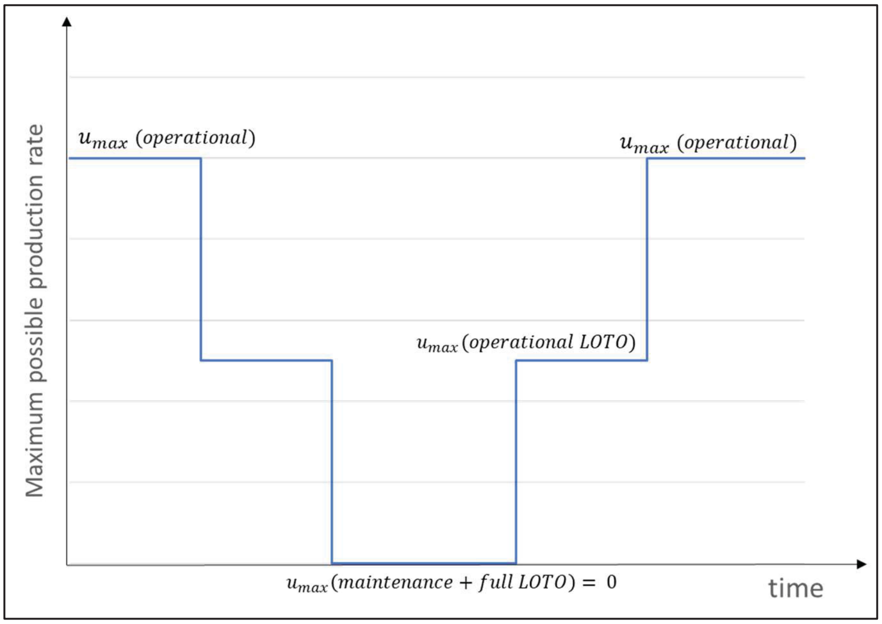

Figure 3.3 Production rate according to the state of the machine

The system can be described by a Markov process $\{\xi(t), t \geq 0\}$, with t the time. The probabilities (P) of transition from mode α to mode β are given by:

$$P[\xi(t+\delta t) = \beta \,/\, \xi(t) = \alpha] = \begin{cases} q_{\alpha\beta}\delta t + o(\delta t) \;\; if \; \alpha \neq \beta \\ 1 + q_{\alpha\alpha}\delta t + o(\delta t) \;\; if \; \alpha = \beta \end{cases} \qquad \alpha, \beta \in B \qquad (3.1)$$

where $q_{\alpha\beta}$ represents the transition rate from mode α to mode β of the stochastic process $\xi(t)$ for α, β ∈ B, which satisfies the following conditions:

$$\begin{cases} q_{\alpha\beta} \geq 0 \;\; if \; \alpha \neq \beta \\ q_{\alpha\alpha} = -\sum\limits_{\substack{\beta \in B \\ \beta \neq \alpha}} q_{\alpha\beta} \;\; if \; \alpha = \beta \end{cases} \qquad \alpha, \beta \in B \qquad (3.2)$$

The different modes $\alpha \in B = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ of the system are given in Equation (3.3) and they follow the transition diagram presented in Figure 3.4.

$$\xi(t) = \begin{cases} 1 & \text{if the machine is in operation} \\ 2 & \text{if the machine is in operational lockout for preventive maintenance} \\ 3 & \text{if the machine is in full lockout for preventive maintenance} \\ 4 & \text{if the machine is in preventive maintenance} \\ 5 & \text{if machine is in full tagout after preventive maintenance} \\ 6 & \text{if the machine is in operational tagout after preventive maintenance} \\ 7 & \text{if the machine is in full lockout for repair} \\ 8 & \text{if the machine is in repair} \\ 9 & \text{if the machine is in full tagout after repair} \end{cases} \tag{3.3}$$

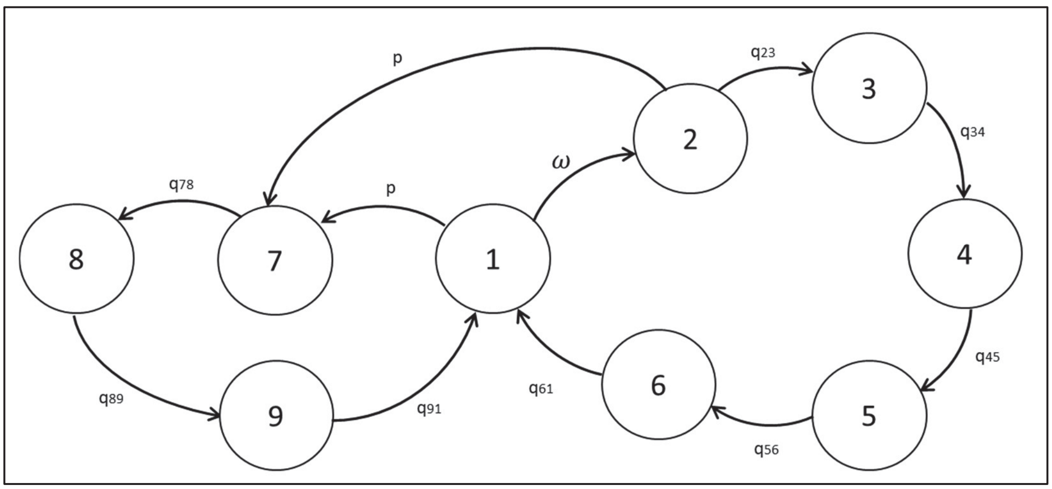

Figure 3.4 State transition diagram

The failure rate of the machine depends on its age and is approximated by the generally used Equation (3.4) (Abubakar, Nyoungue et Hajej, 2020):

$$q_{17}(t) = q_{27}(t) = p\big(a(t)\big) = \ A_0 + A_t(1 - \exp\big(-K.a^3(t)\big)\big) \tag{3.4}$$

Here *a(t)* is the age of the machine at time *t*; and A_0, A_t and K are constants that depend on the machine. The resulting machine age dependant failure rate $p\big(a(t)\big)$ is shown in Figure 3.5.

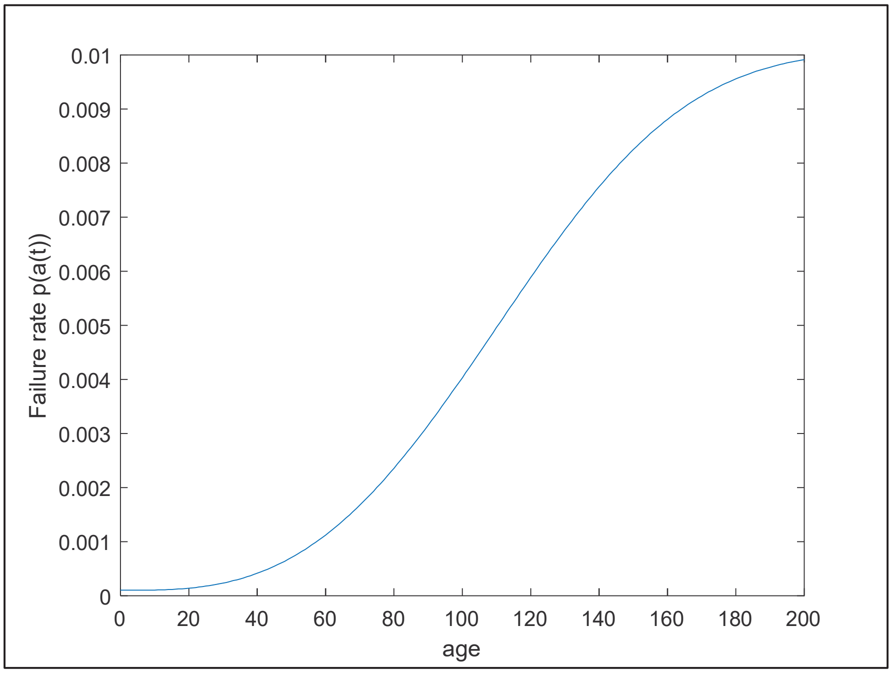

Figure 3.5 Failure rate of the machine according to its age

The machine degrades during production. We define the machine production dynamics by its age (Dehayem Nodem, Kenne et Gharbi, 2011):

$$\dot{a} = K_u . u(t) \tag{3.5}$$

with K_u a constant that depends on the machine.

After preventive maintenance, the machine is considered as new. The age of the machine is considered to increase again from the moment that the maintenance is completed. Consequently, we can define the function:

$$\varphi(a) = \begin{cases} 0 \; if \; \alpha^- \in \{5,6\} \\ a \; otherwise \end{cases} \tag{3.6}$$

where α^- denotes the mode prior to the current mode. This φ function resets the age of the machine after preventive maintenance.

We note $q_{12}(.) = \omega(.)$ the preventive maintenance rate. The transition rates matrix Q of our system becomes then:

$$Q = \begin{pmatrix} -(\omega+p) & \omega & 0 & 0 & 0 & 0 & p & 0 & 0 \\ 0 & -(q_{23}+p) & q_{23} & 0 & 0 & 0 & p & 0 & 0 \\ 0 & 0 & -q_{34} & q_{34} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -q_{45} & q_{45} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -q_{56} & q_{56} & 0 & 0 & 0 \\ q_{61} & 0 & 0 & 0 & 0 & -q_{61} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -q_{78} & q_{78} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -q_{89} & q_{89} \\ q_{91} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -q_{91} \end{pmatrix} \quad (3.7)$$

The present work seeks to determine the production rate of the machine when it is in operation or in partial LOTO, as well as to decide the rate of sending the machine for preventive maintenance, depending on its age and the inventory.

The admissible control domain $\Gamma(\alpha)$ associated with the mode α is given by:

$$\Gamma(\alpha) = \{(u(\cdot), \omega(\cdot) / \ 0 \le u(\cdot) \le u_{max}(\alpha), \omega_{min} < \ \omega(\cdot) \le \ \omega_{max}\} \quad (3.8)$$

Let the vector $\pi(\cdot) = (\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6, \pi_7, \pi_8, \pi_9)$, corresponding to the limiting probability vector of modes 1 to 9. For a Markov process, the limit probabilities respect equation (3.9):

$$\begin{cases} \pi(\cdot)Q(\cdot) = 0 \\ \sum_{i=1}^{9} \pi_i = 1 \end{cases} \quad (3.9)$$

The system is considered feasible if:

$$\pi_1.u_{max}(1) + \pi_2.u_{max}(2) + \pi_6.u_{max}(6) > d \quad (3.10)$$

If we consider a constant rate of demand, the differential equation that describes the dynamics of the stock is given by:

$$\frac{dx}{dt} = u(t) - d, \qquad x(0) = x_0 \tag{3.11}$$

The instantaneous cost is defined as follows:

$$g(\alpha, x, u, a) = c_\alpha Ind\{\xi(t) = \alpha\} + c^+x^+ + c^-x^-, \qquad \forall\alpha \in B \tag{3.12}$$

With $x^+ = \max(0, x)$ and $x^- = \min(-x, 0)$.

The total discounted production cost (*J*) is expressed as:

$$J(\alpha, x, u) = E\left\{\int_0^{t=\infty} e^{-\rho t}.\, g(\alpha, x, u)dt | x(0) = x, \xi(0) = \alpha\right\}, \forall\alpha \in B \tag{3.13}$$

Let $v(\alpha, x, a)$ refer to the value function or minimum discounted cost as stated in Equation (3.14):

$$v(\alpha, x, a) = \inf_{(u,\omega)\in\Gamma(\alpha)} J(\alpha, x, u, a), \forall\alpha \in B \tag{3.14}$$

The notations and assumptions have been presented in Sections 3.5.1 and 3.5.2 respectively to support the comprehension of the formulation of the stochastic model. The problem has then been formulated, which allows the development of the optimal conditions for minimizing the cost, which is outlined in Section 3.5.

3.5 Optimality conditions and numerical approach

The value function $v(\alpha, x, a)$ given by Equation (3.14) satisfies the Hamilton-Jacobi-Bellman (HJB) equations (Emami-Mehrgani, Kenné et Nadeau, 2013). The optimality conditions, expressed as HJB equations, for the problem under study are given by Equation (3.15) and correspond to a set of 9 coupled partial differential equations. Annex I (Equation (AI.1) to Equation (AI.13)) explains in detail how the optimality conditions presented in Equation (3.15) were obtained:

$$\rho v(\alpha, x, a) = \min_{(u,\omega)\in\Gamma(\alpha)} \begin{bmatrix} g(\alpha, x, u, a) + \sum_{\beta\in B} q_{\alpha\beta}. v\big(\beta, x, \varphi(a)\big) \\ +(u-d)\dfrac{\partial v(\alpha, x, a)}{\partial x} + K_u u. \dfrac{\partial v(\alpha, x, a)}{\partial a} \end{bmatrix} \tag{3.15}$$

Numerical methods, following the approach of Kushner et Dupuis (2001), are used to solve the optimality conditions introduced in Equation (3.15). The concept of this approach is to employ a discrete function $v^h(\alpha, x, a)$ for the directional derivative of the value function $v(\alpha, x, a)$. Here, let h be the step of the finite difference interval of the state variable x and h_a the step of the finite difference interval of the state variable a. Kushner's approach is an algorithm of successive approximations.

The properties of the value function $v(\alpha, x, a)$ and the details for obtaining the optimal conditions are documented in Annex I. Here, we replace $\frac{\partial v(\alpha,x,a)}{\partial a}$ and $\frac{\partial v(\alpha,x,a)}{\partial x}$ with Equations (AI.14) and (AI.15), respectively, in Equation (3.15) to obtain HJB Equations (3.16). The details of this calculation are outlined in Annex I (Equation (AI. 16) to Equation (AI.18)).

$$v^h(\alpha,x,u,a) = \min_{(u,\omega)\in\Gamma^h(\alpha)} \left[\frac{g(\alpha,x,u,a)}{\Omega_h^\alpha\left(1+\frac{\rho}{\Omega_h^\alpha}\right)} \right.$$

$$+ \frac{1}{1+\frac{\rho}{\Omega_h^\alpha}} \left[p_x^+(\alpha)\, v^h(\alpha,x+h,u,a) + \; p_x^-(\alpha) v^h(\alpha,x-h,u,a) \right. \tag{3.16}$$

$$\left.\left. + \sum_{\substack{\beta\in B\\ \beta\neq\alpha}} p^\beta(\alpha) v^h\big(x,\beta,u,\varphi(a)\big) + P_a(\alpha) v^h(x,\alpha,u,a+h_a) \right]\right]$$

With :

$$\Omega_h^\alpha = -q_{\alpha\alpha} + \frac{|u-d|}{h} + \frac{K_u u}{h_a} \tag{3.17}$$

$$p_x^+(\alpha) = \begin{Bmatrix} \frac{u-d}{h\,\Omega_h^\alpha} if\ (u-d) > 0 \\ 0\ otherwise \end{Bmatrix} \tag{3.18}$$

$$p_x^-(\alpha) = \begin{Bmatrix} \frac{d-u}{h\,\Omega_h^\alpha} if\ (u-d) \le 0 \\ 0\ otherwise \end{Bmatrix} \tag{3.19}$$

$$p^\beta(\alpha) = \frac{q_{\alpha\beta}}{\Omega_h^\alpha} \tag{3.20}$$

$$P_a(\alpha) = \frac{K_u u}{h_a \Omega_h^\alpha} \tag{3.21}$$

Hence, these successive approximations will be done according to a discrete grid of values of x and a. The solution of $v^h(\alpha,x,a)$ is an approximation which will converge to the solution $v(\alpha,x,a)$ for $h \to 0$ and for $h_a \to 0$. The algorithm of this technique can be consulted in Kushner et Dupuis (2001).

In a next step, to implement this method, boundary conditions on the control policy (u, ω) must be defined. To compute the value function at a point, it is necessary to have a value before and after in the same discrete grid. However, the problem states that no value exists at the limit of the grid, which will cause a problem for the calculation. To address this issue, these values will be approximated. Moreover, as reported by Yan and Zhang Yan et Zhang (1997), for large values of $x > 0$ (or very small values when $x < 0$), the optimal ordering policy has little variation. Therefore, this optimal policy is not found at the boundaries, which reduces the aforementioned calculation problematic and approximation error.

For the stock vector x, we can define a domain D_x:

$$D_x = \{x / -x_{lim}^{-} \leq x \leq x_{lim}^{+}\} \tag{3.22}$$

which will be discretized by the increment h.
For the age vector a, we can define a domain D_a:

$$D_a = \{a / -a_{lim}^{-} \leq a \leq a_{lim}^{+}\} \tag{3.23}$$

which will be discretized by the increment h_a.

Having defined the numerical approach and the optimal conditions for the joint production, maintenance and operational LOTO problem, section 3.6 introduces a numerical example to validate and further discuss the developed approach.

3.6 Numerical example

In this section, the developed numerical method is applied to determine the minimum costs and the optimal values of the decision variables, which defines the joint production, maintenance and operational LOTO policies. A numerical example and pertinent sensitivity analysis are also presented in this section.

3.6.1 Base case

The numerical values of the different parameters that are deployed for the base case are given in Table 3.2. Without losing the generality of the proposed approach and for illustration purposes, the values of these parameters are similar to values in the scientific literature (Badiane et al., 2016).

Table 3.2 Numerical values of the base case parameters

c^+	c^-	ω_{max}	ω_{min}	q_{23}	q_{34}	q_{45}	q_{56}	q_{61}	q_{78}	q_{89}	q_{91}
1	10	1	1.10^{-5}	0.8	0.8	0.5	0.8	0.8	0.8	0.002	0.8
c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	h	h_α	ρ
0	50	50	100	50	50	2000	5000	200	0.5	1	0.01
x_{lim}^-	x_{lim}^+	a_{lim}^-	a_{lim}^+	K_u	A_0	A_t	K	d	$u_{max}(1)$	$u_{max}(2)$	$u_{max}(6)$
15	45	0	60	1	1.10^{-4}	0.01	5.10^{-6}	0.45	0.5	0.25	0.25

After solving Equation (3.16), the production rate and preventive maintenance rate are obtained as presented below in Figure 3.6 and Figure 3.7.

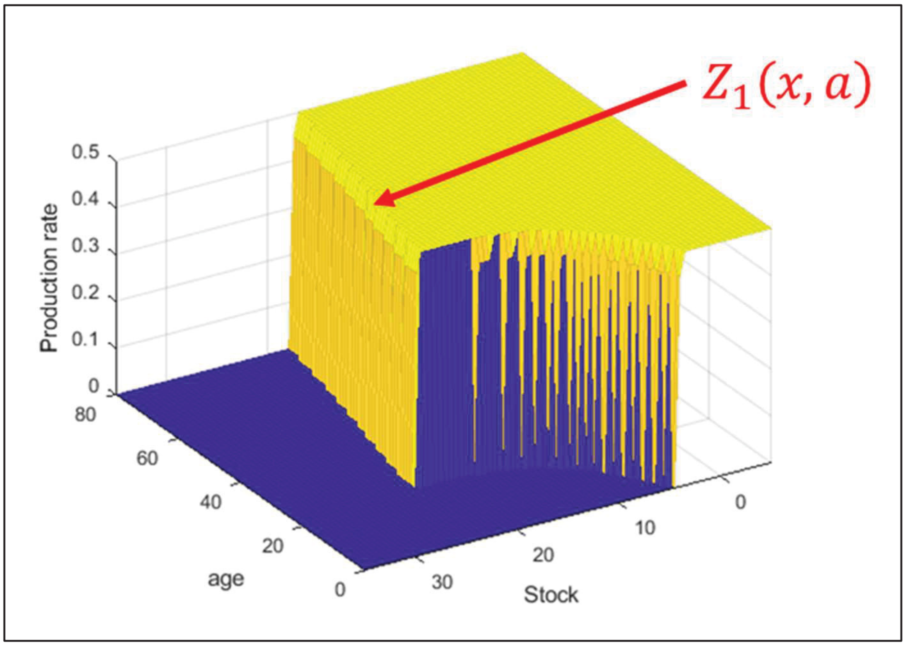

Figure 3.6 Production rate $u(1, x, a)$ and threshold value $Z_1(x, a)$

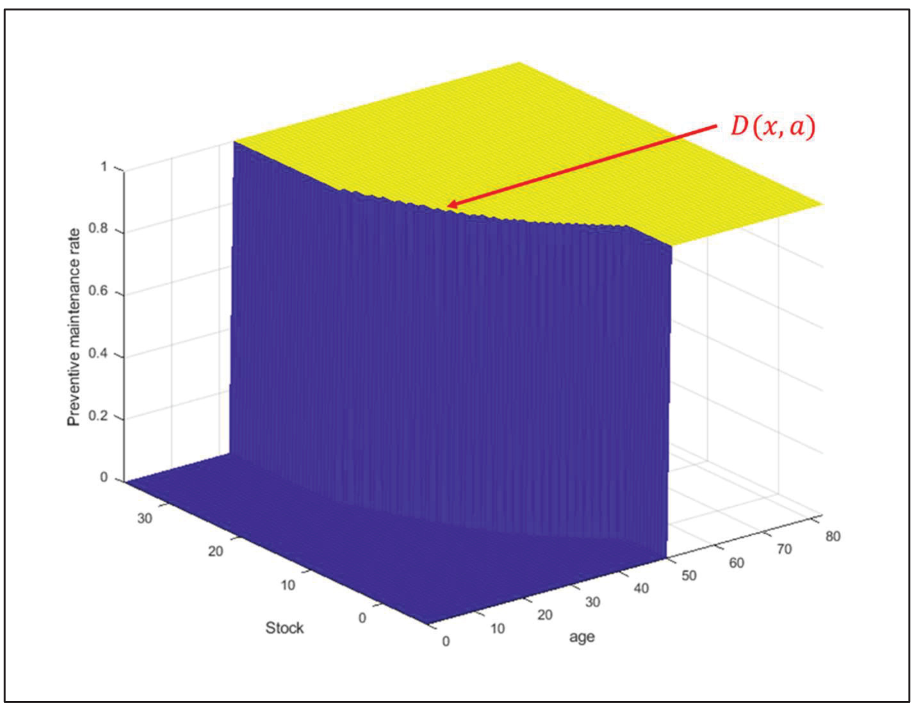

Figure 3.7 Preventive maintenance rate $\omega(x, a)$
and threshold function $D(x, a)$

For the production rate u, as demonstrated in Figure 3.6, a critical threshold $Z_1(x, a)$ production policy defined by Equation (3.24) can be chosen.

$$D_u = \left\{ u(\alpha) \;/\; u(\alpha) = \begin{cases} u_{max}(\alpha) \; if \; x < Z_\alpha(a) \\ d \; if \; x = Z_\alpha(a) \\ 0 \; if \; x > Z_\alpha(a) \end{cases} \right\} \tag{3.24}$$

For the preventive maintenance rate ω, as illustrated in Figure 3.7, a critical threshold $D(x, a)$ policy defined by Equation (3.25) can be chosen.

$$D_\omega = \left\{ \omega(1) \;/\; \omega(1) = \begin{cases} \omega_{max} \; if \; a \geq D(x) \\ \omega_{min} \; if \; a < D(x) \end{cases} \right\} \tag{3.25}$$

In Figure 3.8, the $Z_1(x, a)$ and $D(x, a)$ threshold values are represented graphically. At the age of *a=23*, the slope of $p(a)$ increases abruptly, as shown in Figure 3.8, hence it is necessary to avoid aging the machine by producing (because $\dot{a} = K_u.u$) if one already has enough stock, which explains the negative slope of $Z_1(x, a)$ in this zone.

It is also observed in Figure 3.8, by graphically representing the $D(x, a)$ values, that a high level of stock, higher than *x=23*, allows to send the machine for preventive maintenance at a lower age because the demand can be absorbed by the inventory and the risk of breakdown is reduced. In addition, beyond the age *a=52*, it is preferable to send the machine for preventive maintenance regardless of the stock level because the risk of breakdown is too high.

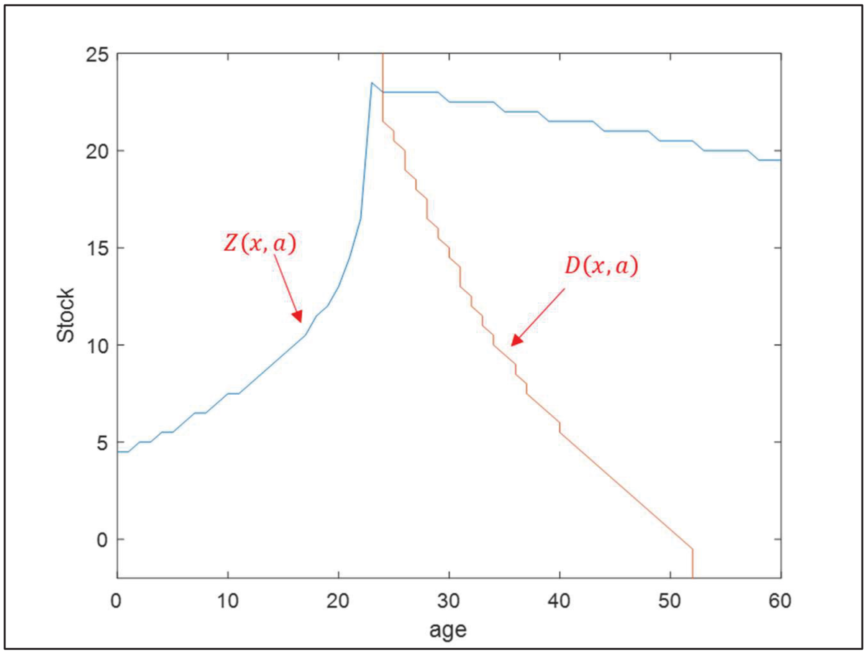

Figure 3.8 Threshold value $Z_1(x,a)$ and threshold value $D(x,a)$

In the case of operational lockout, the maximum production rate in this mode is lower than the demand rate, the production rate at this mode is given in Figure 3.9. We observe a negative slope of $Z_2(x,a)$for the same reasons as the negative slope of $Z_1(x,a)$ described above.

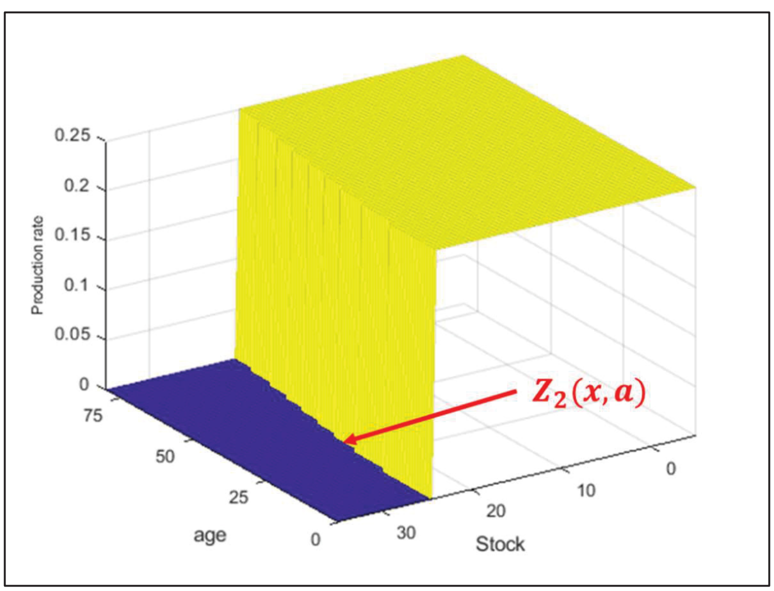

Figure 3.9 Production rate $u(2,x,a)$ and threshold value $Z_2(x,a)$

In the case of operational tagout (the maximum production rate in this mode is lower than the demand rate) the machine will produce regardless of its age, which is illustrated in Figure 3.10. The age of the machine is considered to be zero throughout this step, and the machine only starts to age again after any lockout operation is completed, hence $Z_6(x, a)$ is not age dependent.

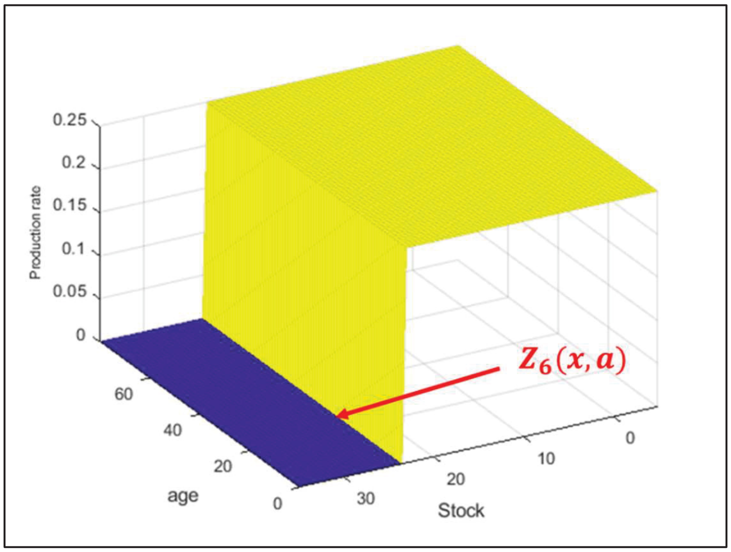

Figure 3.10 Production rate $u(6, x, a)$ and
threshold value $Z_6(x, a)$

3.6.2 Sensitivity analysis

In order to study and validate our model, we perform a sensitivity analysis on inventory costs, shortage costs, preventive maintenance costs and demand rate.

3.6.2.1 Holding cost

In the case of a high inventory cost, we notice in Figure 3.11.a that the system will accumulate stock from a high age only, due to the higher probability of failure and the need to absorb demand. In fact, the higher the inventory cost becomes, the more advanced this age will be.

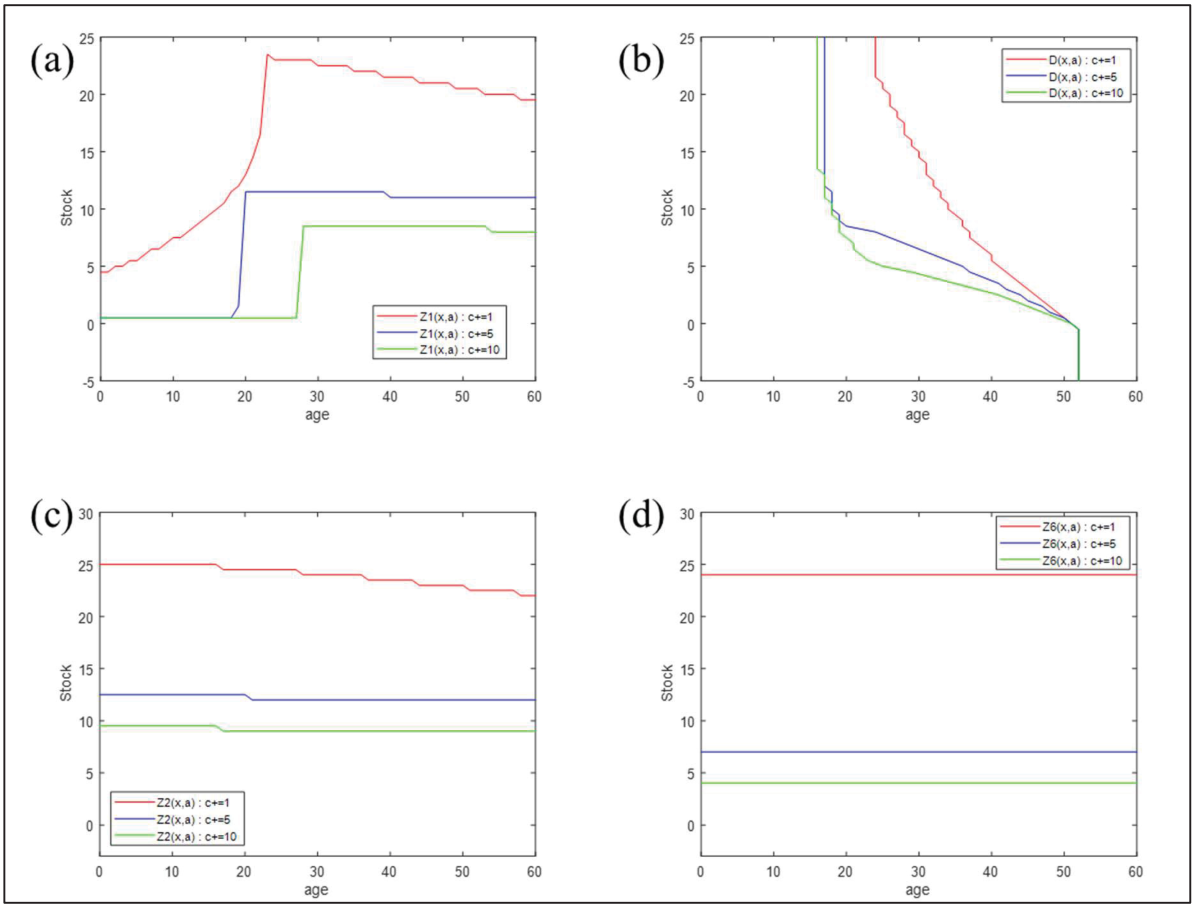

Figure 3.11 Sensitivity analysis of the holding cost: threshold values (a) $Z_1(x, a)$, (b) $D(x, a)$, (c) $Z_2(x, a)$, (d) $Z_6(x, a)$

It can also be observed that an increase in the cost of inventory causes more frequent sending of the machine for preventive maintenance as shown in Figure 3.11.b. Indeed, it becomes more profitable to perform maintenance more frequently than to have inventory absorbing the demand in case of breakdown.

In the case of operational lockout, presented in Figure 3.11.c, the maximum production rate in this mode being lower than the demand rate, the machine will produce regardless of its age. The system will produce for large inventories at low inventory costs. The same observation can be made for the production rate during operational tagout in Figure 3.11.d.

3.6.2.2 Backlog cost

In the case of a high shortage cost, we notice that the system will build up inventory to prevent itself from a shortage in case of failure as shown in Figure 3.12.a.

In Figure 3.12.b, we can see that an increase in shortage costs increases the age of preventive maintenance for a given inventory. Indeed, it becomes more profitable to repair a breakdown when the machine is old than to have a shortage during a maintenance operation.

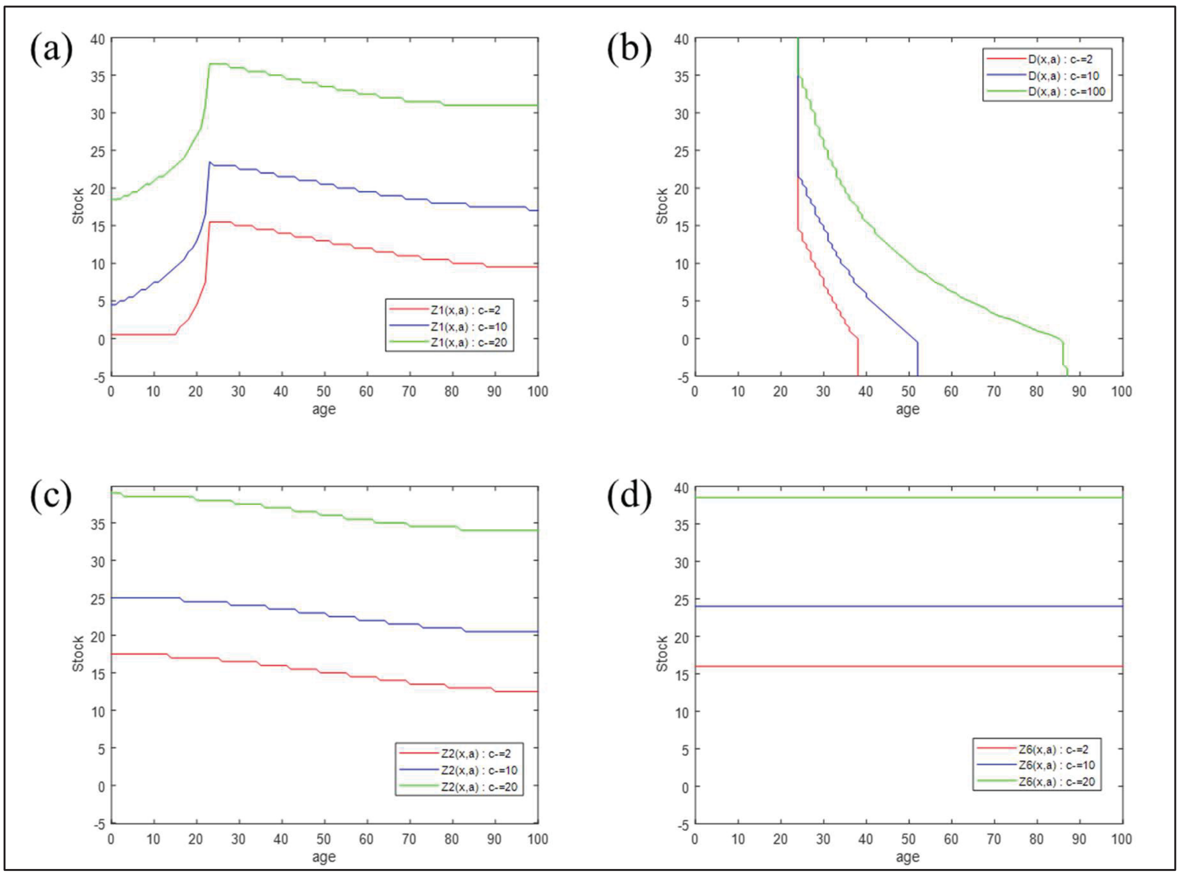

Figure 3.12 Sensitivity analysis of the backlog cost: threshold values (a) $Z_1(x,a)$, (b) $D(x,a)$, (c) $Z_2(x,a)$, (d) $Z_6(x,a)$

In the case of operational lockout, illustrated in Figure 3.12.c, the system will produce in the presence of high inventory for high scarcity costs to prevent a failure. The same observation is made for the production rate during operational tagout in Figure 3.12.d.

3.6.2.3 Preventive maintenance cost

We can see in Figure 3.13.a that an increase in preventive maintenance costs increases the age at which, for a given stock, the machine is sent for preventive maintenance. Indeed, we try to send the machine for maintenance as late as possible, when the breakdown becomes more probable.

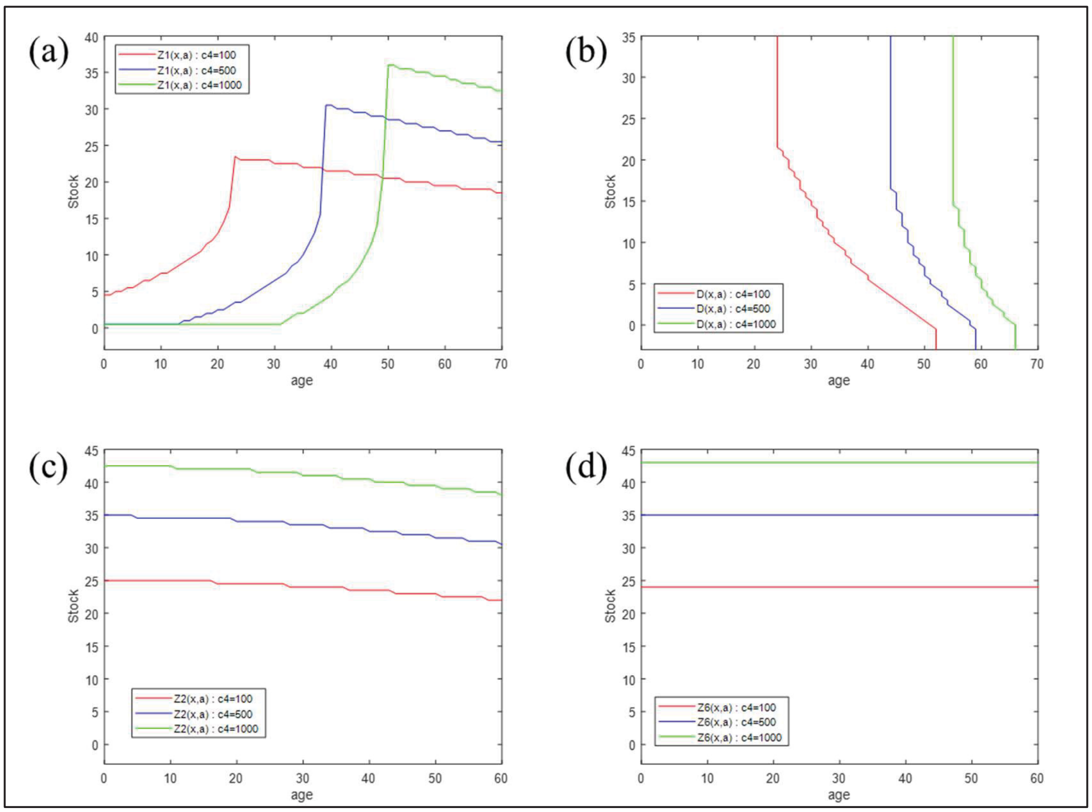

Figure 3.13 Sensitivity analysis of the cost of preventive maintenance: threshold values (a) $Z_1(x,a)$, (b) $D(x,a)$, (c) $Z_2(x,a)$, (d) $Z_6(x,a)$

In Figure 3.13.b, as preventive maintenance is done at a later age for a higher maintenance cost, the need to create inventory to absorb the demand during preventive maintenance will occur later in time. On the other hand, the risk of failure being greater at these ages, a relatively large quantity of stock is created.

In the case of operational lockout, outlined in Figure 3.13.c., when the maximum production rate is lower than the demand rate for this mode, the machine will produce regardless of its age. The system will produce at high inventory levels for high maintenance costs to absorb the demand in case of failure, which would postpone preventive maintenance, and therefore the refurbishment of the machine. The same observation is made for the production rate during operational lockout in Figure 3.13.d.

3.6.2.4 Demand rate

For a low demand rate, the system will tend to have less inventory as shown in Figure 3.14.a. It will indeed be easier to absorb the demand during breakdowns and preventive maintenance for low demand.

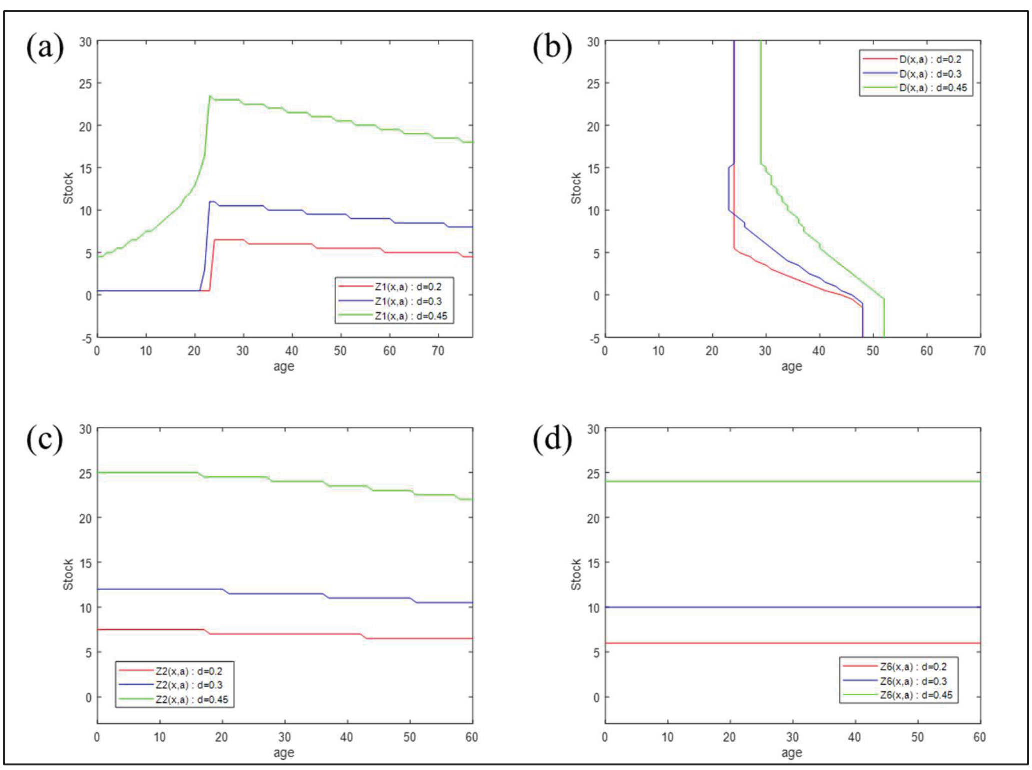

Figure 3.14 Sensitivity analysis of the demand rate: threshold values (a) $Z_1(x,a)$, (b) $D(x,a)$, (c) $Z_2(x,a)$, (d) $Z_6(x,a)$

In Figure 3.14.b, the sending in preventive maintenance will also be done for a relatively newer machine if the demand is low. Indeed, a low inventory will make it possible to absorb the demand during maintenance, it will thus be not very expensive to constitute this inventory and it will be profitable to refurbish the machine more regularly.

For operational lockout/tagout, the lower the demand, the less inventory the system will need to accumulate to meet the demand as shown in Figure 3.14.c and Figure 3.14.d.

3.7 Comparative analysis

In this section, we perform a comparative study of the cost of the system in operation, i.e., at mode $\alpha = 1$, represented by the value function $v(1, x, a)$ when the optimal solution is applied. The developed manufacturing system, considering the operational LOTO, is compared to a system close to the one developed by Badiane et al. (2016) that does not consider an operational LOTO. The model and these different modes are given in Equation (3.26) and its state transition diagram is illustrated in Figure 3.15.

$$\xi(t) = \begin{cases} 1 & \text{if the machine is in operation} \\ 2 & \text{if the machine is in lockout for preventive maintenance} \\ 3 & \text{if the machine is in preventive maintenance} \\ 4 & \text{if the machine is in full lockout for repair} \\ 5 & \text{if machine is in repair, then in full tagout} \end{cases} \tag{3.26}$$

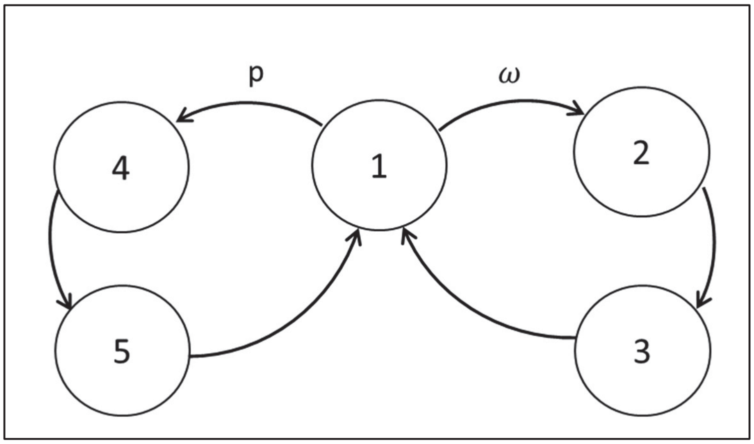

Figure 3.15 State transition diagram for the model without operational LOTO

In this model, tagout is included in repair and preventive maintenance. The same failure rate is considered as in our developed model and the parameters for the costs associated with the operational LOTO have been added to the lockout, maintenance and repair operations.

The policy that is developed in this article, which considers the operational LOTO procedure, is called *Policy I*. The production and maintenance policy without operational LOTO, resulting from the model in Figure 3.15, is referred to as *Policy II*. The comparison is made for three given inventory levels. The numerical approach, which is described in this paper is used to calculate the induced costs.

Figure 3.16.a, Figure 3.16.b and Figure 3.16.c show that regardless of the stock levels, *Policy I* including the operational LOTO has a lower production cost than *Policy II*. This difference in cost tends to be reduced in the case of a stock $x=17$ for a high age as shown in Figure 3.16.c. Indeed, for an older machine, the risk of failure becomes more important according to Equation (4). It is therefore not preferable to produce during the operational LOTO, so the benefit of this mode is reduced. This comparative analysis confirms that an operational LOTO procedure optimizes the joint production, maintenance and LOTO policies compared to policies without such type of LOTO integration.

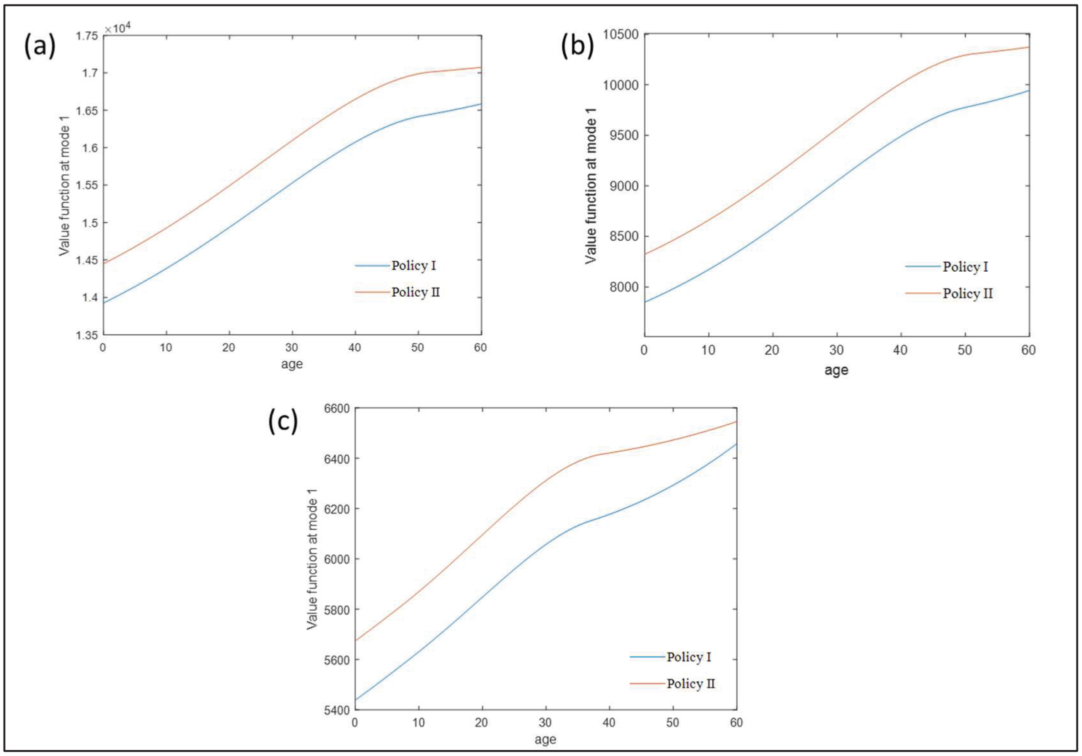

Figure 3.16 Comparison of value function $v(1, x, a)$ against machine age for different stock levels: (a) *x=3*, (b) *x=10*, (c) *x =17*

3.8 Managerial insights

One of the main challenges for smart production systems is to make the right decisions about scheduling operations based on the state of the system. In the case presented in this study, the state of the system varies depending on the age of the machine and the available inventory. The system and its managers must find the best production, maintenance and LOTO policy to reduce the total cost. The following discussion, based on the results of this study, presents new managerial insights for production decision makers regarding the management of operational LOTO strategies.

When the machine is in operation (α = 1), four zones (A, B, C, and D) can be identified graphically in Figure 3.17. They are bounded by the plotted values of $Z_1(x, a)$ and $D(x, a)$. In zone A, we observe that when the machine is still relatively new, it is not profitable to produce to create a large inventory. This can be explained by the fact that the machine is unlikely to break down, as there is no statistical need to support the demand without producing, and there is no need to refurbish the machine by maintenance. In Zone B, the inventory level is relatively high, since there is no need to increase production. As the machine starts to getting older, it is recommended to send it for preventive maintenance. In zone C, since the stock level is low, one has to produce to satisfy the demand. However, the older the machine, the more stock will be accumulated to avoid a shortage if a breakdown occurs. In zone D, when the machine is old, it is preferable to send it for preventive maintenance. If maintenance is not possible, production continues because the stock level is not very high and it is intelligent to produce in order to prevent a shortage if there is a breakdown. The older the machine gets, the lower the minimum stock level before sending it for maintenance, because the risk of breakdown becomes too high and a breakdown is very costly.

The zone D is the optimal zone to send the machine for preventive maintenance because it respects the dynamics of the system, contrary to the zone B. Indeed, if we respect the production policy, we should never have the stock levels as represented by zones A and B.

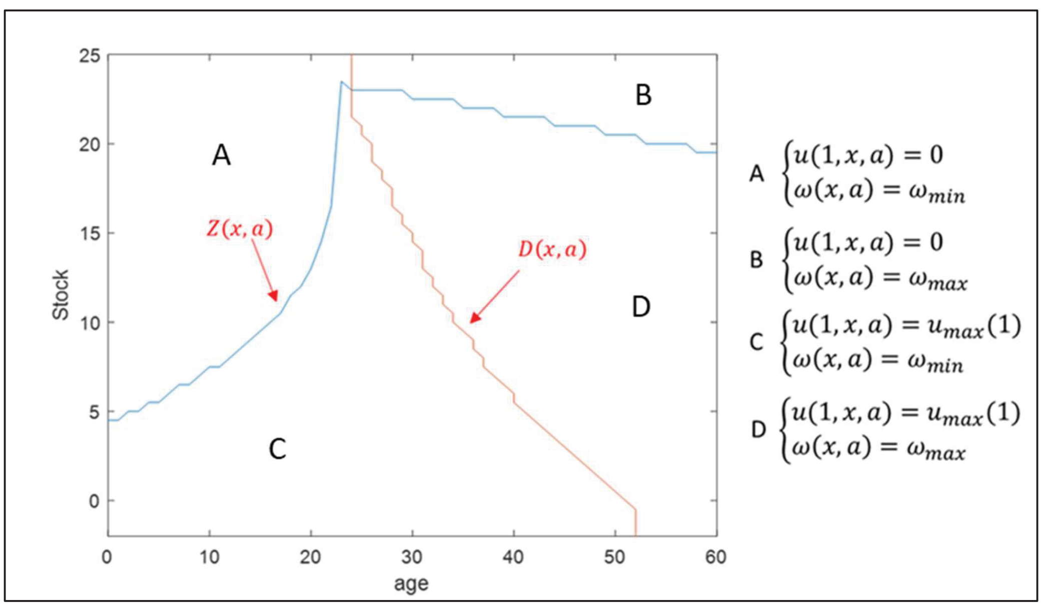

Figure 3.17 Implementation for managerial insight

When the machine is in operational lockout ($\alpha = 2$), two zones are defined as graphically presented in Figure 3.18. If we are located above the threshold value $Z_2(x, a)$, the inventory is too large and there is no need to produce. However, below this value, production is required to avoid shortages.

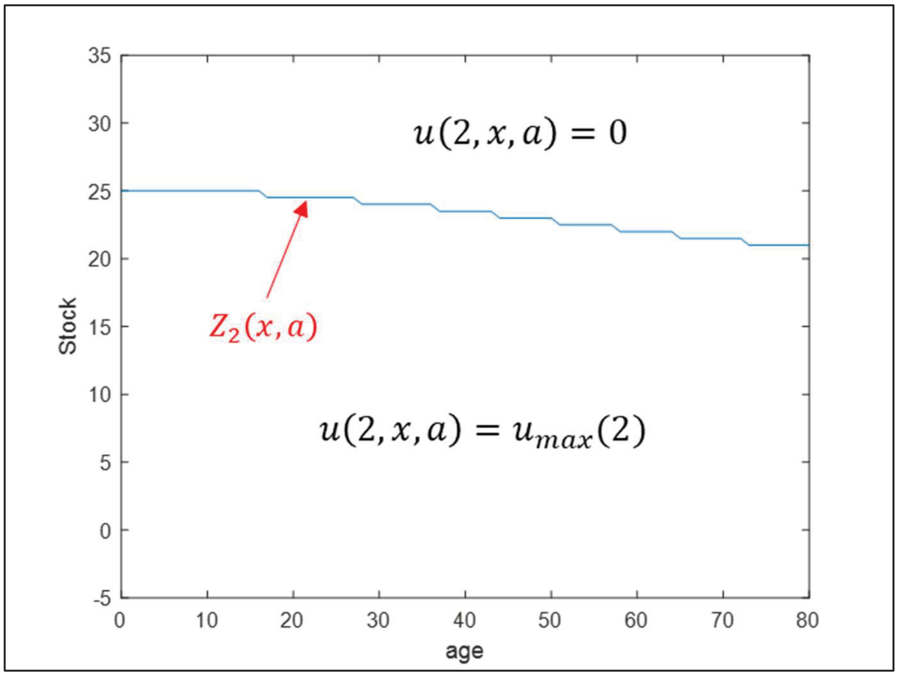

Figure 3.18 Trend of threshold value $Z_2(x, a)$ of the production rate $u(2, x, a)$

When the machine is in operational tagout ($\alpha = 6$), two zones can be defined as shown in Figure 3.19. If we are above threshold value $Z_6(x, a)$, the inventory is too large and there is no need to produce. Below this threshold value, production is required to avoid shortages.

Therefore, the system can know, depending on the age of the machine and the stock level, when to produce or not, and when to send for preventive maintenance or not. When the decision is made to send the machine for preventive maintenance, depending on the age of the machine and the stock level, it will be either preferable or not recommended to produce during the operational LOTO.

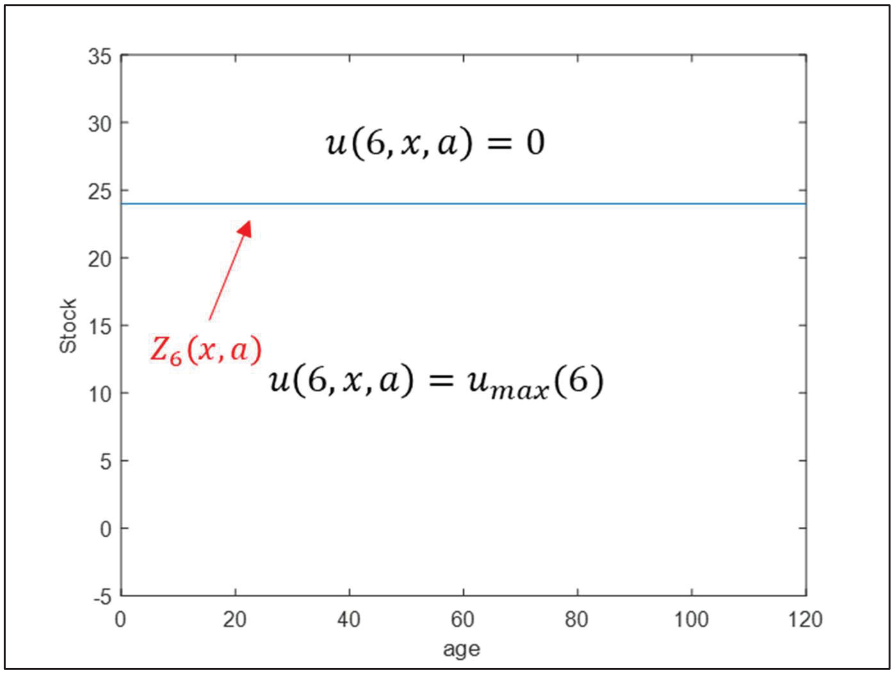

Figure 3.19 Trend of threshold value $Z_6(x, a)$ of the production rate $u(6, x, a)$

3.9 Conclusion

In this paper, we have developed a joint optimal production and maintenance policy for a manufacturing system subject to random failures and repairs while ensuring worker safety during preventive and corrective maintenance activities. We have, for the first time in the literature, introduced operational LOTO in joint production and maintenance policies, which allows to ensure the continuity of the production during the securing of the energy sources. A stochastic dynamic programming approach was used to determine the optimality conditions of the HJB type equations. These equations were then solved numerically to define the structure of the joint production and preventive maintenance policies. The results showed that these policies depend on the inventory level of the finished products and the age of the machine. The obtained optimal control policies can be defined as Machine Age Dependent LOTO Hedging Point Policies (MAD-LOTO-HPP). A sensitivity analysis was performed to show the effect of the variation of several parameters on the obtained policies in order to validate the proposed model. A comparative study was then carried out to position the policies developed in this paper in relation to those existing in the literature. This study showed a clear contribution in the research domain of simultaneous control of production and maintenance in a dynamic and stochastic context, guaranteeing the safety of the workers within the framework of a novel LOTO integration concept. Finally, we have presented a managerial implementation guide for the proposed policies in order to facilitate the control of the manufacturing system by the production managers. These new managerial perspectives in terms of implementation of operational LOTO implementation are essential for decision makers aiming to optimize the safety and the maintenance of complex machines in industrial processes.

Nevertheless, the proposed SPS is here semi-autonomous: the production manager sets the objective to be reached, here cost minimization, and either validates or rejects the recommendations of the SPS. In a fully autonomous system, the SPS decides on its own on the improvement objectives without instructions from the operational management. To achieve this, the SPS must have information from all levels of the company, from decision makers to operators and machines in the plant. In practice, such systems are not yet applicable (Alavian et al., 2020). For this reason, an Industry 4.0 approach and advanced technologies such as Internet-of-Things or artificial intelligence still need to be developed and integrated into manufacturing systems. LOTO and workplace safety in general can also benefit from such new technologies to become more efficient (Illankoon et Tretten, 2020). It would be relevant to study the integration behavior of these technologies (Angelopoulos et al., 2019). Moreover, the studied manufacturing systems are relatively simple and consider only a few machines in a few possible states. Models considering complex manufacturing contexts could not be solved in reasonable times with the used numerical methods. It would then be necessary to employ new solution methods such as machine learning methods (Candanedo et al., 2018), which is recommended for future research in this field.

CHAPITRE 4

A NOVEL APPROACH FOR PREDICTING LOCKOUT/TAGOUT SAFETY PROCEDURES FOR SMART MAINTENANCE STRATEGIES

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Abstract

This article presents an approach for predicting Lockout/Tagout (LOTO) procedure sheets, which are commonly used in the manufacturing industry to prevent premature equipment restart during maintenance. The prediction problem of energetic devices to lock from machine names is regarded as a multi-task classification problem. The dataset was obtained by processing LOTO sheets in Portable Document Format (PDF). The K-Nearest Neighbors (KNN), Random Forest (RF), and Deep Neural Network (DNN) algorithms were compared for this problem. The best prediction performance was achieved with the DNN method, with top-1 accuracies exceeding 63% and top-2 accuracies exceeding 90% for all devices. The sensitivity analysis conducted on the results indicates that the approach is robust and reliable, regardless of the industrial sector considered. In other words, the approach is not significantly affected by variations in the industry or its specific characteristics. These results suggest that the proposed approach can be used to assist workers in drafting LOTO sheets, and offers strong potential for concrete applications in safety management in the era of smart manufacturing.

Keywords: Environment, Health and Safety (EHS); Maintenance safety; Lockout/Tagout; Text mining; Neural network; Smart Manufacturing

4.1 Introduction

Workplace accidents can have severe consequences for both people and equipment, making it necessary for industries to take precautions to prevent them. Maintenance work is particularly risky, with high chances of injury or death for workers (Bulzacchelli et al., 2007). To address this, the Occupational Safety and Health Administration (1989) mandated the Lockout/Tagout (LOTO) standard for hazardous energy controls. Hence, LOTO requires employers to follow an energy control process to secure and disconnect equipment. Also, the ISO 14118 standard provides guidelines for safe entry of workers into hazardous areas with machinery. Lockout involves the locking of the device that isolates equipment from the various energies that supply it to prevent accidental restart during maintenance work. The tagout operation is the deactivation of the lock, and the entire procedure is known as LOTO. Different mechanisms are used to achieve LOTO operations, depending on the type of device. For example, a circuit breaker can be locked with a circuit breaker lock, and these mechanisms are secured with padlocks whose unique key is held by workers performing maintenance operations. Inadequate LOTO procedures are recognized as one of the causes of fatal accidents in the manufacturing industry and 17.2% of fatal accidents occur during maintenance and repair, the area with the highest number of accidents, ahead of production operations (Ruff, Coleman et Martini, 2011). However, the LOTO procedure is a commonly used method employing traditional tools, but its reliability can be enhanced through the integration of AI technologies (Dewi, 2018).

Indeed, the safety of workers in the manufacturing industry is a critical concern, particularly during maintenance operations, which are associated with physical injury and fatalities (Bulzacchelli et al., 2008). One possibility to improve safety is through the use of smart technologies, such as Artificial Intelligence (AI), which have shown potential in predicting and preventing accidents in the manufacturing industry (Jamwal et al., 2021 ; Kumar, et al. 2021). Predictive models and AI techniques, including machine learning and deep learning, can be embedded in production flows to improve maintenance and safety. In particular, the use of smart technologies can enhance the effectiveness and security of LOTO, which is a standard safety procedure for securing and disconnecting equipment during maintenance operations.

Recent studies in North America and the Middle East have examined Lockout-Tagout (LOTO) process implementation. Gauthier et al. (2021) addressed safety practices among machinery designers in Quebec, emphasizing the need for safety improvements. Burlet-Vienney et al. (2021) discussed safety in construction, particularly regarding hazardous energy control. Memarian et al. (2022) focused on high-risk electrical tasks in Australia, stressing the importance of training and protective equipment. Almutairi, Albeladi et Elrashidi (2023) evaluated hazards at a Saudi Arabian workshop. These studies highlight the need for training and awareness to enhance workplace safety. However, they mainly focus on worker training for LOTO procedures without exploring the connection between safety and maintenance effectiveness. Nevertheless, these issues are relevant for improving workplace safety and integrating LOTO into production and maintenance policies.

As well, with the arrival of smart manufacturing concepts (Kusiak, 2018), most contributions focus on the integration of smart technologies, e.g. AI, Internet-of-Things (IoT), Cyber-Physical-Systems (CPS), to increase the efficiency of the manufacturing value chain. An often-overlooked aspect is, however, the application of smart technologies in the manufacturing industry towards the implementation and execution of safety procedures (e.g. LOTO) for maintenance operations, such as a system to assist in establishing LOTO sheets using machine learning and deep learning algorithms. To address this open research question, the present study aims to develop a practical solution for predicting LOTO sheet writing in the industry using multi-task classification modelling, such as preliminary explored by (Delpla et al., 2022). The present study seeks to compare the prediction performance of different proposed solutions and determine if LOTO sheet writing can be modelled as a multi-task classification problem. By using elements of smart technology, e.g. AI, this solution has the potential to improve worker safety in the manufacturing industry and enhance the efficiency of LOTO procedures. This research contribution will first present a review of the scientific literature in Section 4.2. The industrial context is presented in Section 4.3 and the objectives of the identified research are outlined in Section 4.4. Section 4.5 presents the methodology approach for predicting LOTO safety procedures. The research results are discussed in Section 4.6. Finally, a conclusion is given on the progress made and the scope of future work in Section 4.7.

4.2 Literature review

The literature review will discuss environment, health and safety (EHS) perspectives in smart manufacturing, and then more precisely on text mining applications in this context. Then a review of text pre-processing methods and multi-task classification prediction methods will be presented.

4.2.1 Challenge of safety in Smart Manufacturing

Reducing operating costs, improving production efficiency and ensuring worker safety have become an economic imperative for the manufacturing industry. Smart manufacturing is a form of production that seeks to achieve these goals with new communication and computing technologies (Kusiak, 2018). Many manufacturing companies have implemented processes to identify and evaluate relevant risks. As a result, industrial activities are more systematically concerned with security as shown by the improved risk priority number and analytic network process, which are two different multi-criteria decision-making techniques (Silvestri, De Felice et Petrillo, 2012).

Industry 4.0 technologies such as IoT, CPS, cloud computing and smart sensors are solutions for managing operational security in the context of smart manufacturing. For example, in smart factories, personal protective equipment incorporating automation technologies can improve worker safety in intelligent environments driven by a CPS model (Podgórski et al., 2017). Another example in the domain of Industry 4.0 and safety management involves the creation of an Internet of Things (IoT)-based Lockout-Tagout (LOTO) device that automates the LOTO procedure for electrical devices. This device is equipped with various components, including a microcontroller, GSM SIM module, servo motors, and switches. It can be programmed using widely accessible platforms like Arduino IDE, which is an open-source platform. It provides additional security by automatically locking and sending text messages to authorized personnel (Kumar et Tauseef, 2021a). Safety-aware robots that can recognize susceptible actions that might hurt workers could also enhance safety in work areas. This type of robot is achievable by incorporating humans, physical interaction events, and motion in the planning process

(Beetz et al., 2015). In addition, autonomous robots enhance employee engagement by relieving workers of repetitive and alienating tasks while increasing the level of workplace safety through real-time mobile communication capabilities to share information and exchange messages about their location, status, operational status, and availability to improve machine reliability (Ciano et al., 2021). Industry 4.0 also has a significant effect on manufacturing organizations when new technologies are centred around workers. This is because manufacturers can improve their process through the workforce and adaptive features of technologies, including workplace safety processes as revealed in a qualitative data analysis of multiple Italian manufacturers (Margherita et Braccini, 2020).

The expectations of the society concerning Industry 4.0 have also evolved. This is a challenge in the digital transformation of companies in the current era. Indeed, a recent study reported the analysis of social conditions from the point of view of the consumer, the producer and the employee and it was pointed out that safety at work was one of the points where expectations were high according to a quantitative study on consumers (Saniuk, Grabowska et Gajdzik, 2020). The work of (Ruppert et Abonyi, 2018) demonstrated that safety management can be automated by emerging digital safety equipment, including smartphones, personal protective equipment, proximity sensors, smart cameras, and robots. Safety managers can check the safety condition of employees on their portable devices instantly thanks to real-time information provided by intelligent wireless sensors and an internal positioning system placed on the production line (Ruppert et Abonyi, 2018).

However, these discussed studies concentrate more on the new technology aspects of Industry 4.0 than actual safety management systems. One of the major challenges in managing safety and maintenance issues in manufacturing systems is the ability to respond to system variations and disruptions. The main workplace safety risks come from the many variations that can disrupt manufacturing systems. In Industry 4.0, shorter production cycles and mass customization of products are factors that increase these variations. Production systems must consequently be flexible, including their securing mechanisms. Nevertheless, a quantitative analysis of the literature related to the applications of smart technologies in production systems has highlighted that current research does not focus sufficiently on the direct implementation of these technologies on real systems, in particular safety and reliability aspects are still not well developed in the context of Industry 4.0 (Panzer et Bender, 2022). AI-assisted smart manufacturing systems could anticipate these changes and provide proactive measures to solve the problems encountered as shown in the literature reviews (Zhou et al., 2022). In general, machine learning (ML) algorithms offer many opportunities for smart manufacturing applications as evidenced by the significant amount of academic papers intersecting these two research areas (Rai et al., 2021). Multiple case studies have illustrated that these adaptations would be feasible for both large companies and small and medium-sized enterprises (SMEs) (Mittal et al., 2020). Safety-related applications in the manufacturing industry include ML detection of leaks or fire on equipment (Sankarasubramanian, 2023), or material degradation due to corrosion (Hakimian, Pourrahimi et Hof, 2022). ML can also be used to identify and quantify the causes of major accident risks in certain industrial fields, such as the offshore oil industry (Zhen et al., 2023), or for certain types of risk, such as workers falling from heights (Zermane et al., 2023). The ML algorithms can thus be used to implement appropriate prevention, maintenance and training policies for the manufacturing industry.

Recently, the concept of Industry 5.0 has emerged, emphasizing the synergy between human expertise and AI to create solutions that prioritize human involvement. This complementarity is possible with the development of intelligent system architectures managing human-machine interactions, which was validated by real-world cases (Rožanec et al., 2022). Such collaborations highlighted by Industry 5.0 frameworks will improve safety performance in manufacturing environments through real-time system control (Ivanov, 2022). Romero et Stahre (2021) defined the “Operator 5.0” as an intelligent, resourceful, and inventive operator whose human innovation is achieved by using information and technology to create new solutions that support manufacturing and maintenance operations. In Industry 5.0, the goal is to optimize human operators integration into intelligent manufacturing systems to improve processes in coordination with machines (Leng et al., 2022). Table 4.1 summarizes the various articles reviewed in this literature review by presenting the research purposes and the suggested technologies to achieve these goals.

The conducted literature analysis has highlighted that safety management in the paradigm of smart manufacturing presents a significant research deficit. It is observed that LOTO procedures are generally ignored in the smart manufacturing paradigm. Indeed, only the work by Kumar et Tauseef (2021a) addresses this issue from the perspective of the actual locking of energy control devices, however it lacks addressing of the LOTO procedure preparation. More generally, the consideration of safety management in Industry 4.0 is not well advanced and current research focuses on the exploitation of information rather than on the practical integration of safety management (Liu et al., 2020). The objective of this research paper is to provide a concrete application to assist in the management of LOTO procedures using AI-based strategies in the context of smart manufacturing.

Table 4.1 Summary of research purposes and suggested technologies for manufacturing safety improvement

	Purpose of the research					**Suggested technologies or tools**					
	Minimizing safety cost and time	Monitoring safety	Reducing accident risk factors	Improving human-machine	Assisting the LOTO procedure	Risk priority number	Internet of Things (IoT)	Cyber-physical systems	Robotic	Machine Learning (ML)	Deep Neural Network (DNN)
Kusiak (2018)	✓						✓				
Silvestri, De Felice, and Petrillo (2012)	✓					✓					
Podgórski et al. (2017)		✓					✓	✓			
Kumar (2021)			✓				✓				
Beetz et al. (2015)				✓					✓		
Ciano et al. (2021)		✓					✓				
Margherita and Braccini (2020)			✓					✓			

Table 4.1 (suite) Summary of research purposes and suggested technologies for manufacturing safety improvement

	Purpose of the research					**Suggested technologies or tools**					
	Minimizing safety cost and time	Monitoring safety	Reducing accident risk factors	Improving human-machine interraction	Assisting the LOTO procedure	Risk priority number	Internet of Things (IoT)	Cyber-physical systems (CPS)	Robotic	Machine Learning (ML)	Deep Neural Network (DNN)
Saniuk, Grabowska, and Gajdzik (2020)			✓						✓		
Ruppert and Abonyi (2018)		✓					✓				
Panzer and Bender (2022)			✓							✓	
Zhou et al. (2022)		✓					✓		✓	✓	
Rai et al. (2021)		✓								✓	
Mittal et al. (2020)		✓					✓	✓			
Hakimian, Pourrahimi, Hof (2022)			✓							✓	
Sankasubramian (2023)		✓	✓								✓
Zhen et al. (2023)			✓							✓	
Zermane et al. (2023)			✓							✓	
Rožanec et al. (2022)				✓							
Ivanov (2022)		✓					✓		✓		
Romero and Stahre (2021)				✓						✓	✓
Leng et al. (2022)				✓			✓	✓	✓		
This article	✓				✓					✓	✓

4.2.2 Natural language processing in manufacturing industry

The problem addressed in this work is the prediction of LOTO sheets in order to support the drafting and validation of energy isolation protocols for equipment shutdown before maintenance. It is thus necessary to analyse the existing LOTO sheets, i.e. technical textual documents. Locating key information in documents is an essential challenge: arranging it in a usable format for all manufacturing companies would promote cooperative and collaborative decision-making (Ittoo, Nguyen, and van den Bosch 2016). Text mining is a promising technology to address this challenge (Jo, 2019b). Text mining, also referred to as text analytics, is an artificial intelligence (AI) technology that applies natural language processing (NLP) to convert unstructured text found in documents and databases into structured data. This structured data can then be analyzed or utilized to drive machine learning (ML) algorithms. It relies on existing written resources to perform this analysis and the extraction of key data. Different methods for retrieving textual information are used to find similarities between the words in a dictionary and the words in the studied documents. LOTO sheets processing and writing require the extraction of pertinent information to form usable data to automatically predict the sheets' content. The available LOTO sheets are typically in Portable Document Format (PDF) like many other text documents in the industry that are intended for humans. Different steps of text mining can be highlighted, such as the conversion of the document into a computer interpretable version, tokenization, stop words removal and information extraction (Mohan, 2015).

The comprehension and manipulation of texts is called natural language processing (NLP). This area of research is present in many scientific disciplines such as computer science, linguistics or information science, AI or robotics (Jusoh et Al Fawareh, 2007). Research also focuses on textual entailment, i.e. the relationships between different parts of a text (Sha et al., 2016). Technical writing support has also been addressed by studying the structures of these texts (Anthony et Lashkia, 2003). Many advances in text document generation have been made, opening new possibilities for industry (Qiu et al., 2020). In the manufacturing industry, NLP is overall understudied and behind other domains, such as medicine. The maintenance field is also negatively impacted by this underdevelopment (Brundage et al., 2021). In this work, the textual documents concerning safety were also examined. In the construction sector, accident reports are analysed by experts, which takes time and increases overhead costs. Risk identification by NLP can identify risks faster and can provide a prediction of possible accidents in the future (Na et al., 2021). Similarly, analysing aviation incident reports across the globe provided also valuable insights. The processing and classification of these reports offers experts a precious database for their investigations (Tanguy et al., 2016). More recently, the development of large language models (LLMs)¸ such as Chat GPT, offers new scientific opportunities in terms of text generation by artificial intelligence (Almarie et al., 2023).

This literature review in Section 4.2.2 has identified research gaps in the analysis of textual documents for the manufacturing industry. Specifically, the writing of secure LOTO procedures has not been well studied. Therefore, this research work contributes to providing a practical application of intelligent strategies to assist in the development of safety protocols for manufacturing systems, particularly the writing of LOTO procedures which are a critical factor in ensuring worker safety. To be able to process textual documents, it is necessary to study the approaches that can be used to accomplish this processing. Delpla et al. (2022) suggest that this problem can be approached as a multi-task classification problem.

4.2.3 Multi-task classification

In order to address the stated research objective of this study, it is necessary to briefly review the classification problem techniques. Classification is a supervised learning technique used for prediction purposes by developing a model that can predict the class or label of unknown data samples (Aggarwal, Singh et Gupta, 2018). Multi-task classification, a subtype of classification, is useful for categorizing various types of data and predicting multiple outputs (Bielza, Li et Larrañaga, 2011). K-nearest neighbors (KNN), Random Forest (RF), and Deep Neural Network (DNN) are common classification algorithms used to solve multi-task classification problems (Al-Tarawneh et Bani-Salameh, 2022). KNN classifier is a simple approach that determines similarities between available training data and new data to be predicted, while RF combines decision trees to form a model that shows good performance and robustness. DNN, on the other hand, uses the information contained in multiple related input features to improve prediction performance (Charbuty et Abdulazeez, 2021). Therefore, comparing these three algorithms is important as each has its advantages and disadvantages, and choosing the most appropriate algorithm depends on the dataset and the problem being solved (Al-Tarawneh et Bani-Salameh, 2022).

In multi-task classification, the K-nearest neighbors (KNN) classifier is a popular and straightforward approach (Al-Hawari, Najadat et Shatnawi, 2021). Such a KNN algorithm calculates the similarity between new data and available training data and predicts the class with the highest similarity based on input features (Jindal, Malhotra et Jain, 2015). Unlike other classification algorithms, the KNN algorithm does not learn from the training data, but instead performs at classification time, i.e. it needs to be executed for each prediction (Jayaprakash et Balamurugan, 2022). While the KNN algorithm is efficient for heterogeneous data and easy to implement, it has limitations when the number of classes is large, and finding the right K-nearest neighbors can be challenging (Boateng, Otoo et Abaye, 2020).

Random Forest (RF) is a leading multi-task classification algorithm in ML due to its diversity and simplicity (Al-Hawari, Najadat et Shatnawi, 2021). Combining multiple decision trees, the RF algorithm is effective in achieving high accuracy (Khanday et al., 2020). Decision tree classifiers are known for their robustness and good performance (Charbuty et Abdulazeez, 2021). However, the RF algorithm may be slow with large datasets (Boateng, Otoo et Abaye, 2020).

Artificial neural networks (ANNs), particularly deep neural networks (DNNs), have recently emerged as an effective solution for multi-task classification problems in manufacturing systems (Bodendorf, Merkl et Franke, 2022). Indeed, DNNs can effectively handle multi-task classification problems, particularly when dealing with textual data and limited training data (Li et al., 2021). DNNs use multiple related input features to improve prediction performance for all output tasks or classes (Zhang et Yang, 2017). The input layer of the DNN recovers input features, and hidden layers share information to improve learning from training samples. These hidden layers allow the model to link outputs of different tasks together, and the final layers are used to obtain class and task-specific values (Ghosh et al., 2019).

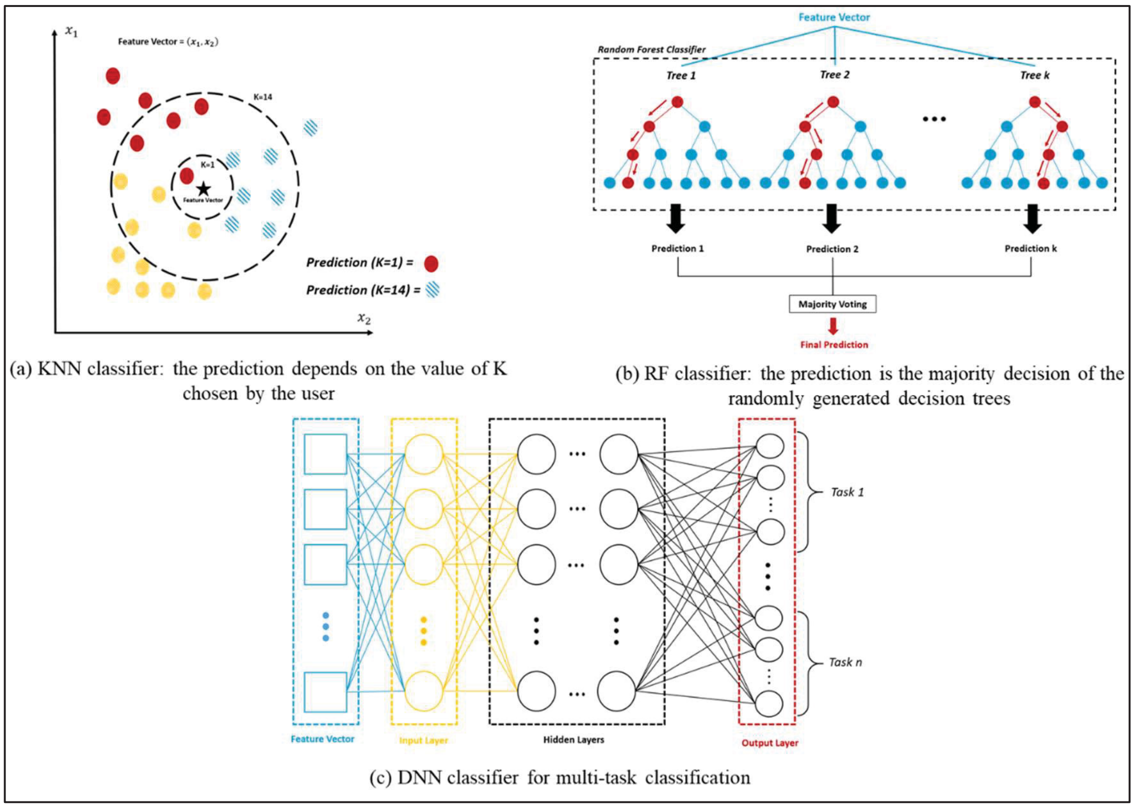

Figure 4.1 Multi-task classification classifiers principles

Table 4.2 Comparison of multi-task classification algorithms

Advantages	KNN	RF	DNN
Easy to understand and implement	✓		
Used for classification and regression	✓		
No assumptions about the data distribution	✓		
Robust to non-linear or complex problems	✓		
Capable of handling large-scale and high-dimensional datasets		✓	✓
Robust to outliers, missing data and data noise		✓	
Provides variable importance for assessing feature contribution		✓	
Capable of learning complex features and non-linear relationships in data			✓
Potential for high performance when properly configured and trained			✓
Suitable for various types of data (text, images, sequences)			✓
Provides backpropagation for adjusting network weights during training			✓
Limitations	**KNN**	**RF**	**DNN**
Computationally expensive	✓		
May overfit on noisy data if databases are not balanced		✓	
Requires large amounts of training data and computing power			✓

In this section, we have reviewed some methods for solving multi-task classification problems. The principles of the different algorithms are summarized in Figure 4.1. Each of these algorithms has its limitations and advantages, which are summarized in Table 4.2. It is thus pertinent to test each method for the solution of the prediction problem in the present study. In order to apply these algorithms, it is therefore necessary to specify the multi-task classification problem that could model the generation of LOTO sheets. A comparison of these algorithms would be necessary to compare their respective accuracies.

4.2.4 Contributions

Following the literature review, various research gaps were identified. The contributions of this paper, aiming to contribute in addressing these gaps, are summarized as follows:

- Propose an approach to predicting LOTO sheets considering this problem as a multi-task classification and thus propose a novel intelligent strategy for writing safety protocols in manufacturing systems;
- Compare the prediction performance of KNN, RF and DNN classification algorithms for this problem and investigate which classifier has the best accuracy;
- Propose a specific application of an EHS transformation in the context of smart manufacturing.

4.3 Industrial context

The implementation of Lockout/Tagout (LOTO) procedures is essential in ensuring the safety of maintenance operators before carrying out any equipment maintenance operation in industrial settings (Emami-Mehrgani, Kenné et Nadeau, 2013). However, some production sites may have an extensive array of equipment, exceeding 1000 machines or devices, which need to be secured before maintenance. Unfortunately, the LOTO sheets are not always updated systematically, creating potential safety risks for maintenance personnel.

To minimize the risks associated with equipment shutdown, maintenance operators must ensure that the Lockout/Tagout (LOTO) sheet is updated and validated by equipment experts. However, this process is time-consuming and requires significant resources due to the multiple steps involved, including equipment information collection, form writing, information validation, and form approval. The experience of workers, their knowledge of the equipment and the analysis of LOTO reports by managers after maintenance are important for preserving safety. Companies maintain records of LOTO procedures, e.g. using ESH management software, but these need to be retrieved and checked periodically. This operation can be particularly penalizing for a company, especially where managers have changed in the meantime (Ouellet, 2022). In a typical industrial use case, Figure 4.2 summarizes the different steps involved in the LOTO implementation process and the time required for each step. It is imperative to effectively implement LOTO procedures to prevent accidents and ensure the safety of maintenance personnel in industrial settings.

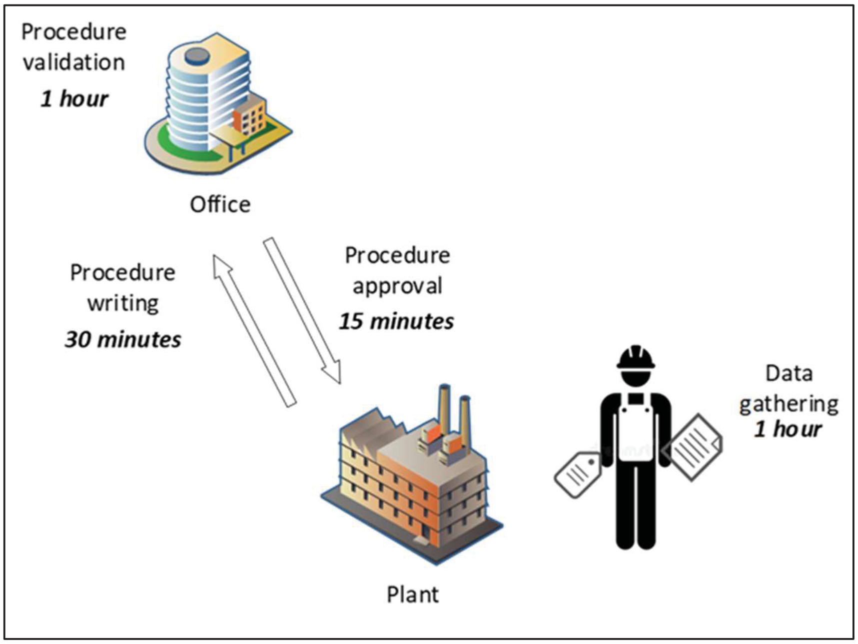

Figure 4.2 Time required to implement a LOTO procedure

Resource improvements are multiple and categorized as technical, clerical, and staff management. On a complete industrial facility, these efforts can accumulate to hundreds of hours (Ouellet, 2022) as demonstrated in Table 4.3.

Table 4.3 Typical effort required by the implementation of LOTO by each resources type

Resource Type	**Effort for 100 machines**
Technical resources	*250 hours*
Clerical resources	*50 hours*
Management	*25 hours*

In the era of Industry 4.0, where process optimization is a primary goal, traditional LOTO procedures are increasingly perceived as outdated and restrictive, failing to leverage the potential of emerging technologies. The currently widely adopted LOTO system presents a significant impediment to efficient production and maintenance planning. To overcome this challenge, this study proposes an approach to predict the devices that require locking on industrial equipment prior to maintenance, based on the machine names. This predictive model has the potential to significantly reduce the time and resources allocated to the LOTO process, enabling higher production efficiency and optimization, while ensuring process safety.

4.4 Problem description

CONFORMiT, a Canadian company that develops, commercializes and implements EHS management software for industry, is providing thousands of LOTO sheets for this research study. An example of such LOTO sheets in PDF format is presented in Figure AII.1. Key data is highlighted and easily understandable to a human reader (e.g. a factory operator). We can identify two types of prediction. Figure 4.3.a presents the pairing of the machine name with a group of devices to be locked before a maintenance operation, while Figure 4.3.b illustrates the pairing of a device with the corresponding instructions. These two prediction levels can be treated independently: the instructions to lock a device do not differ with the type of machine.

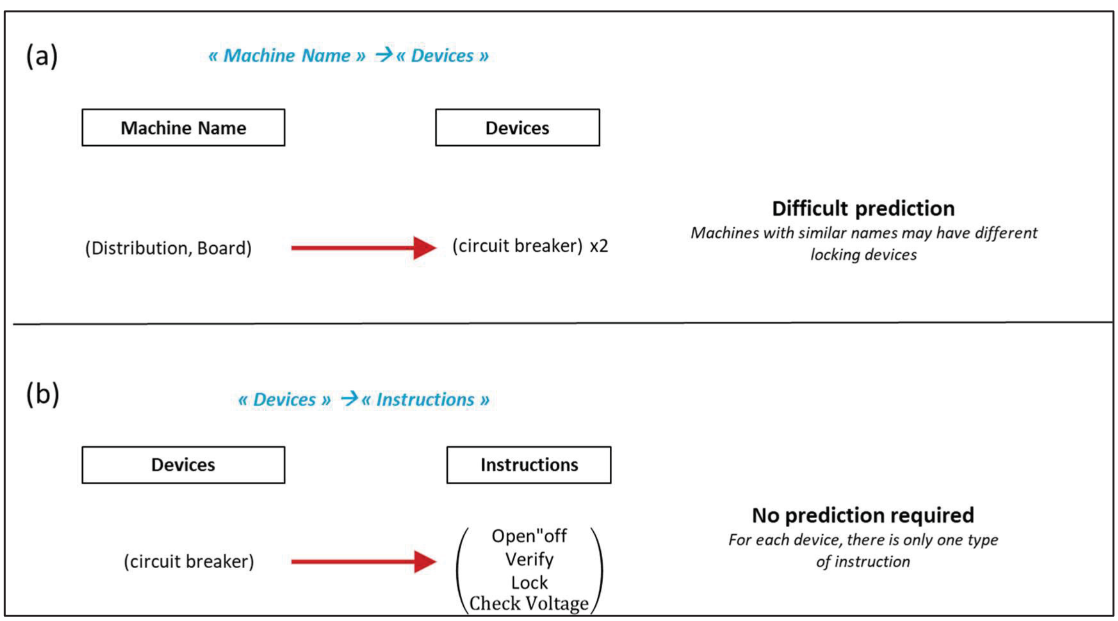

Figure 4.3 Predictions to generate a LOTO sheet: (a) Predictions of devices based on the name of the machine; (b) Predictions of the instructions based on the devices

The first type of prediction (Figure 4.3.a) presents a challenging task, given the wide range of machines and the possibility of similar machine names that can have vastly different energy interlocking requirements, particularly with respect to the number of needed circuit breakers or valves. The second association (Figure 4.3.b.) is less complex to handle, because there is only one type of instruction per device. In this case, the names of the machines can be contained in a dictionary of 267 words and there are 12 devices ("sectionneur", "valve", "disjoncteur", "fiche", "alimentation électrique", "raccord", "terre", "vanne", "boite", "interrupteur", "coupe-circuit", "master-switch") that can lock the energies. Then, writing LOTO sheets is equivalent to a prediction problem of the devices to be locked based on the machine name. This problem is modelled by a multi-task classification problem, where the features are the words that indicate the machine names and the outputs are the number of each type of device to be locked.

4.5 Methodology

In this section, the methodology for the novel approach, consisting of different steps to process the LOTO sheets, and to build and validate the proposed prediction models is described. Figure 4.4 is a graphical representation of the complete developed methodology from LOTO sheets conversion to multi-task classification model development and its evaluation.

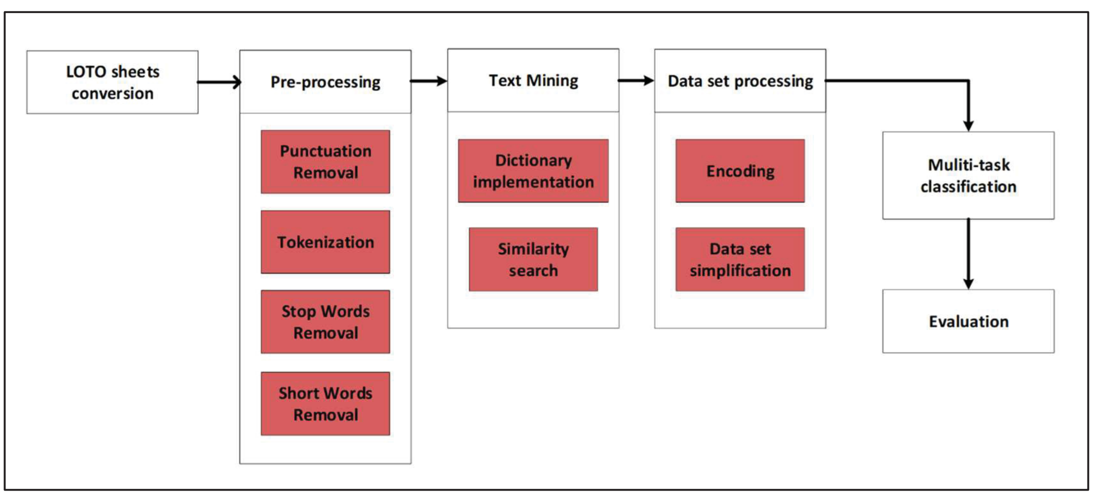

Figure 4.4 Visualisation of the proposed methodology

4.5.1 Pre-processing and text mining

To perform text mining on PDF files, they must first be converted into strings that can be processed. The Python libraries "PyPDF2" and "pdfminer" are effective tools to convert PDFs to .txt format, which can be easily processed by programming languages like Python (Kulkarni et Shivananda, 2021; Shinyama, 2014). After conversion, the next step is to tokenize the text by segmenting the content into individual words. However, irrelevant stop words such as articles, prepositions, and pronouns must be eliminated from the text. Various pre-registered stop word lists are available in open databases in different languages (Jivani, 2011).

The final step is information extraction, which involves identifying the keywords that carry significant information. This can be done by searching for the keywords using predefined dictionaries or sequences. The Jaro-Winkler distance algorithm is a method of measuring the similarity between two words and is commonly used in this process (Yulianto et Nurhasanah, 2021). This approach returns a ratio between 0 and 1, where a ratio of 1 indicates identical words. Single letter reversals are also weighted, reducing the influence of typing errors (Dreßler et Ngonga Ngomo, 2017). Many tools are available for processing textual documents, such as the NLTK library in Python, which offers various tools for applying ML and deep learning algorithms.

In order to use the LOTO sheets as a database, the first step is to convert them from PDF format to strings. This was achieved using the "PyPDF2" library in Python, however, this library had difficulties in maintaining text order and preserving characters such as spaces and punctuations. As a result, the "pdfminer" library was used instead to ensure that important words, such as machine names, were extracted accurately. Once the files were converted to strings, they were imported into Python as LOTO sheets for further analysis.
In order to detect the machine and device names to lock from the LOTO sheets, dictionaries which contain the specific words will be implemented. Some pre-processing setup needs to be done on the character string related to each sheet. The following tasks were performed with the NLTK python library:

- Punctuation removal;
- Tokenization of the string to isolate each word present;
- Stop words removal;
- Short words removal (less than 2 characters). These words are removed because they can cause problems during the similarity search;
- Similarities search: the words in the pre-processed LOTO sheet will then be compared to dictionaries of machine and device names to detect similar words. After several tests, the Jaro-Winkler distance is chosen because it provides better similarity recognition for shorter words. When a word in the dictionary is detected, it is paired with the analyzed sheet. The relevant data from each LOTO sheet are extracted.

4.5.2 Data set processing

In order to perform NLP, texts from the PDF sheets, originally unstructured, must be transformed. Indeed, the tools that are applied on classical databases are generally used on structured encoded data, i.e. on relational databases or tables of values to apply the classification algorithms. Table 4.4 represents the information collected from the LOTO sheets for the example sheet introduced in Figure A.1.

Table 4.4 Pertinent information collected from LOTO sheets: machine names and devices

<table>
<tr><th colspan="2">Machine Names</th><th>Devices</th></tr>
<tr><td>Word 1</td><td>Word 2</td><td>Principal</td></tr>
<tr><td rowspan="2">Panneau</td><td rowspan="2">Distribution</td><td>Disjoncteur</td></tr>
<tr><td>Disjoncteur</td></tr>
</table>

A multi-label encoding of this data is performed, where the information concerning the name of the machines and the devices are transformed in the form of vectors as shown in Figure 4.5.

For the DNN, a device matrix was constructed, which is presented in Figure 4.5. In this matrix, the rows correspond to the devices, and the columns to the occurrence of this device.

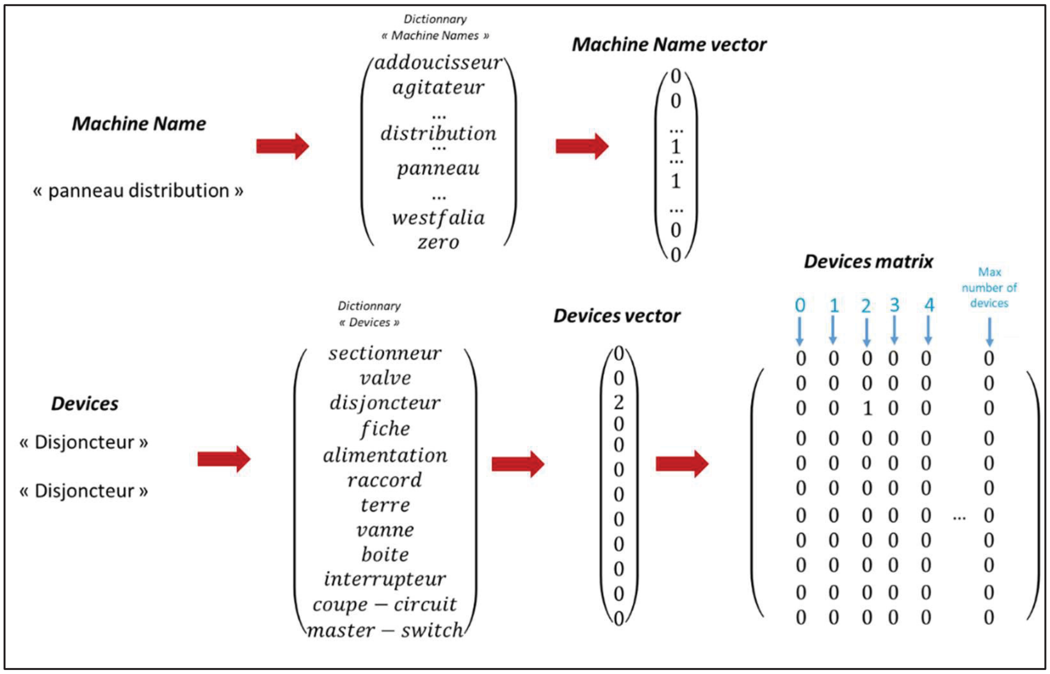

Figure 4.5 Proposed encoding of the dataset for the example presented in Table 4.4

The number of devices in the dataset rarely exceeds 9, so any occurrences of 10 or more will be grouped together as a single output. This simplification is not expected to cause problems in practical situations, as machines with a large number of devices are rare and difficult to predict without errors. Machines with more than 10 devices represent less than 2.5% of the equipment in the dataset. Prediction needs are mostly concentrated on simpler machines, which are commonly found on typical production sites. Figure 4.6 displays the transformation made to simplify a device vector.

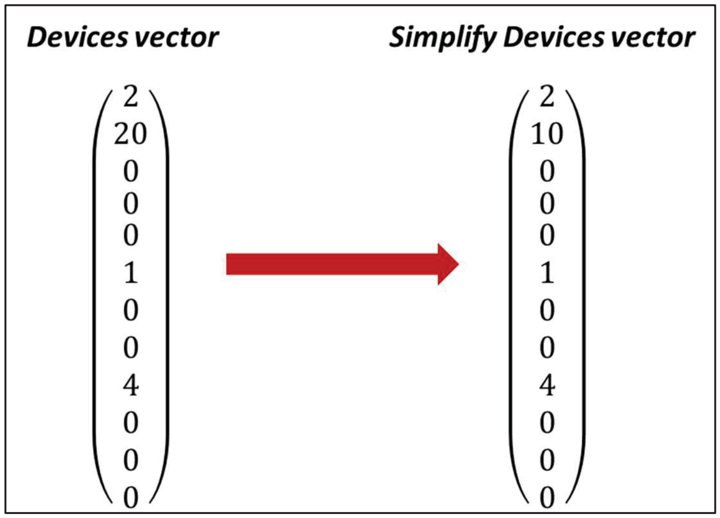

Figure 4.6 Simplification of the encoding of the device vector

4.5.3 Multi-task classification and model evaluation

The classification problem is solved with the KNN, RF and DNN algorithms. The prediction accuracy is defined in this section and is a key performance metric to evaluate the algorithms. The architecture of each algorithm is also described in this section.

4.5.3.1 Performance measures

In order to evaluate the different classification methods, firstly we will choose the accuracy, which allows us to judge the overall efficiency of a classifier (Chapron et al., 2018). The calculation of the top-1 accuracy is given by (Sokolova et Lapalme, 2009):

$$Top1\ accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{4.1}$$

In a second step, we will consider the top-2 accuracy for the most accurate algorithm. This performance measure considers the 2 classes that have the best predictions scores for the model (Rahimi et al., 2020).

In a multi-task classification, the accuracy is calculated for each of the tasks. In this study, the accuracy on the prediction of the number of each device will be calculated as follows: “sectionneur” accuracy, “valve” accuracy, “disjoncteur” accuracy, “fiche” accuracy, “alimentation électrique” accuracy, “raccord” accuracy, “terre” accuracy, “vanne” accuracy, “boite” accuracy, “interrupteur” accuracy, “coupe-circuit” accuracy, “master-switch” accuracy.

4.5.3.2 K-Nearest Neighbor

As it is not possible to give more importance to one machine than another, we consider that all the neighbors are equally valid, and thus that the weight function of our KNN algorithm is uniform. The nearest neighbor is determined from the Euclidean distances. The KNN algorithm is a supervised ML technique where the user is required to inform the number K of nearest neighbours from which the magnitude of similarity will be estimated. The K-value is non-trivial and an analysis must be done to determine the best one (Bin, 2015). To determine the optimal neighboring K-value, we scan for different values and compare their accuracy performance. We test K-values ranging in [5, 10, 15, 20, 25, 30] based on preliminary trial and error testing.

4.5.3.3 Random Forest

In this work, we use a RF algorithm whose criterion for separating samples to form DTs is the entropy criterion. This is an appropriate criterion in this work, because the features in the data are highly scattered and unbalanced (Aning et Przybyła-Kasperek, 2022). The other bagging criterion is not recommended when the output classes are highly unbalanced categories as in our case (Boulesteix et al., 2012). To determine the optimal number of decision trees, we will test [100, 300, 400, 500, 600, 700, 800] trees per RF.

4.5.3.4 Deep Neural Network

In order to solve our classification problem, we parameterize the DNN as illustrated in Figure 4.7. This network is composed of:

- An input layer that receives features consisting of the machine name vector. This input layer is a dense layer of 248 neurons. The activation function of the input layer is a rectified linear unit (ReLU) function, since this is efficient to easily obtain a NN to act with sparse representations (Glorot, Bordes et Bengio, 2011);
- Four hidden layers consisting of two dense layers of 64 and 32 neurons with ReLU activation functions, each followed by a dropout layer that improves NN performance and avoids overlifting problems (Srivastava et al., 2014). We apply dropouts of 20% which is a good value to reduce the impact of overlifting (Srivastava et al., 2014);
- An output layer composed of 12 dense layers (one for each device) each having 11 neutrons (each neuron corresponding to a number of devices). The activation function of these neurons is the softmax function that predicts the probability of each output class for multi-task classifications (Liu, Qiu et Huang, 2017);
- A backpropagation during training using the Adam optimizer to minimize our loss functions for multi-tasking architectures (Singh et al., 2022).

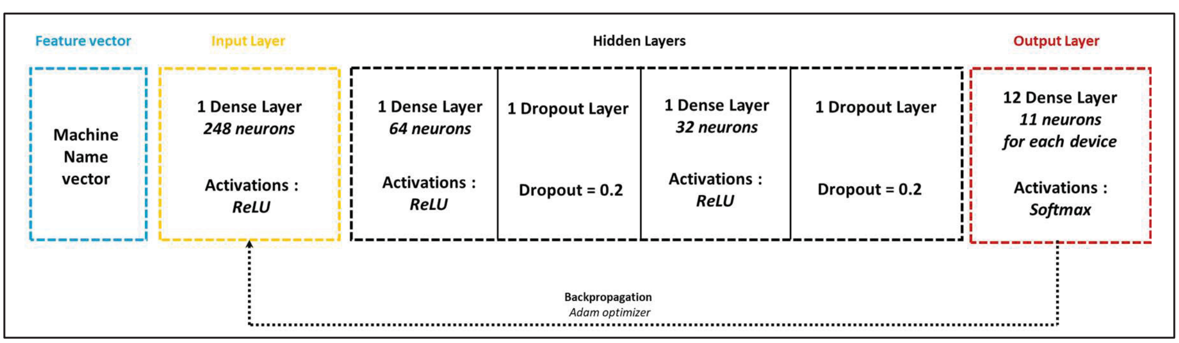

Figure 4.7 Proposed multi-task DNN model to predict devices from machine names

DNNs have the benefit of representing training data very well, however significant calculation time is needed to set parameters such as the number of epochs and the batch size of training

samples (Boateng, Otoo et Abaye, 2020). We use the grid search method to find the optimal number of epochs and the optimal batch size. The details of the grid search are as follows:
- The different batch sizes used are [1000, 1500, 2000, 2500].
- The different number of epochs used are [25, 50, 75, 100, 125, 150, 200, 250, 300, 350, 400].

4.6 Results and discussion

This section presents the obtained results using the developed LOTO sheet prediction method and it discusses their impact on safety management in the manufacturing industry.

4.6.1 Prediction method results and analysis

We used a windows system with 16 GB of RAM and an Intel core 2.26 GHz processor for performing this work. The Scikit learn library on Python is used for the KNN and RF algorithms. For deep learning with ANN, the Keras library on Python is used. The data is composed of 5870 LOTO sheets divided in an 80:20 ratio, where the initial 80% is used to train the model and the remaining 20% is used to test and validate it. These LOTO sheets are derived from various industrial sectors: food industry (2327 sheets), mining industry (2224 sheets), hospital facilities (211 sheets), port industry (456 sheets), and paper industry (352 sheets).
In order to reduce the risk of overfitting, the initial data set is divided into distinct test and training subsets. Stratified cross-validation is performed on our dataset and average accuracy scores (over 10 folds) are collected to evaluate model performance. This type of strategy reduces the sampling bias induced by separating the data into test and training subsets.

4.6.1.1 Prediction method accuracy comparison analysis

Table 4.5 represents the accuracy results for the different devices for a random fold. These first results show that the main challenge is on the prediction of the number of “disjoncteur” and “valve”, because these devices are present on many mechanisms with a great disparity in quantity. The computation times for each algorithm are given in Table 4.5.

The hyperparameters for each algorithm were selected through a grid search approach, utilizing the values listed in Section 4.5.4. The results of the grid search revealed that the KNN algorithm achieves optimal accuracy for both "sectionneur" and "valve" classifications when using 10 nearest neighbors, as illustrated in Figure 4.8.a. For the RF algorithm, the number of decision trees yielding the highest accuracy was determined to be 500, as displayed in Figure 4.8.b. Regarding the DNN algorithm, the grid search identified the best accuracy was attained when using 300 epochs and a batch size of 1500. Figure 4.8.c. illustrates the accuracy progression for "sectionneur" and "valve" as a function of the epochs, utilizing a batch size of 1500. Figure 4.8.d. displays the accuracy progression for both classifications as a function of the batch size, using 300 epochs.

Table 4.5 Accuracy from different algorithms in predicting the number of each device for a random folding

	Top-1 accuracy KNN	**Top-1 accuracy RF**	**Top-1 accuracy DNN**	**Top-2 accuracy DNN**
"sectionneur"	*0.57*	*0.6*	*0.63*	*0.98*
"valve"	*0.73*	*0.74*	*0.82*	*0.9*
"alimentation électrique"	*1*	*1*	*0.83*	*0.98*
"disjoncteur"	*0.75*	*0.78*	*0.92*	*0.99*
"raccord"	*1*	*1*	*0.99*	*0.99*
"terre"	*0.93*	*0.94*	*1*	*1*
"vanne"	*0.88*	*0.91*	*1*	*0.99*
"boîte"	*0.99*	*0.99*	*0.99*	*0.99*
"interrupteur"	*0.99*	*0.99*	*1*	*1*
"coupe-circuit"	*0.99*	*0.99*	*1*	*0.99*
"master switch"	*0.99*	*0.99*	*0.99*	*1*
Computation time	0.78 s	0.6 s	29.12 s	

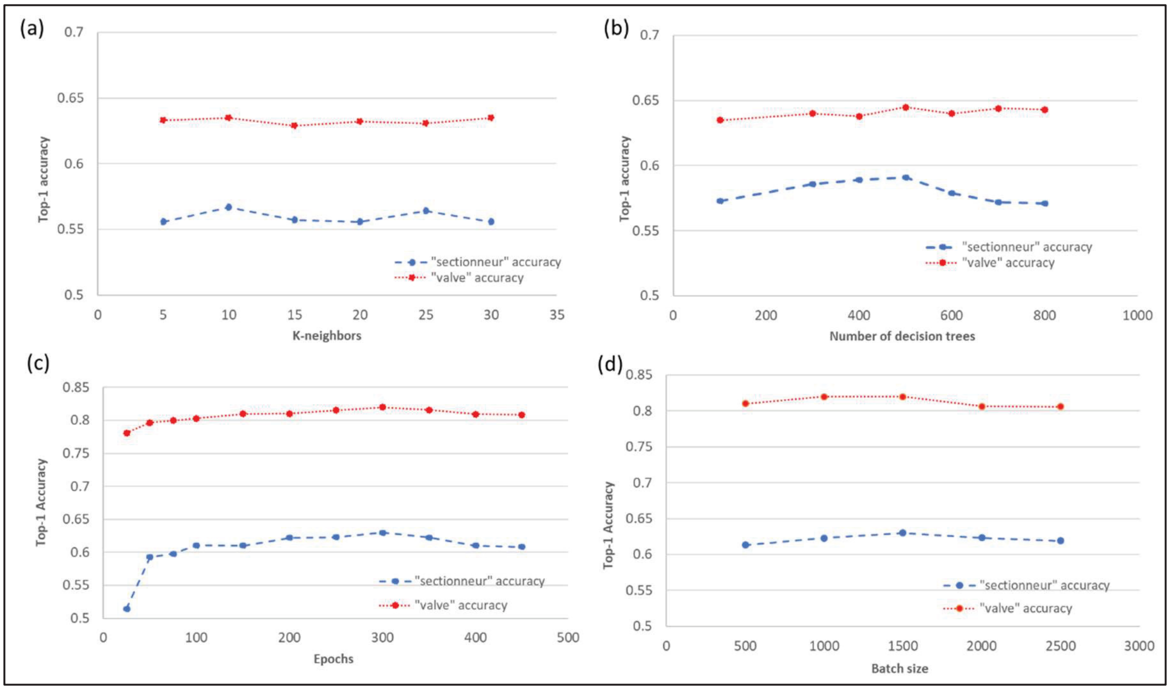

Figure 4.8 Evolution of the accuracy on the prediction of the disconnector and valve quantities:
a. as a function of the number of K nearest neighbors with the KNN algorithm;
b. as a function of the number of decision trees for the RF algorithm;
c. as a function of the number of epochs for the DNN (batch size = 1500);
d. as a function of the batch size for the DNN (epochs = 300)

A comparative analysis of the different methods used with specific hyperparameters is presented in Figure 4.9. As the accuracy performances are the same for all devices except for “sectionneur”, “valve” and “disjoncteur”, the comparison is relevant for these devices only. The results demonstrate that DNNs give the best results with an accuracy of 63% on the number of “sectionneur”, 82% on the number of “valve”, and 92% on the number of “disjoncteur”. RF is the algorithm with the second-best performance, achieving average accuracies of 60%, 74%, and 78%, respectively, on the predictions of the number of "sectionneur", “valve” and “disjoncteur”. In contrast, KNN has the worst performance with average accuracies of 57%, 73%, and 75%, respectively, on the predictions of the number of "sectionneur", “valve” and “disjoncteur”. The top-2 accuracies were calculated for the DNN, as this algorithm demonstrated the best performance in terms of accuracy. The top-2 accuracies are obtained for the same epochs and batch size as the top-1 accuracy (epochs = 300, batch size = 1500). The top-2 accuracies are 98% for the number of "sectionneur", 90% for the number of “valve”, and 99% for the number of “disjoncteur”. Therefore, it can be concluded that the top-2 predictions increase dramatically the robustness of the device prediction.

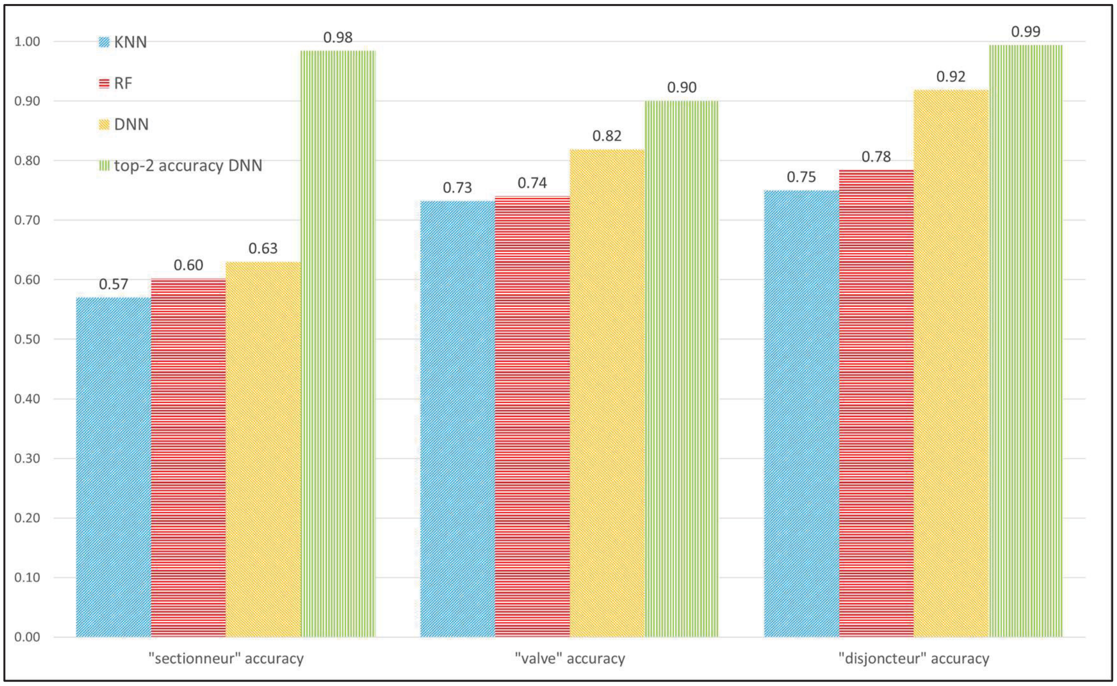

Figure 4.9 Accuracy comparative analysis of KNN, RF and DNN methods for the “sectionneur”, “valve” and “disjoncteur” accuracies

4.6.1.2 Sensitivity analysis

The accuracy of the proposed approach is compared across different industrial domains. Analyzing the sensitivity of the devices for each domain is relevant because these devices are commonly found in all of the studied industrial domains. We compare the top-1 accuracy obtained with the DNN for 300 epochs and a batch size equal to 30% of the number of sheets in each domain. The comparison is performed on the “sectionneur“, “valve“ and “disjoncteur“ as shown in Figure 4.10.

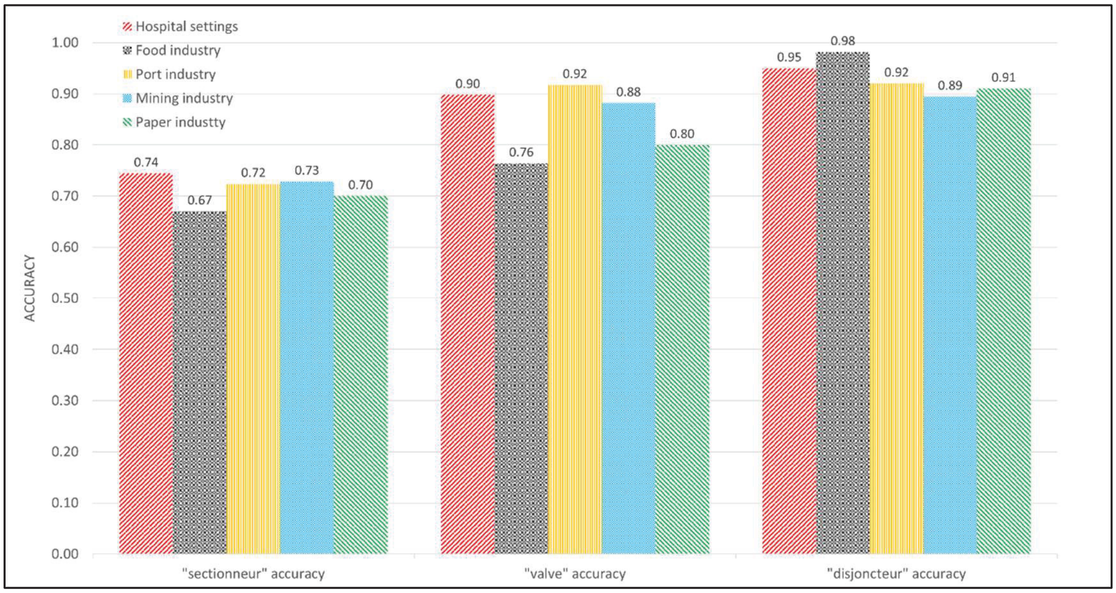

Figure 4.10 DNN top-1 accuracy on predicting the number of “sectionneur”, “valve” and “disjoncteur” for datasets exclusively included in a single industrial domain

Figure 4.10 Alt Text: Bar chart presenting a sensitivity analysis of the top-1 accuracy on the prediction of the number of disconnectors, valves and circuit breakers depending on the industrial domain considered. The top-1 accuracy remains constant independently of the domain.

Regarding the number of "sectionneur", the accuracy rates range from 67% to 74%. For the number of "valve", the accuracy rates are between 76% and 92%. Finally, for the number of "disjoncteur", the accuracy rates range from 98% to 89%. The variation according to the industrial domain is more pronounced for the prediction of the number of "valve". This can be explained by the fact that the number of valves per equipment is higher than for other devices in certain studied domains, such as the food industry.

A sensitivity analysis was also conducted across various industrial domains to assess the accuracy of the KNN (with 10 neighbors) and RF algorithms (with 500 decision trees). These results are compared with the accuracy of the DNN approach. Appendix II.B presents three comparative graphs showing the accuracy of the DNN, KNN and RF algorithms on the prediction of the number of " sectionneur" (see Figure B1), "valve" (see Figure B2) and "disjoncteur" (see Figure B3) in each of the studied industrial fields (e.g. food, port, mining and paper industries and hospitals). Indeed, the superiority of DNN in terms of accuracy of prediction can be observed in all industrial fields, as when all LOTO sheets from all domains are processed jointly in the model.

4.6.2 Discussions

The aim of this study was to address the gaps in the current research, as presented in section 4.2.4. The obtained results do indeed contribute to address these gaps.

The results demonstrate the performance of the proposed model in predicting the number of devices to be locked in LOTO procedures prior to equipment maintenance, using a multi-task classification approach. Prediction accuracy proved to be relatively good, exceeding 60% in the majority of cases. These results are primarily limited by the data set. Machines with identical names may have different configurations in their energy connections, which can create difficulties in prediction. Therefore, the top-2 accuracy is much higher, as it absorbs this variability of machines. Additionally, the wide variety of machines make some of them unique. These single machines have no equivalent in the training database, which makes it impossible to predict the devices to be locked. Therefore, the prediction of LOTO sheets should focus on machines that are redundant in manufacturing sites and can be found in different industries, such as ventilation units, for example. Machines that are too complex with many connections will often be excluded and will always require manual work from operators to write their LOTO sheets. However, most industrial equipment consists of several simpler units, such as pumps for example. Thus, predicting basic machines can handle a vast majority of industrial equipment. The conducted sensitivity analysis shows that the accuracy remains stable regardless of the industrial sector of origin of the data sheets in the dataset. Hence, the model is relatively stable and robust for different types of industries. The proposed approach for predicting LOTO devices is therefore reproducible for various industries and could be extended to industrial domains beyond those studied in the paper, which increases the practical relevance of the developed LOTO prediction method.

Moreover, as shown in Table 4.5, a comparison of the performance of the KNN, RF and DNN classification algorithms shows that DNN delivers better accuracy than the other two algorithms for all devices. The sensitivity analysis, which is detailed in Annex II, has demonstrated that the DNN algorithm is preferable compared to KNN and RF for all the diverse industrial sectors studied (hospital settings, food industry, port industry, mining industry, paper industry). In fact, the accuracies of RF and KNN are lower than those of DNN in all considered cases. Hence, DNN is the recommended prediction approach for aiding in the drafting of LOTO procedures.

Finally, a specific application of ESH transformation in the context of smart manufacturing is proposed. By generating pre-written LOTO sheets with multiple possibilities, the predictions obtained from this work can help workers to retrieve information for the LOTO sheet more efficiently, thereby reducing overhead time and costs. The use of AI could also expedite the writing process by providing multiple sheet options to choose from. However, it is important to note that the final validation and approval of the LOTO sheets would still be dependent on human oversight to ensure the safety of workers. Despite this limitation, the integration of AI technology in safety management could be seen as a promising step towards more comprehensive smart and sustainable human-centered manufacturing systems in the context of Industry 5.0. As the goal of this work is to assist in writing LOTO sheets to help workers, especially those new to a given industrial environment, a prediction with a top-2 accuracy of over 90% would be beneficial. Human validation will remain necessary, but the steps of data gathering and procedure writing, as shown in Figure 4.5, would be executed in shorter time.

4.7 Conclusion, limitations and future directions

This article discusses the difficulties associated with predicting Lockout Tagout (LOTO) sheets and proposes the use of intelligent assistance to streamline the process of designing, writing, validating and approving these procedure sheets, ultimately saving companies time and human resources. A crucial aspect of this process is to determine which devices need to be locked. This paper seeks to contribute to three research gaps. The first contribution is the proposed approach for predicting LOTO sheets. Secondly, the performance of the KNN, RF and DNN classification algorithms in the framework of the developed approach was compared. Finally, an application of EHS in a smart manufacturing context was suggested.

The research problem has been formulated as a multi-task classification problem in this study. Specifically, the input parameters consist of machine names, while the output is a list of numbers indicating the type of devices that should be locked.

To evaluate the proposed approach, a dataset comprising real-world LOTO sheets in PDF format from various industrial sectors was utilized. This dataset was first pre-processed and subsequently transformed into a digital database. Three different algorithms, KNN, RF, and DNN, were employed to solve the classification problem. After conducting a comparative analysis, the results suggest that the DNN classifier yields the highest accuracy in predicting the devices that require locking.

Despite the high accuracy achieved by the DNN classifier, predicting the exact number of devices to be locked for machines with similar names but different energy connections, and for devices with large fluctuations in quantity, remains a challenge. To overcome this issue, the proposed approach compiles the top predictions and presents them to the LOTO operators, ensuring consistency in the process. When the top-2 predictions are considered, the accuracy in predicting all devices to be locked exceeds 90%, thereby significantly improving production and human resource availability. Additionally, a sensitivity analysis demonstrated that the proposed approach is universally applicable across different industrial areas. Based on these findings, this study proposes an AI-assisted safety management approach that aligns with the "Operator 5.0" vision, promoting human-technology collaboration to enhance processes.

In future research, it would be beneficial to include additional input data to the model, such as specific machine characteristics, including the connections to power sources. The machine plans and integration plans within the plant could also be incorporated to generate LOTO sheets based on the equipment targeted for locking. The use of these supplementary data sources could improve the accuracy of the predictions and further streamline the LOTO sheet writing process. Supporting workers during lockout operations with augmented reality devices or training using virtual reality could also be considered and explored in future work.

CHAPITRE 5

DEVELOPMENT OF AN INTELLIGENT AND GEOGRAPHICAL-ORIENTED LOCKOUT/TAGOUT PROCEDURE MERGER APPROACH FOR MANUFACTURING INDUSTRIES

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Abstract

Lockout/tagout (LOTO), essential for ensuring worker safety, can be prohibitively costly due to the complexity of machine involved. Merging LOTO procedures and exploiting connections between energy devices can streamline multiple maintenance tasks, reducing the overall workload. However, organizing energy devices for locking in an efficient sequence and understanding device interconnections is labor-intensive, requiring extensive knowledge from plant supervisors. In addition, the development of technologies, such as the Internet-of-Things will allow the merging of LOTO procedures based on the geographical location of energy devices. This research work aims to develop a bi-objective model to efficiently merge LOTO procedures, in order to minimize lockout time by optimizing worker routes. Safety standards will be maintained and unnecessary machine lockout avoided. The developed model could also propose a geographical-oriented LOTO process. This paper details the mathematical formulation of the Mixed Integer Nonlinear Programming model and explores the proposed solution approaches. A comparative analysis will also assess the model's efficiency in comparison with supervisor-driven LOTO procedure mergers. In particular, the developed model streamlines the execution of the LOTO procedure, by accurately anticipating which devices require locking, thus saving considerable time in the preparation of the LOTO

procedure. Finally, the routes proposed by the model to workers are reliable, i.e., the devices that need to be secured are locked.

Keywords: Lockout/Tagout; Safety; Non-dominated Sorting Genetic Algorithm-II; Bi-Objective Model; Sustainable Manufacturing Systems

5.1 Introduction

Accidents in the workplace can have serious consequences for both individuals and machine, highlighting the importance of risk prevention for industry. In particular, maintenance work presents high risks for workers, with an increased risk of injury or death (Montanaro et al., 2023). To address this situation, the Occupational Safety and Health Administration (1989) introduced the Lockout/Tagout (LOTO) standard for hazardous energy control. This standard requires all industries to follow an energy control process to secure and isolate machine, before maintenance operations. In addition, the international standard ISO 14118 provides guidelines for the safe entry of workers into hazardous areas where machines are located. In fact, lockout involves locking the device to isolate the machine from various energy sources to prevent accidental restart during maintenance work, while tagout involves deactivating this lock. LOTO is known to be effective in protecting plant workers from exposure to hazardous energy sources (Guner, 2023). Due to the complexity of a plant, maintenance managers spend relatively long time, up to 3 or 4 hours for a medium-sized plant, preparing LOTO plans for maintenance. Manufacturing process flow and layout information are essential to such maintenance planning, and optimization models are therefore a critical resource.

In this study, we consider an industrial system with a variety of machine types, powered by different circuit breakers and valves. In order to secure the machine prior to maintenance, it is necessary to lock all circuit breakers and valves associated with this machine. For example, in Figure 5.1, a manufacturing system consisting of pumps and a triturator supplied by valves and circuit breakers is considered. Machine 1 (pump), framed in red, is secured by locking circuit breaker 3 and valves 1 and 2. Machine 2 (triturator), framed in green, requires the locking of circuit-breaker 1 and valves 4, 5, 6, and 7.

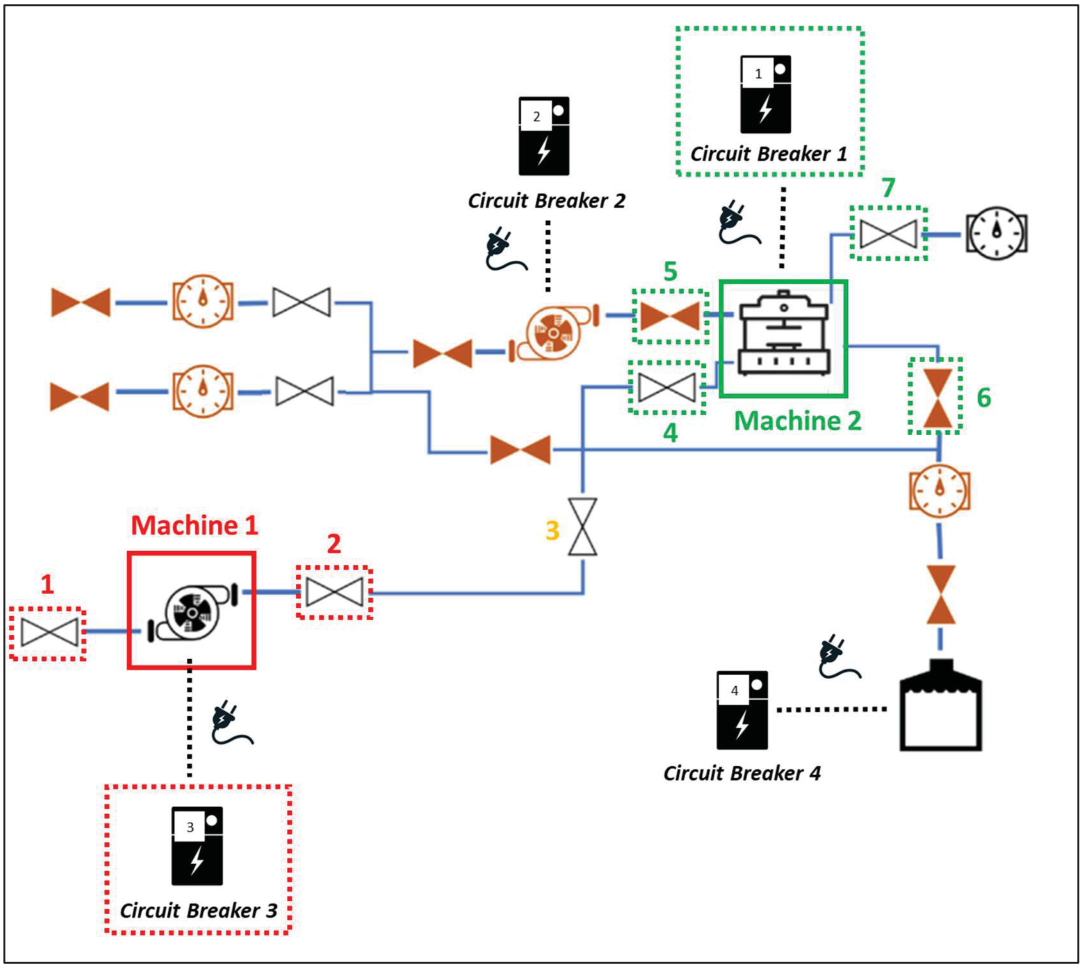


Figure.5.1. Example of an industrial system with interconnected machine, valves and circuit breakers

Figure 5.2 indicates the geographical location of the devices on a plant floor plan. Machine 1 and 2 can be padlocked separately. The routes taken by operators to separately padlock each machine are shown in Figure 5.2.a.

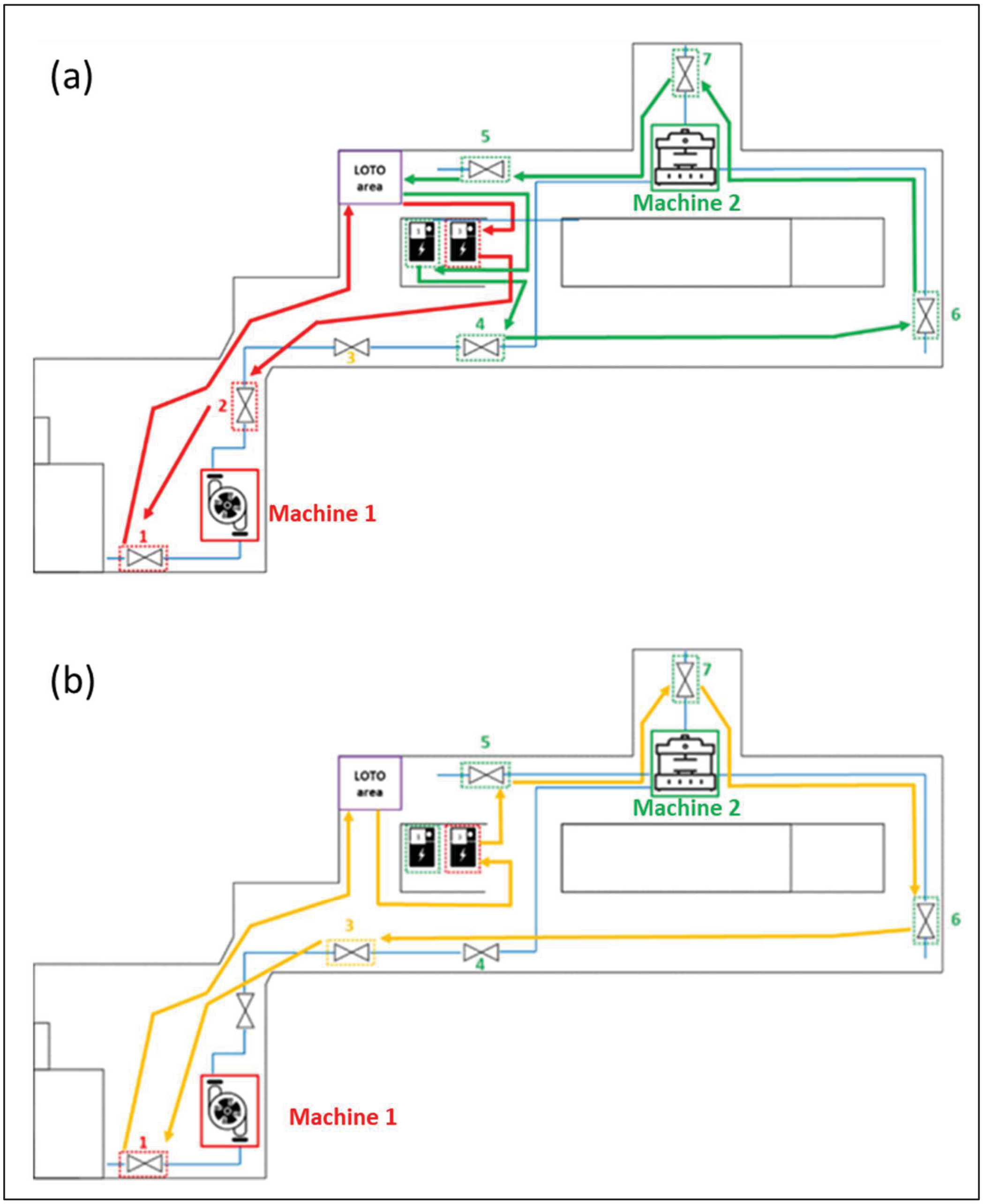


Figure 5.2. Position of machine in the plant and (a) worker routes without merging LOTO procedures (b) with merging LOTO procedures

During multiple maintenance operations, where a large quantity of machines needs to be locked, it may be preferable to merge the lockout of certain pieces of machine, indeed, then several LOTO sheets can be grouped together to alleviate the work involved in securing them. Furthermore, when merging sheets, certain interconnected valves can secure the same machine. Hence, it is then not necessary to secure all the valves, and only one can be secured. For example, in Figure 5.1, valve 3 can be locked to secure the flow leaving machine 1 from valve 2, and the flow entering machine 2 through valve 4. Merging the automated LOTO sheets of machines 1 and 2 would reduce lockout time. The route taken by workers when procedures are merged is shown in Figure 5.2.b. Then, the travelled distance is shorter, because the same locations are not visited several times.

Currently, to find the location of devices to be interlocked and the interconnections between valves require considerable knowledge by specialized supervisors, and a huge preparation effort before major maintenance work. Supervisors need to reorganize the locking order of devices and add interconnections based on their experience and understanding of the plant. Indeed, in some industries, maintenance may involve up to a hundred operators, with typically many LOTO procedures merged together. In addition, the industry has to deal with staff changeovers and the loss of unrecorded information. Automating complex tasks such as LOTO preparation and optimization is one solution to these challenges.

The aim of this research work is to develop a model for predicting LOTO procedures when several units of machine are merged, in order to reduce operating time, while avoiding the locking of machine that does not need to be locked.

When several procedures are merged, and different teams of operators work in parallel to complete the LOTO procedures, another approach to lockout is possible. Then, all the devices to be locked and all merged procedures could be considered, and routes can be determined for all the worker teams to minimize the overall LOTO processing time. In fact, the locking sequence could then be more geographically oriented instead of machine oriented. To illustrate, in Figure 5.3.a, r two mergers of LOTO procedures are considered; a merger with the red padlocks and a merger with the green padlocks. One team will follow the red path to padlock the red LOTO procedure, while the other team will follow the green path for the other procedure. A geographical approach is suggested in Figure 5.3.b.; one team will follow the orange path and the other the blue path. The same padlocks are locked, but the paths do not cross, and the teams manage separate areas of the plant. As a result, traveling distances, and resulting route times, between the two teams are reduced overall and are more balanced. Such an approach for lockout would be possible using padlocks connected via the Internet of Things (IoT) (Douglass et al., 2020), so that several teams could lock out a device without the need of physically visit it.

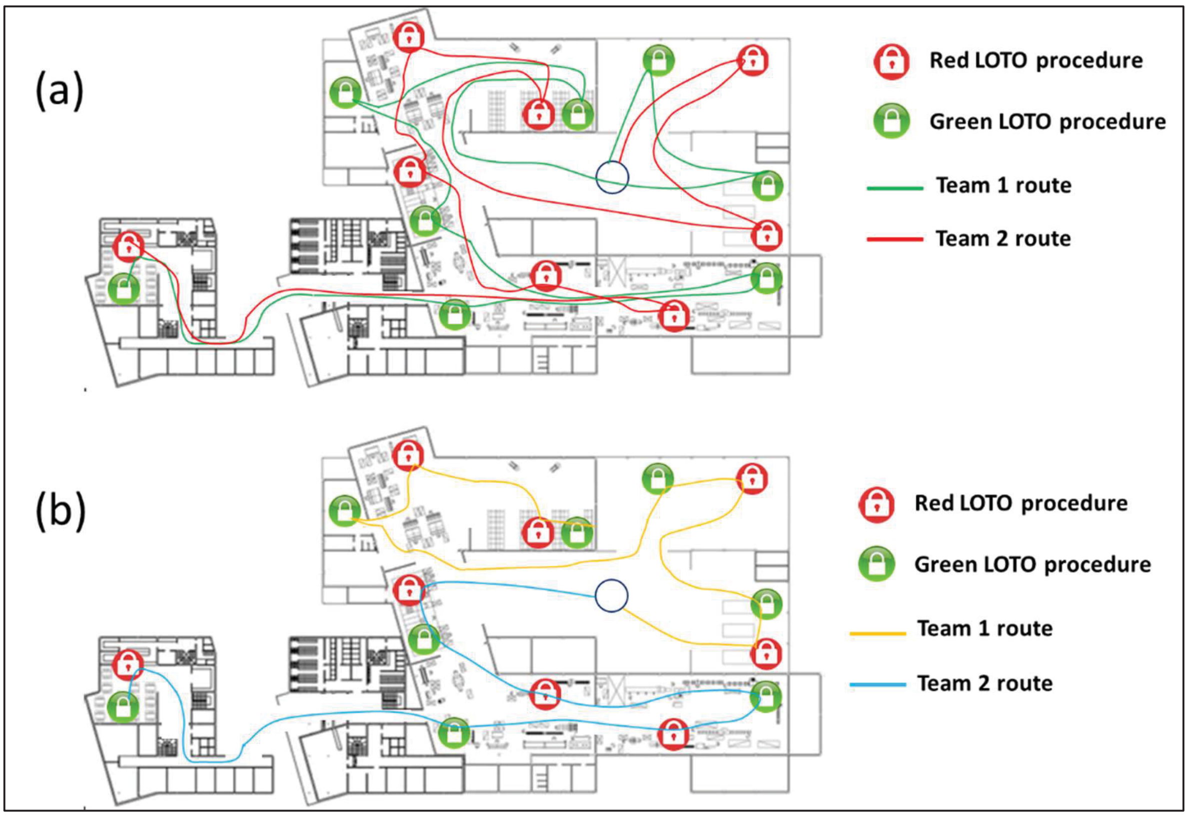


Figure.5.3 Route followed by two teams of workers (a) one team for the red LOTO procedure and one for the green LOTO procedure (b) teams share the devices according to their geographical position

In this study, we define a predictive fusion model for LOTO procedures and LOTO operation sharing oriented to the geographical positions of energy devices in the plant. The formulated problem is solved using a multi-objective optimization approach by Mixed-Integer Nonlinear Programming (MINLP).

The presentation of this paper is structured as follows. In section 5.2, a literature review on relevant work will be provided. In section 5.3, the mathematical problem will be formulated. Then, section 5.4 presents the proposed solution strategies for the various problems and sub-problems, with descriptions of the selected algorithms. In section 5.5, the model and solution approach will be validated by a test performed on a real and complex industrial use case. Finally, Section 5.6 will present the conclusion of this paper.

5.2 Literature review

The following literature review investigates various aspects of optimizing LOTO procedures in the manufacturing sector. Furthermore, it explores the development of route search algorithms with precedence constraints to optimize worker movements during LOTO procedures. Finally, it discusses multi-objective optimization techniques for solving complex problems efficiently. Through these subsections, this review aims to provide insights into recent advancements and identify areas for further research in enhancing safety and operational efficiency in industrial settings.

5.2.1 Lockout/Tagout procedure optimization

LOTO procedures are a constraining process for the manufacturing industry. Various prospects for its improvement have been proposed in the literature, e.g., for quicker procedure preparation (Delpla et al., 2022), more efficient implementation of padlocks, and better integration of LOTO procedures into production and maintenance planning policies (Delpla, Kenné et Hof, 2023). A computer-aided design (CAD) of LOTO procedures determining the areas to be secured using CAD files of a manufacturing plant has already been proposed to reduce downtime and workload based on balanced binary search trees (Matsuoka et Muraki, 2001). The writing process of LOTO procedures has also been studied. LOTO procedures could be predicted from machine names, in the case of simple machine, by solving a multitasking classification problem returning the devices to be locked. Hence, the writing of safety protocols in manufacturing systems could be automated (Delpla et al., 2023).

In addition to the preparation of LOTO procedures, the operational and physical automation of the LOTO procedure for electrical machine was also addressed, including the installation of padlocks during the LOTO process. Microcontrollers and servomotors can indeed secure circuit breakers offering increased safety by automatically locking them (Kumar et Tauseef, 2021b). In the era of Industry 4.0 and advanced technologies in the manufacturing industry, such as the IoT, artificial intelligence or augmented reality (Mejía-Moncayo, Kenné et Hof, 2023), LOTO procedures and workplace safety in general can also benefit from new technologies to become more efficient. In fact, connected padlocks used for lockout could be used for remote locking by workers (Illankoon, 2020).

At the planning level, studies are more numerous (Emami-Mehrgani, Nadeau et Kenné, 2014). Joint production, maintenance and LOTO policies have been developed to provide decision-making tools for production managers in industry (Delpla, Kenné et Hof, 2023). Preventive maintenance policies aimed at minimizing costs (Badiane et al., 2016) or taking human error into account have also been proposed (Diop, Nadeau et Emami-Mehrgani, 2019). The integration of an operational LOTO policy assuring production continuity while machine is secured would also be a solution that ensures worker safety, while maximizing machine efficiency (Delpla et al., 2023).

Nevertheless, these studies have so far been limited to small industrial environments with only few energy devices to secure. This is far from the industrial reality at complex factories where LOTO procedures can take several hours to complete (Ouellet, 2022).

5.2.2 Route search algorithm with precedence constraints

As introduced in Section 5.1, the present research aims to determine the fastest route for workers performing the LOTO procedure prior to a planned maintenance shutdown. Indeed, travel and transport in plants is a vast field of research, where many problems remain to be solved (Hosseini, Otto et Pesch, 2023). In the specific case of LOTO related problems in the manufacturing industry, where operators need to get from one device to another as efficiently as possible, this problem is equivalent to solving a vehicle routing problem (VRP). This is one of the most studied problems in the field of operational research (OR), and over fifty (50) variants of this problem have been reported in literature (Bai et al., 2023). In the classical VRP problem, the objective is to optimize delivery vehicle routes to minimize the total traveled distance (Çil et al., 2023). Because of the relationships of precedence between devices, this specific type of constraint poses complex resolution problems. Indeed, the VRP problem with precedence constraints is a variant of VRP that includes precedence constraints between customer visits (Ju, Kim et Moon, 2021). However, with precedence constraints, order relationships are imposed, indicating that some visits must be completed before others. These precedence constraints may reflect temporal dependencies (Roohnavazfar, Pasandideh et Tadei), specific logistical requirements or other constraints related to the order in which customers should be served (Pilati et Tronconi, 2023). Effectively addressing a VRP problem with precedence constraints necessitates employing advanced solution techniques, frequently relying on heuristic search algorithms or precise methodologies to navigate the solution space while adhering to the problem's specific constraints (Frey et al., 2023).

VRP problems are classified as nondeterministic polynomial time hardness (NP-hard), meaning that the time required to find a solution grows exponentially with the number of variables that need to be determined (Öztaş et Tuş, 2022). These problems can take long time to solve These problems can take long time to solve if the number of devices to be locked is high. Solving the VRP problem with precedence constraints can be typically performed using the OR-Tools library (Cuvelier et al., 2023). This library is considered as one of the most complete ones, including optimized algorithms, parallel processing, customization, multilingual support, active development and open-source collaboration (Febria, Dewi et Mailoa, 2021).

In the research presented in this article, solving the VRP problem is a sub-problem of a multi-objective optimization problem. The resolution of the multi-objective optimization problem is performed by other algorithms.

5.2.3 Multi-objective optimization

Due to the nature of population-based multi-objective optimization problems, genetic algorithms are able to approximate the Pareto front of solutions in a single run (Selçuklu, 2023). The Pareto front represents the solutions of a multi-objective problem with the best compromise between conflicting objectives. Multi-objective evolutionary algorithms are deemed particularly appropriate for addressing scheduling problems due to their suitability for multi-objective optimization tasks (Gen et Lin, 2014). Among the diverse approaches developed for tackling such optimization challenges (Van Veldhuizen et Lamont, 2000), posterior preference articulation stands out as the most efficient method (Ghodratnama, Jolai et Tavakkoli-Moghaddam, 2015).

For such cases, the Non-dominated Genetic Algorithm II (NSGA-II) algorithm was developed to overcome the difficulties caused by posterior preference articulation (Blank et Deb, 2020). This algorithm has proved to be highly efficient in solving multi-objective optimization problems of various kinds and in a wide range of research fields, such as composites manufacturing (Chen et al., 2023), dynamic shop floor scheduling (Wang et al., 2023), production and inventory planning (Lv et Shen, 2023) or cost-delay optimization in additive manufacturing (Altekin et Bukchin, 2022). In addition, NSGA-II promotes solution diversity by using mechanisms such as crowd distance, which contributes to a uniform distribution of solutions in the objective space (Lin et al., 2019). Its ease of implementation and ability to adapt to different problem types are attractive to researchers and practitioners working on multi-objective optimization challenges (Ma et al., 2023).

The justification for choosing the NSGA-II algorithm for bi-objective optimization lies in its proven ability to produce high-quality solutions while maintaining a diversity of solutions on the Pareto front. NSGA-II is often compared to other algorithms such as SPEA2 (Strength Pareto Evolutionary Algorithm 2) and MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition), which are also widely used for solving multi-objective problems.

For example, SPEA2 uses an external archive for storing non-dominated solutions and incorporates a fitness model that considers the strength of solutions, improving its ability to handle problems with complex Pareto fronts. However, NSGA-II is often preferred for its simplicity of implementation and efficiency in terms of convergence and maintaining diversity among solutions (Maurya et Nanda, 2023).

On the other hand, MOEA/D decomposes the multi-objective problem into a set of scalar subproblems, each of which is solved simultaneously. This method is particularly effective for large-scale problems, but it may require careful tuning of weights and parameters to achieve optimal results, where NSGA-II offers a more balanced approach that is less dependent on specific settings (Guo et Sun, 2024).

Moreover, more recent algorithms like the Pareto Envelope-based Selection Algorithm (PESA) (Nikoubin, Mahnam et Moslehi, 2023) and the Non-dominated Sorting Algorithm with Diversity Preservation (NSGA-III) (Opris et al., 2024) have been developed to improve specific aspects such as convergence in high-dimensional solution spaces. However, NSGA-II remains a popular choice due to its balance between performance, simplicity, and flexibility in many industrial contexts (Seada et Deb, 2015).

5.2.4 Research gap identification

This literature review delves into optimizing LOTO procedures in manufacturing, exploring CAD-based solutions, automation of padlock installation, and planning integration. It highlights challenges in large-scale industrial environments and introduces a route search algorithm for efficient worker movement. Furthermore, it discusses multi-objective optimization using genetic algorithms like NSGA-II, emphasizing solution diversity and applicability across various fields.

After conducting the literature review, it was observed that previous scientific research primarily focused on integrating LOTO procedures into production policies rather than addressing the merging of LOTO procedures for complex cases approaching real-world scenarios. Research on the operational optimization of LOTO execution has not yet been addressed, although such optimization has the potential to unlock considerable potential gains for manufacturers in a wide range of application fields. Hence, the proposed research work aims to address these challenges and research gaps by proposing a novel approach that leverages advanced optimization techniques to streamline LOTO procedures and enhance workplace safety.

5.2.5 Contributions of the present research study

Automating the merging of LOTO procedures consists of proposing lockout plans on complex large-scale industrial facilities, where hundreds of devices are involved. This would have an impact on the LOTO operations and its efficiency in several ways. In terms of preparation, dedicated supervisors would not have to carry out lengthy preparations before the maintenance. Execution of the LOTO procedures would also be facilitated, because workers then only have to follow an efficient locking order to perform their LOTO tasks as fast as possible. As well, a precise execution time known in advance would also improve maintenance planning and production stoppages. Moreover, a geographical approach to LOTO would reduce execution time even further, and allow a better balance of team workloads for parallel lockout operations. This approach, not yet explored, could become possible when using IoT-connected padlocks. A geographic LOTO plan can be obtained using algorithms for solving multi-objective optimization problems and VRP problems with precedence.

The main contribution of this research study is to propose a bi-objective optimization model utilizing Mixed-Integer Nonlinear Programming (MINLP) in order to streamline LOTO procedures in complex manufacturing settings. Specifically, it aims to:

- Minimize lockout time by optimizing worker routes while ensuring adherence to safety standards and minimizing unnecessary machine lockout;
- Develop a decision-support tool for managers to enhance LOTO procedure preparation and integration into planning, ultimately facilitating more efficient execution by workers;
- Estimate the potential time savings when employing parallel LOTO procedures based on the geographical position of devices.

These specific contributions not only advance the optimization of LOTO procedures but also provide practical tools to enhance workplace safety and operational efficiency, hence resulting in more sustainable operations in the manufacturing industry.

5.3 Problem statement

This section presents a MINLP model for efficiently merging LOTO procedures. Indeed, the following sections introduce notations (5.3.1), outline assumptions (5.3.2), define constraints (5.3.3), and specify objective functions (5.3.4) governing the optimization of LOTO procedure merging.

5.3.1 Notations

The defined problem includes a manufacturing system with N energy devices (J valves and K circuit breakers) and M machines. Table 5.1 presents the notations that are used in this article.

Table 5.1. Problem notations

Indices	
$j = 0 \ldots J\text{-}1$	Sets of valves
$k = 0 \ldots K\text{-}1$	Sets of circuit-breakers
$m = 0 \ldots M\text{-}1$	Sets of machines
$n = 0 \ldots N{=}K + J - 1$	Sets of energy devices
$w = 0 \ldots W - 1$	Sets of workers
Input Parameters	
Z	State of the machines
A1	Matrices of machine input flows through valves
A2	Matrix of machine outgoing flows via valves
D	Matrix of power supplies via circuit breakers
B1	Upstream valve connection matrix
B2	Downstream valve connection matrix
P	Precedence matrix
F1	Machine ingoing flow state
F2	Machine outgoing flow state
TIME	Travel time between devices
TIME_CAD	Lockout time of a device
Decision Variables	
Xv(j)	State of the valve *j*
Xd(k)	State of the circuit breaker *k*
O(n)	Position of the device n in the locking sequence

When maintenance is planned, it needs to be determined which devices (in this case, circuit breakers and valves) need to be locked out to ensure worker safety. The state of the decision variables is given by open binary variables.

The state of each valve is stored in a vector such as presented in Equation (5.1) below:

$$X_v(j) = \begin{cases} 0 \text{ if the valve } j \text{ is locked} \\ 1 \text{ otherwise} \end{cases}, \forall j < J \tag{5.1}$$

The state of each circuit breaker is stored in a vector such that:

$$X_d(k) = \begin{cases} 0 \text{ if the circuit breaker } k \text{ is locked} \\ 1 \text{ otherwise} \end{cases}, \forall k < K \tag{5.2}$$

The position of device n in the locking sequence is defined as follows:

$$O(n) = \begin{cases} y \text{ if the device } n \text{ is locked in } y^{th} \text{ position} \\ 0 \text{ if the device } n \text{ does not need to be locked} \end{cases}, \forall n < N \tag{5.3}$$

with:

$$0 < y \leq \sum_{0}^{J-1} (1 - X_v(j)) + \sum_{0}^{K-1} (1 - X_d(k)) \tag{5.4}$$

The state of the machine, i.e.,in maintenance or operational, is given by the vector Z composed by normally open binary variables such that:

$$Z(m) = \begin{cases} 0 \text{ if equipment } m \text{ is in maintenance} \\ 1 \text{ otherwise} \end{cases} \tag{5.5}$$

The direct connections of the valves to the different machine are given by the matrices A_1 and A_2 :

$$A_1(m,j) = \begin{cases} 1\ if \text{ a flow enters equipment } m \text{ via valve } j \\ 0 \text{ otherwise} \end{cases} \tag{5.6}$$

$$A_2(m,j) = \begin{cases} 1\ if \text{ a flow exits equipment } m \text{ via valve } j \\ 0 \text{ otherwise} \end{cases} \tag{5.7}$$

The supply of machine by circuit breakers is given by the matrix D:

$$D(m,j) = \begin{cases} 1 \text{ if equipment } m \text{ is supplied by circuit breaker} \\ 0 \text{ otherwise} \end{cases} \tag{5.8}$$

The connections between the valves are given by the matrices B_1 and B_2 :

$$B_1(i,j) = \begin{cases} 1 \text{ if valve } j \text{ is upstream of valve } i \\ 0 \text{ otherwise} \end{cases} \tag{5.9}$$

$$B_2(i,j) = \begin{cases} 1 \text{ if valve } j \text{ is downstream of valve } i \\ 0 \text{ otherwise} \end{cases} \tag{5.10}$$

Figure 5.4 illustrates the construction of matrices A_1, A_2, B_1 and B_2 for a typical example in the manufacturing industry including machine and valves:

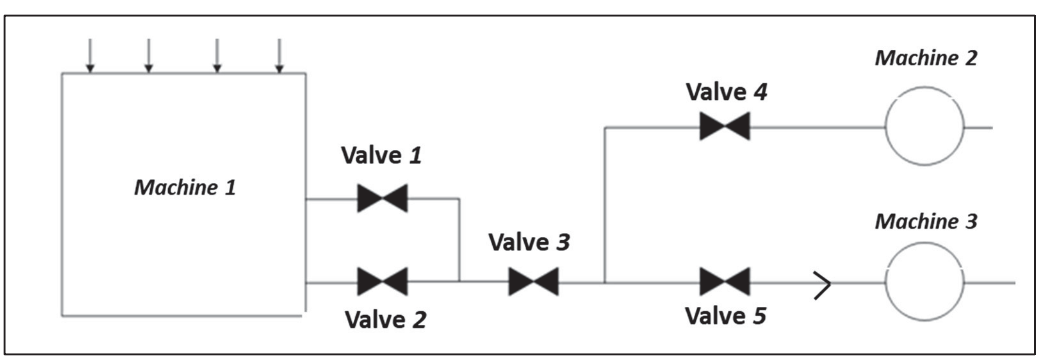


Figure 5.4 Schematic illustration for the construction of matrices A_1, A_2, B_1 and B_2

In this example, a flow enters machine *3* via valve *5:*

$$A_1(3,5) = 1 \tag{5.11}$$

Locking valve *3* is sufficient to secure the flow entering valve *5*:

$$B_1(5,3) = 1 \tag{5.12}$$

Locking valve *5* is sufficient to secure the flow entering valve *5*. More generally, there is always $B_1(j,j) = 1$ for all *j*.

$$B_1(5,5) = 1 \tag{5.13}$$

Locking valve *1* is not enough to secure the flow entering valve *3*: valve *2* also needs to be locked:

$$B_1(3,1) = 0 \tag{5.14}$$

A flow exits machine *1* via valve *1*:

$$A_2(1,1) = 1 \tag{5.15}$$

Locking valve *3* is sufficient to secure the exit flow through valve *1*:

$$B_2(1,3) = 1 \tag{5.16}$$

Locking valve *1* is sufficient to secure the exit flow through valve *1*. More generally, there is always $B_2(j,j) = 1$ for all *j*.

$$B_2(1,1) = 1 \tag{5.17}$$

Locking valve *5* is not enough to secure the exit flow through valve *3*: valve *4* also needs to be locked:

$$B_2(3,5) = 0 \tag{5.18}$$

5.3.2 Assumptions

This study considers the assumptions as described below:

- *The positions of the devices (valves and circuit breakers) are known*: assumption of known device positions ensures the feasibility of planning and executing the merging of LOTO procedures, as accurate spatial information is crucial for efficient procedure optimization.
- *Machine power supply is defined:* defined machine power supply ensures clarity regarding the energy state of the machine, which is essential for determining the appropriate lockout requirements and ensuring worker safety during maintenance activities.
- *Valves connected to machines are clearly identified*: clear identification of valves connected to machines enables precise identification of the components requiring lockout, facilitating the development of an accurate procedure merging strategy.
- *Interconnections between valves are known*: knowledge of interconnections between valves is central for understanding the dependencies and interactions among different components, which is necessary for devising an efficient procedure merging approach.
- *Locking operations run flawlessly:* assuming flawless locking operations eliminates potential uncertainties or complications that could arise during the locking process, allowing for a simplified and deterministic modeling of the procedure merging problem.
- *Workers move at a fixed speed of 80 m/min* (Zhou, Nie et Liu, 2024): utilizing a fixed worker speed simplifies the modeling process by removing the variability in worker movement, enabling straightforward calculations for optimizing worker routes and estimating time requirements for completing LOTO procedures.

5.3.3 Constraints

Matrices B_1 and B_2 are used to calculate matrices F_1 and F_2, which respectively define the state of incoming and outgoing flows from a piece of machine. F_1 and F_2 are defined as follows:

$$F_1(m,j) = \begin{cases} 0 \text{ } if \text{ the inflow from equipment } m \text{ } t\text{hrough valve } j \text{ is safe} \\ 1 \text{ otherwise} \end{cases} \tag{5.19}$$

$$F_1(m,j) = A_1(m,j) \prod_i B_1(j,i) \,.\, X_v(i) \,, \forall\, m < M, \forall\, \mathrm{j} < \mathrm{J} \tag{5.20}$$

$$F_2(m,j) = \begin{cases} 0 \text{ if the flow leaving equipment } m \text{ through valve } j \text{ is safe} \\ 1 \text{ otherwise} \end{cases} \tag{5.21}$$

$$F_2(m,j) = A_2(m,j) \prod_i B_2(j,i) \,.\, X_v(i) \,, \forall m < M, \forall\, j < J \tag{5.22}$$

In the example of the schematic diagrams demonstrated in Figure 5.3, the machine ingoing flow state F_1 can be determined as below.

$$F_1(m = B, j = 6) = A_1(m = B, j = 6) \times \prod_{i=0}^{I} X(i) \; = X(i = 4) \times X(i = 6) \tag{5.23}$$

Indeed, the flow entering pump B through valve 6 depends on the state of valves 4 and 6. If one of these valves is locked (i.e. $X(i = 4) = 0$ or $X(i = 6) = 0$), this flow is secured. If they are both locked (i.e. $X(i = 4) = 0$ and $X(i = 6) = 0$), this is also the case. If both are not locked ($X(i = 4) = 1$ or $X(i = 6) = 1$), this flow is still active.

A machine *m* is safe if all its incoming/outgoing flows, through any valves connected to it, are secure. A machine *m* that is not shut down can have secured or unsecured incoming/outgoing flows.

$$F_1(m,j) \leq Z(m), \qquad \forall\, j < J \tag{5.24}$$

$$F_2(m,j) \leq Z(m), \qquad \forall\, j < J \tag{5.25}$$

These inequality constraints give flexibility to the model. If machine *m* is in maintenance, *Z(m)=0*, then all incoming and outgoing flows are deactivated (i.e. $F_1(m,j) = 0$ and $F_2(m,j) = 0$ for all *j*).

If machine *m* is not under maintenance, *Z(m)=1*, incoming and outgoing flows can be active, but they can also be inactive, e.g., in the case where locking a valve would secure two pieces of machine, although only one is under maintenance. This flexibility avoids problem-solving errors by over-constraining the problem.

A machine *m* is safe if all the circuit-breakers/disconnectors supplying it are safe:

$$\text{if } Z(m) = 0 \text{ and } D(m,k) = 1, \qquad X_d(k) = 0, \forall m < M, \forall k < K \tag{5.26}$$

Some energy devices can only be secured after others. For example, on a typical machine, circuit breakers are usually locked before valves. In the same way, the inlet and outlet valves of a pump are usually locked before the drain valve. The precedence relations are stored in the matrix *P* defined as:

$$P(p,q) = \begin{cases} 1 \text{ if device } p \text{ can only be secured after device } q \\ \qquad 0 \text{ otherwise} \end{cases}, \quad \forall p < N, \forall q < N \tag{5.27}$$

The constraints on the device position in the locking sequence are then:

$$\text{if } O(p) \neq 0 \text{ and } O(q) \neq 0 \text{ and } P(p,q) = 1, \qquad O(p) > O(q), \quad \forall p < N, \forall q < N \tag{5.28}$$

5.3.4 Objective functions

The model for predicting the merging of lockout sheets seeks to satisfy objectives that may be contradictory. The first is to reduce lockout time, i.e., the time it takes to lock devices and the time needed to lockout workers to travel between devices.

The main objective of the developed model is to minimize lockout time $T_{VRP,max}$ as much as possible. The first objective function is therefore the minimization of this time, returned by solving the VRP problem. $T_{VRP,max}$ corresponds to the maximum lockout time for the various teams of workers w, represented by travel time and device lockout time. Locked devices are given by the values of the decision variables $X_d(k)$ and $X_v(j)$. The first objective function is written as:

$$MIN_1 = T_{VRP,max} \tag{5.29}$$

On the other hand, in order to guarantee faster unlocking of machine after maintenance, the aim is to minimize the number N_1 of locking devices and the number N_2 of flows entering and leaving the machine that are shut down. There may indeed be cases, with the interconnections between valves, where locking a single valve common to many machines would save time; but this would stop the operation of machine that do not need to be locked. These two numbers can be calculated as follows:

$$N_1 = \sum_{j=0}^{J-1} X_v(j) + \sum_{k=0}^{K-1} X_d(k) \tag{5.30}$$

$$N_2 = \sum_{j=0}^{J-1} \sum_{m=0}^{M-1} F_1(m,j) + F_2(m,j) \tag{5.31}$$

The second objective function is given by:

$$MIN_2 = -N_1 - N_2 \tag{5.32}$$

After a detailed description of the MINLP mathematical model and its various components in Section 5.3, solution approaches for addressing the complexities inherent in the efficient merging of LOTO procedures will be explored.

5.4 Solution approaches

In this section, the methodologies employed to address the complexities of optimizing routes for lockout teams are investigated, particularly focusing on a variant of the (Gupta et Lehal, 2009) with precedence constraints. Route optimization for lockout teams presents a challenging task, necessitating the consideration of various factors, such as the sequencing of tasks and the efficient allocation of resources. To tackle these challenges, we explore two distinct solution approaches: a route search algorithm tailored to handle precedence constraints and the widely adopted NSGA-II algorithm for multi-objective optimization. Through a combination of algorithmic strategies and mathematical modeling, these approaches aim to find optimal solutions while balancing conflicting objectives inherent in lockout procedures.

5.4.1 Route search algorithm with precedence constraints

The search for optimal routes for lockout teams is related to a VRP problem of precedence constraints.

The key characteristics of the VRP with precedence constraints include:

- *Nodes (Customers and Warehouse)*: A set of customers to be served and a central warehouse from which vehicles depart and return. In the case of lockout, the devices to be locked are customers, and the area where teams meet prior to lockout is the warehouse.
- *Vehicles*: A limited number of vehicles, each with a fixed capacity. In the case of lockout, the vehicles correspond to the lockout teams.

- *Distance or Cost Matrix*: A matrix that specifies the distance or cost between each pair of nodes. In the case of lockout, the cost matrix is the matrix that specifies the travel times between all devices. A fixed cost must also be added, which is the time taken to lock out the device.
- *Precedence constraints*: Constraints that specify the order in which certain visits must be made. For example, customer A must be serviced before customer B. In the case of lockout, certain devices must be locked before others.
- *Objective*: Minimize the total distance covered by all vehicles, while respecting capacity and precedence constraints. In the case of lockout, minimizing the distance traveled by lockout devices is one of the objectives of the proposed model. Lockout devices must respect precedence constraints in valve locking.

Figure 5.5 illustrates the solution of a VRP with precedence constraints, indicating the different elements of the problem. The OR-Tools library (Cuvelier et al., 2023) will be used to solve the VRP problem with precedence constraints.

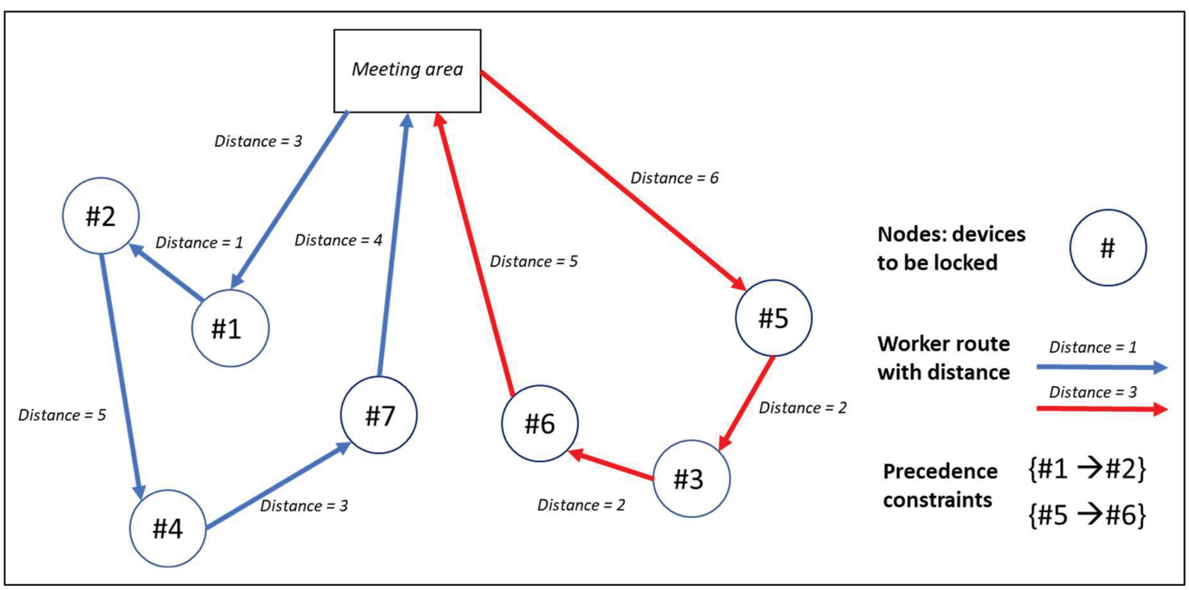


Figure 5.5 VRP with precedence constraints with a worker travelling between different devices to lock

5.4.2 NSGA-II algorithm

The NSGA-II algorithm is widely used to solve bi-objective optimization problems, based on its efficiency and ability to find a diverse set of high-quality solutions. NSGA-II excels at maintaining diversity among solutions and converging towards the optimal Pareto front. The process begins by generating an initial population of candidate solutions, or individuals. Each individual is then evaluated based on multiple objectives, and non-dominated sorting is performed to rank the solutions into different strata according to their dominance. Lower-ranked (less dominated) solutions are preferred for selection. NSGA-II uses crossover and mutation to create a new generation of solutions. To preserve diversity, it introduces a crowding distance mechanism, which helps maintain a uniform distribution of solutions. This process repeats over several generations, gradually refining the solutions towards a diverse and optimal set of competing objectives.

Algorithm 5.1 provides the developed pseudo-code of the NSGA-II algorithm, adapted to the mathematical model proposed in this study and integrating the calculation of various objective functions, such as worker travel time, number of locked devices and number of disabled flows. The algorithm employed to solve the VRP in this study consistently ensures adherence to the precedence constraints in Equation (5.28). Consequently, it is redundant to verify the compliance of this constraint within the NSGA-II algorithm adapted for this specific bi-objective optimization problem. Only the energy shutdown constraints, in Equation (5.24), Equation (5.25) and Equation (5.26), will be checked.

Hence, in Algorithm 5.1, an individual of the populations $P(t)$ is a vector of size N with values indicating the state of all devices (valves and circuit breakers). The locking sequence is determined in a second step to calculate its fitness if the energy shutdown constraints are satisfied.

Algorithm 5.1 Non-dominated Sorting Genetic Algorithm II (NSGA-II) including optimal route search

Algorithm 1

Notations:

- *P(t)*: Population at generation *t*
- *Q(t)*: Offspring population at generation *t*
- *R(t)*: Merged population of *P(t)* and *Q(t)*
- *S*: Population size
- *T*: Total number of generations
- |*P(t+1)*|: Number of individuals in the new population at generation *t+1*

1: Initialization:

Generate an initial population *P(t)* of size *S*

2: Evaluate the fitness of each individual in P(t):

for each individual in population P(t) **do**

a. Decode the individual's representation to obtain a feasible solution ***#Equations (5.1)-(5.2)***

b. Check if the solution satisfies optimization constraints:

- Check if the solution meets all energy shutdown constraints ***#Equations (5.24)-(5.25)-(5.26)***

c. **If** the solution violates any constraint:

- Penalize the fitness score accordingly

d. **If** the solution satisfies all energy shutdown constraints:

- Use a VRP algorithm with precedence constraints to compute the travel time $T_{VRP}(w)$ for each team w of workers
- Hold the maximum time $T_{VRP,max}$ among the $T_{VRP}(w)$ ***#Equation (5.29)***

- Compute the number of disabled devices N_1 and disabled flows N_2 ***#Equations (5.30)-(5.31)-(5.32)***

Algorithm 5.1 (suite) Non-dominated Sorting Genetic Algorithm II (NSGA-II) including optimal route search

- Calculate the fitness based on the two objectives:

fitness_objective_1 = 1 / $T_{VRP,max}$

fitness_objective_2 = 1 / $(N_1 + N_2)$

3: Main Loop:

for each generation *t = 1* to *T* **do**

a. Reproduction:

Select parents from *P(t)* using binary tournament selection

Perform crossover and mutation to generate offspring *Q(t)* of size *N*

b. Combine Populations:

Merge *P(t)* and *Q(t)* to create *R(t)* of size *2N*

c. Non-dominated Sorting:

Divide *R(t)* into different fronts based on non-dominated sorting

Assign a rank to each individual indicating its front

d. Crowding Distance Calculation:

Calculate the crowding distance for individuals in each front

e. Environmental Selection:

Create a new population *P(t+1)* by selecting individuals from *R(t)* based on their ranks and crowding distances

If $|P(t+1)| > S$, use truncation selection based on rank and crowding distance

If $|P(t+1)| < S$, use elitism to fill the remaining slots

4: Output:

Return the final non-dominated set of solutions from the last generation.

Return the optimal locking sequence after using the VRP algorithm with precedence constraints for each final solution.

The multi-objective optimization problem is solved using the NSGA-II algorithm using the Pymoo library on Python (Blank et Deb, 2020). The strategies for addressing the diverse problems outlined in this study have been discussed in Section 5.4. Subsequently, the model's efficiency can be evaluated through real-world industrial case studies, as presented in this study.

5.5 Computational tests

In this section, the proposed solution approaches are used to validate the developed LOTO procedure merger model. A comparative study of the results is carried out between actual LOTO procedures from the plant that was modeled and the LOTO sheets of the developed model's predictions. The estimated lockout time will be calculated and a representation of the operators' route will be given. To solve the problem, a Windows-based system was employed, featuring 16 GB of RAM and an Intel Core processor operating at a speed of 2.26 GHz.

5.5.1 Industrial case study

This case study considers a Canadian based pulp and paper plant including one main machine producing paperboard. This machine operates with several hundred pieces of machine, e.g.,pumps, vats, pulpers, pressure sensors, etc.. A section of the mill is modeled, with $M = 90$ pieces of machine. These machines are supplied by $J=302$ valves and $K=48$ circuit breakers. These energy devices are distributed over two floors: a basement and a first floor, connected by a stairway. Three merged procedures will be examined: the initial one merges procedures for machine *4, 5, 6, 7, 12, 13*; the second combines procedures for machines *29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67*. Lastly, the third combines the machine procedures for machines *57, 33, 34, 37, 38, 39, 40, 47, 48*. In the case of a LOTO procedure merger, we consider $W=1$ team of workers for each merger. Then, a LOTO procedure with a geographical approach will also be determined. All the machine to be locked in the three previous mergers is grouped together and tasks are distributed with $W=3$ teams of workers.

The procedure merger predictions and the geographical-oriented LOTO are compared together and with the straightforward chaining of individual LOTO procedures. This chaining was recently carried out by the supervisors of the plant studied, with updated data.

5.5.2 Results analysis and discussion

This section presents an in-depth analysis of the performed comparative study results that was carried out on the LOTO procedures from the industrial case example.

5.5.2.1 Procedure mergers

For the three proposals to merge the LOTO procedures, a single solution on the Pareto front was returned for all three mergers. This is due to the limited number of possible valve interconnections in the studied machine. Table 5.2, Table 5.3 and Table 5.4 show the devices to be locked on the three mergers, respectively. The devices are shown in the order in which they were locked. Devices are indicated by number: $n=0\ldots J\text{-}1$ for valves, and $n=J\ldots K+J-1$ for circuit breakers. The order of devices in the case of a simple concatenation of procedures is also given for comparison. The forecasted operating time for each route is calculated. The route followed by workers in the plant, for different use cases, is shown in Figure 5.6, Figure 5.7 and Figure 5.8.

Table 5.2 Merge #1: LOTO procedure merging for machines *4, 5, 6, 7, 12, 13*

Merge #1 (*m = 4, 5, 6, 7, 12, 13)*		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
1	322	303
2	304	348

Table 5.2 (suite) Merge #1: LOTO procedure merging for machines *4, 5, 6, 7, 12, 13*

Merge #1 (*m = 4, 5, 6, 7, 12, 13)*		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
3	303	59
4	326	60
5	348	146
6	349	82
7	126	99
8	281	326
9	44	281
10	201	322
11	146	304
12	82	349
13	60	130
14	59	131
15	99	122
16	37	37
17	130	11
18	131	57
19	122	199
20	200	67
21	199	44
22	57	126
23	24	200
24	22	19
25	11	24
26	67	22
27	19	
	Operation time forecast	
	1307s	***1420s***

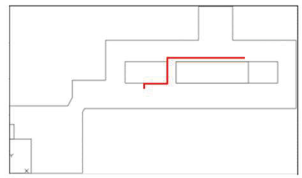
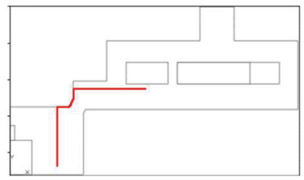
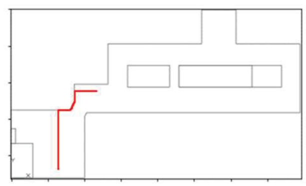
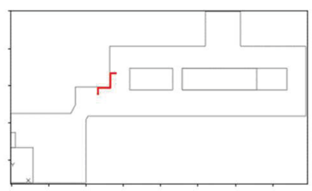
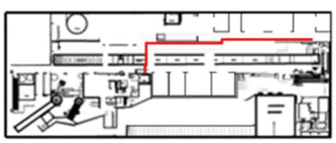
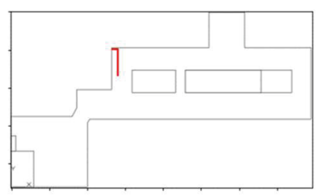
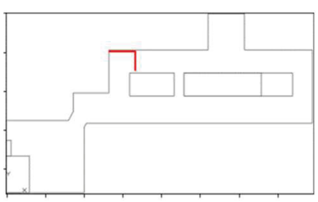
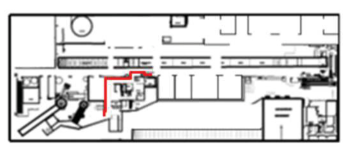
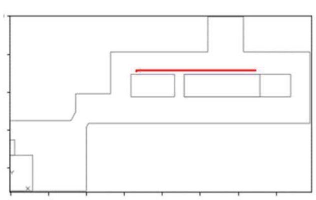
Merge #1 (m = 4, 5, 6, 7, 12, 13)					
	Route	Locking devices		Route	Locking devices
1		#322 #304 #303	8		#146 #82 #60 #59 #99 #37 #130
2		#326	9		#131
3		#348	10		#122
4		#349	11		#199 #200 #57 #24 #22 #11 #67 #19
5		To the basement	12		Back to LOTO area (basement)
6		#126 #281 #44	13		Back to LOTO area (first floor)
7		#201			

Figure 5.6 Route for Merge #1 and devices to be locked in each plant zone

For the first merge, valve *201* is locked in the model prediction, but not in the concatenation of actual procedures. This difference is due to a non-update in the nomenclature. The LOTO procedures on which the prediction model is built are outdated, and device *201* does not designate the same valve in the model data as in the supervisor data. This data error stems from a failure to update the plant's device nomenclatures. Figure 5.6 illustrates the workers' route through the plant. The proposed route is coherent and helps workers to carry out the lockout as efficiently as possible.

Table 5.3 Merge #2: LOTO procedure merging for machines
29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67

Merge #2 (*m = 29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67*)		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
1	318	307
2	317	180
3	315	171
4	313	140
5	311	169
6	307	139
7	337	138
8	180	129
9	169	291
10	140	13
11	139	288
12	138	3
13	129	123
14	93	18
15	292	201
16	285	110
17	186	286

Table 5.3 (suite) Merge #2: LOTO procedure merging for machines 29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67

Merge #2 (*m = 29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67*)		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
18	69	25
19	284	186
20	301	93
21	119	292
22	100	35
23	18	285
24	256	337
25	195	311
26	128	119
27	127	284
28	35	69
29	286	301
30	287	100
31	111	315
32	110	287
33	25	256
34	291	318
35	288	26
36	123	317
37	26	111
38	13	313
39	3	127
40		128
	Operation time forecast	
	1519s	***2461s***

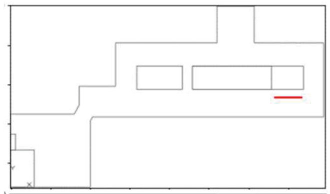
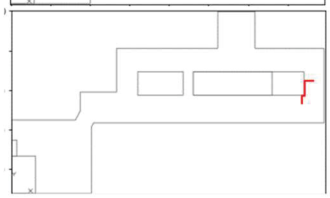
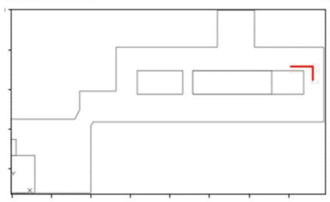
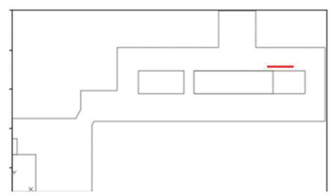
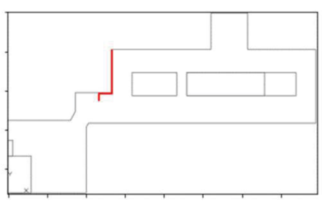
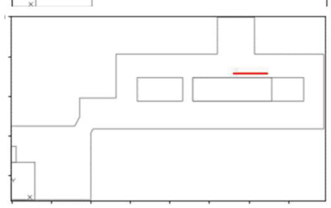
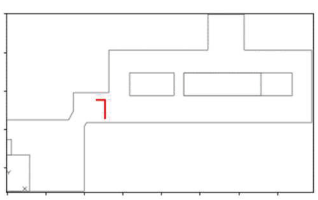
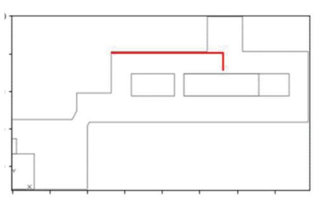
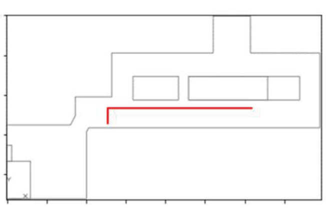
Merge #2 (m = 29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67)					
	Route	Locking devices		Route	Locking devices
1		#318 #317 #315 #313 #311 #307	9		#119 #100
2		#337	10		#256 #195 #128 #127 #35 #18 #254
3		#180 #169 #140 #139 #138	11		#286
4		To the basement	12		#287 #111 #110 #25
5		#129	13		#291 #288 #123 #26 #13 #3
6		#93	14		Back to LOTO area (basement)
7		#292 #285 #186 #69	15		Back to LOTO area (first floor)

Figure 5.7 Route for Merge #2 and devices to be locked in each plant zone

For the second procedure merging, again, a problem was revealed for valve *201*, which does not designate the same valve in the model data as in the supervisor data. Figure 5.7 shows the route for Merge #2. The route is again consistent, whether in the basement or on the ground floor, to ensure smooth execution of the LOTO procedure.

Table 5.4 Merge #3: LOTO procedure merging for machines
57, 33, 34, 37, 38, 39, 40, 47, 48

Merge #3 (*m = 57, 33, 34, 37, 38, 39, 40, 47, 48*)		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
1	314	314
2	310	169
3	309	180
4	308	188
5	336	256
6	334	201
7	9	255
8	286	254
9	196	144
10	283	127
11	118	196
12	116	Unlisted device 1
13	292	Unlisted device 2
14	186	286
15	31	292
16	299	186
17	98	334

Table 5.4 (suite) Merge #3: LOTO procedure merging for machines
57, 33, 34, 37, 38, 39, 40, 47, 48

Merge #3 (*m = 57, 33, 34, 37, 38, 39, 40, 47, 48*)		
Locking sequence	**Indexes of locking devices by MINLP model**	**Indexes of locking devices based on a simple concatenation of procedures**
18	17	78
19	256	121
20	255	308
21	254	31
22	144	309
23	127	9
24	10	116
25	121	10
26	78	336
27	188	310
28	180	98
29	169	299
30		283
31		118
32		17
	Operation time forecast	
	1312s	***1934s***

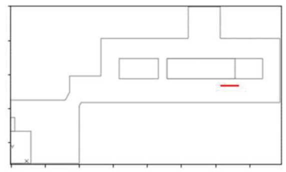
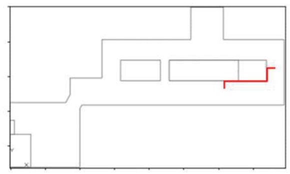
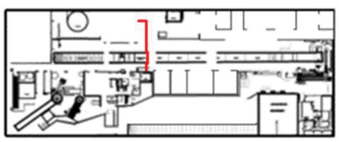
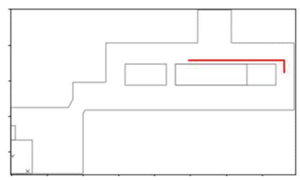
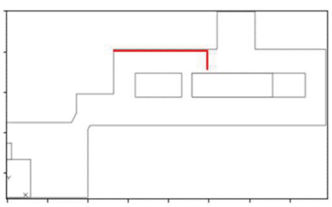
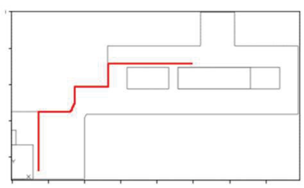
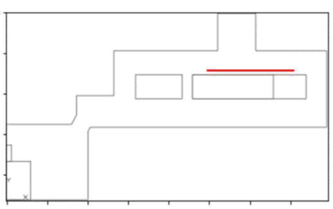
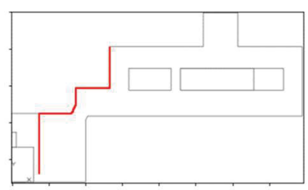
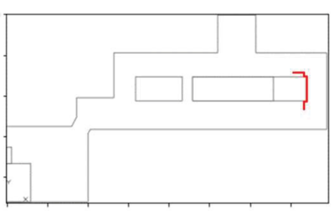
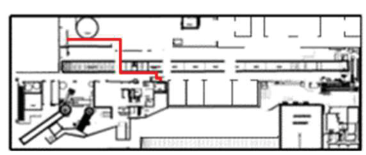
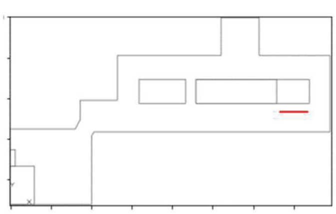
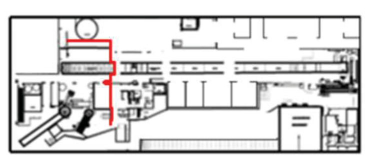
Merge #3 (m = 57, 33, 34, 37, 38, 39, 40, 47, 48)					
	Route	Locking devices		Route	Locking devices
1		#314 #310 #309 #308	8		#292 #186 #31
2		#336 #334	9		#17 #256 #255 #254 #144 #127
3		To the basement	10		#10
4		#9	11		#121 #78
5		#286	12		Back to the first floor
6		#196 #98	13		#188 #169 #350
7		#283 #118 #116 #299	14		Back to LOTO area (first floor)

Figure 5.8 Route for Merge #3 and devices to be locked in each plant zone

For the third procedure merge, the problem with device *201* persists. According to the actual concatenation of procedures, two valves not listed in the model should have been padlocked. These valves are not locked in the *29* machines lockout procedure on which the model is built. The data is therefore not up to date on the model side. Changes were made by supervisors following the identification of risks on the machine. The predictive model of procedure mergers therefore needs to be accurately updated as soon as a change in procedure happens. A centralized system to manage lockout procedures, as proposed by some commercial software, is therefore essential to maintain correct data. In Figure 5.8, the depicted route represents Merge #3, demonstrating a logical and optimized pathway once more.

Table 5.5 summarizes the model's performance on the various tests of procedure mergers performed. In all the studied cases, lockout execution time is faster with the merged procedures than with the concatenated procedures. This gain varies from 8% to 38.8% faster execution times. The larger the number of pieces of machine involved, the higher the gain.

Table 5.5 Performance evaluation of the procedure merging model on the three proposed case studies

	Machine under maintenance ***m***	**Gain in operation time**	**Solving time**
Fusion #1	**4, 5, 6, 7, 12, 13**	**8.0%**	44 minutes
Fusion #2	**29, 30, 49, 50, 55, 56, 58, 59, 64, 65, 66, 67**	**38.3%**	47 minutes
Fusion #3	**57, 33, 34, 37, 38, 39, 40, 47, 48**	**32.2%**	46 minutes

To summarize, it can be concluded, that the model is accurate; the devices to be locked according to the model are the same as when concatenating the procedures. The rare errors that occurred by merging are caused by the data on which the predictions are based. Indeed, some nomenclature errors appear, and some valves locked in the LOTO procedures provided are not locked in the LOTO procedures on which the model is built. Updated data is essential to ensure perfect reliability of procedures prediction. The developed model directly returns the devices to be locked in an order optimized for workers. Hence, it prevents the plant supervisor from reorganizing the order of the devices during a merge. Similarly, the interconnections between valves are considered directly by the model, and the supervisor would not need to make the changes himself.

5.5.2.2 Geographical-oriented LOTO

In this section, a LOTO procedure based on the geographical position of the devices is implemented. Instead of a maintenance supervisor choosing which devices to group together to merge the procedures for his three lockout teams, the algorithm finds the devices to be locked and determines paths for the three teams, considering all devices simultaneously.

To respect the precedence constraints, the teams first lock out the circuit breakers. Once all the breakers are locked, the teams lock the valves. The lockout sequences for the three teams are shown in Table 5.6.

Table 5.6 Device locking sequence for geographical-oriented LOTO

Circuit-breakers Locking Sequence	**Team 1** Indexes of locking devices	**Team 2** Indexes of locking devices	**Team 3** Indexes of locking devices
1	350	350	350
2	308	307	336
3	309	304	334
4	310	303	326
5	311	337	349
6	313	348	
7	314		
8	315		
9	317		
10	318		
11	322		
	Operation time forecast for circuit-breakers		
	346s	***297s***	***252s***
Valves Locking Sequence	**Team 1** Indexes of locking devices	**Team 2** Indexes of locking devices	**Team 3** Indexes of locking devices
1	188	281	67
2	180	292	200
3	171	69	199
4	169	301	57
5	140	100	24
6	139	196	22
7	138	35	11
8	31	127	285

Table 5.6 (suite) Device locking sequence for geographical-oriented LOTO

Valves Locking Sequence	**Team 1** Indexes of locking devices	**Team 2** Indexes of locking devices	**Team 3** Indexes of locking devices
9	284	128	186
10	299	144	146
11	283	195	82
12	118	254	60
13	116	255	59
14	98	256	99
15	119	286	37
16	17	25	93
17	18	110	130
18	287	111	131
19	291	201	121
20	9	3	78
21	10	13	122
22		26	129
23		123	19
24		288	
25		126	
	Operation time forecast for valves		
	794s	***832s***	***872s***

The lockout time is equal to the sum of the breaker lockout time (346 seconds) and the maximum valve lockout time (872 seconds). The total lockout time accumulates therefore to 1218 seconds. By comparison, the highest lockout time for the three previous mergers was

1519 seconds for Merge #2 in Table 5.3. The time saved by this geographical approach is 19.8%. This reduction in time is explained by a better distribution of workloads due to the geographical distribution of the devices: teams travel less distance and work in more specific areas of the plant.

5.6 Managerial insights

Integrating the developed model into merger management in the manufacturing industry could result in significant gains in terms of lock preparation. Indeed, merging procedures takes time and knowledge on the part of supervisors. The complexity of merging procedures often leads to its avoidance, with supervisors opting to keep procedures for each piece of machine separately. Calculating the optimal path for lockout devices removes the workload from supervisors, which also encourages the practice of merging cards. An optimal lockout path has also the potential to ensure that the operation time is reduced almost systematically, without having to rely on an experienced supervisor.

Production time forecasting also enables more precise planning. It is possible to give advance notice of when lockouts will be completed, to prepare for the arrival of maintenance teams. At the operational level, the calculation of the optimal route helps workers during the execution of the LOTO procedure: they can know where to go in the plant to set the padlocks, even if their knowledge of the plant is not optimal, hence improving execution speed. In the case of IoT-connected padlocks enabling remote locking, LOTO based on the geographical position of the devices can reduce lockout execution time by reducing the overall travel time of each team of workers. Figure 5.9 shows a decision tree which forecasts the consequences of LOTO management depending on whether and how process mergers are carried out.

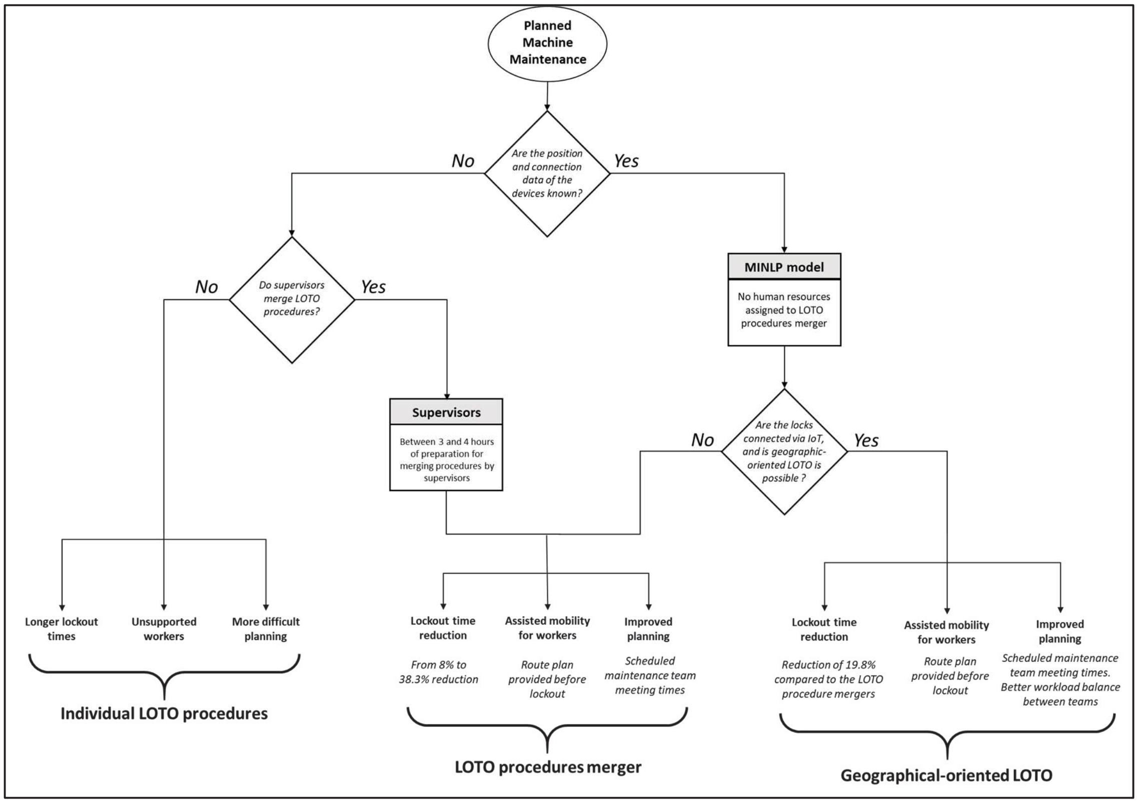


Figure 5.9 Management of the LOTO procedure merger for planned maintenance

For example, for Merger #3, if the positions and connections between the valves are known, the MINLP model would save 32.2% lockout time and provide a map (see Figure 5.8) for workers to navigate around the plant in the optimum sequence. If the start of lockout operations is scheduled, e.g., for 6am, knowing that the predicted operation time is 1312s, or 21 minutes and 52 seconds, the maintenance teams need to be present at the plant from 6:22am. The absence of system data and the lack of implementation of the MINLP model would make it impossible to obtain these supports and forecasts without an effort on the part of supervisors. A geographical-oriented LOTO reduces the time needed to secure machine by 12.5% compared with manual merging of LOTO procedures.

5.7 Conclusion

Automated merging of lockout procedures would drastically save time in preparing pre-maintenance safety operations, and reduce lockout operation time. This research work provided a predictive model for optimal LOTO procedure mergers. After developing the MINLP bi-objective mathematical model, the NSGA-II algorithm was used for the bi-objective optimization problem, coupled with worker path modeling for a VRP problem, to obtain LOTO procedure mergers. A comparative study based on a real industrial case was completed to evaluate the model's performance. The developed model provides predictions with a high degree of accuracy and proposes lockout procedures consistent with the plant's reality. The remaining errors are due to outdated data at the time the model was built. Updated data would make it possible to predict mergers without error.

In the case of IoT-connected padlocks, the MINLP model can also handle multiple procedure mergers in parallel, so that all the devices to be locked can be considered simultaneously. The LOTO would then be geographical: certain areas of the plant would only be visited by a single team during locking operations, reducing overall travel time by offering better sharing of the devices to be locked.

The managerial prospects are fourfold. The first is at the level of LOTO preparation: merging could be encouraged and would be totally automated, thus avoiding hours of preparation by supervisors. The second is at the operational level: LOTO operations would be optimized thanks to a calculation that minimizes workers' routes. The financial gains in terms of staff workloads and machine downtime could be substantial. Thirdly, and still operationally, workers executing the LOTO would be able to move from one device to another efficiently, as the solution indicates the area in the plant to which they should go. This opens up prospects for the development of digital applications to manage the LOTO, and the integration of technologies such as augmented reality to assist workers. Finally, the predicted time of end of locking would be known in advance, enabling maintenance teams to plan their work more effectively. In the case of geographical-oriented LOTO, workloads would also be more balanced between different workers.

CHAPITRE 6

ENHANCING INDUSTRIAL SAFETY MANAGEMENT AND OPERATIONAL EFFICIENCY: IMPLEMENTING A DYNAMIC LOCKOUT/TAGOUT APPROACH DURING PLANNED SHUTDOWNS

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Abstract

Lockout/Tagout (LOTO) is an essential safety measure in industrial settings, ensuring worker protection by isolating energy sources during maintenance. Traditional LOTO practices, often manual and static, may not fully address the complexity of process industry environments today, leading to increased risks and inefficiencies. This study introduces a dynamic approach to LOTO that incorporates advanced planning and simulation techniques, aiming to improve adaptability and effectiveness. A discrete event simulation model has been developed to evaluate both classic and dynamic LOTO methods under various operational conditions in order to estimate the benefits of dynamic LOTO planning. The analysis focuses on the validity of the simulation model and the evaluation of the lockout times of the simulated classic and dynamic LOTO approaches in a pulp and paper mill. Indeed, the results indicate that the dynamic approach significantly reduces lockout times and improves the effectiveness of safety procedures compared with conventional methods. This research contributes to the evolution of LOTO practices by proposing a method that better suits the dynamic nature of modern industrial environments. By adopting a more flexible approach, industries can achieve safer and more efficient maintenance operations.

Keywords: Lockout/Tagout, Dynamic Planning, Simulation, Safety Management, Operational Efficiency, Industry 4.0

6.1 Introduction

According to the Occupational Safety and Health Administration (OSHA, 2024), Lockout/Tagout (LOTO) is an essential procedure for ensuring the safety of workers during maintenance and repair operations in industry, regardless of company size (Ferjencik, 2020). The aim of this practice is to isolate dangerous sources of energy, such as valves, (Sattari et al., 2022) to prevent accidents. Proper implementation of lockout procedures can prevent approximately 120 deaths and 50,000 injuries each year in the United States (Dewi, 2019); hence underlining their significance. In process industry, the causes of accidents through a failure of the LOTO procedure can be varied, such as gases released through an insecure valve (Li et al., 2019).

Traditionally, LOTO procedures are static, which can limit their effectiveness and increase the risk of human error (Kim, Lee et Kang, 2021). Indeed, LOTO procedures are prepared in advance and the locking order of the devices can change once lockout has begun, for safety reasons. In a modern industrial environment, characterised by high-volume production and increasing complexity, these limitations are becoming increasingly problematic (Poisson et Chinniah, 2015). With the advent of Industry 4.0, incorporating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and cyber-physical systems, it has become crucial to modernise lockout practices to improve their effectiveness and adaptability (Delpla et al., 2023). Industry 4.0 offers a framework in which machines and systems can interact autonomously and intelligently, providing opportunities to optimize maintenance and safety procedures. For example, the use of IoT sensors makes it possible to monitor machine conditions in real time and automatically trigger lockout procedures when anomalies are detected. In addition, artificial intelligence algorithms can analyse historical and predictive data to proactively schedule maintenance interventions, reducing unplanned downtime and improving overall operational safety (Dźwiarek, 2022). However, the transition to dynamic (i.e., adapting to circumstances in real time) and intelligent LOTO operations presents challenges. The main ones concern the integration of new technologies into existing infrastructures, and the training of workers in these new systems (Dźwiarek, 2022). Despite these challenges, the potential benefits in terms of reducing lockout times, minimising NVA activities, and improving operational efficiency are significant (Delpla et al., 2023). A modern, flexible approach to lockout, integrated into Industry 4.0, could revolutionise the way companies manage the safety and maintenance of their equipment. Thus, the evolution of LOTO procedures towards dynamic methods integrated with Industry 4.0 represents a crucial step towards improving worker safety and the efficiency of industrial operations. This transformation, although complex, is necessary to meet the growing demands of modern industry and to take full advantage of emerging intelligent technologies.

This article is structured as follows. Section 6.2 reviews the literature. Section 6.3 presents the aim and contribution of the article. Section 6.4 details the proposed dynamic LOTO approach, incorporating advanced planning and simulation techniques. Section 6.5 describes the simulation model used to evaluate both classic and dynamic LOTO methods, including the notations, assumptions, and design of the simulation. Section 6.6 presents the computational tests, using a real industrial case study to compare the performance of classic and dynamic LOTO approaches. Finally, Section 6.7 presents the article managerial insights, highlighting the potential benefits of adopting a dynamic LOTO strategy in modern industrial environments. Section 6.8 concludes this research article.

6.2 Litterature review

The following literature review discusses the current challenges and opportunities for improving LOTO procedures, highlighting the importance of adapting these methods to new technologies. In addition, Section 6.2 also discusses the application of real-time dynamic planning methods that enable adjusting of production plans during operation. Finally, this review examines the use of discrete event simulation (DES) to evaluate complex systems and improve decision-making in various industrial contexts.

6.2.1 Current challenges and opportunities to improve LOTO procedures

LOTO procedures present major gaps and challenges, particularly in terms of adapting to technological advances and managing implementation variability (Karimi et al., 2019). Issues related to situational awareness, such as the perception, understanding and projection of LOTO processes, remain insufficiently addressed (Burlet-Vienney et al., 2021), which can lead to accidents and highlights a critical need for improvements in this area (Illankoon et al., 2019). The application of machine learning (ML) for the automatic generation of LOTO sheets could transform these procedures by making them more intelligent (Delpla, Kenné et Hof, 2023). However, the implementation of best practices in terms of operational efficiency is not uniform across different companies, often leading to regulatory breaches and highlighting the need for stricter standardisation (Dudgeon et Repp, 2015). The integration of LOTO procedures with production planning is also seen as an essential future research direction to ensure adequate time and space for safety operations (Delpla, Kenné et Hof, 2023). The integration of IoT technologies could significantly improve these procedures by enabling authorised access and improved monitoring during maintenance operations, filling the gaps left by manual methods (Kumar et Tauseef, 2021b). Recent patented innovations offer promising solutions, such as IoT-controlled electronic LOTO devices or padlocks that require multiple authentications to unlock, improving overall security (Douglass et al., 2020). The Lean Manufacturing approach (Badhotiya et al., 2024), although distinct in its main objective, can be adapted to improve LOTO procedures by focusing on waste elimination and process optimization (Vinodh, 2022). The integration of Lean practices with advanced and intelligent LOTO procedures can thus improve both the safety and efficiency of industrial processes (Abdel-Jaber, Itani et Al-Hussein, 2022). Integrating Lean principles into IoT components for real-time collection and analysis of operational data is essential in dynamic planning to maintain operational efficiency (Wang et al., 2020). Dynamic scheduling could be a solution to reduce machine lockout times.

6.2.2 Real-time dynamic planning method

Dynamic scheduling is a type of planning that enables production plans to be adjusted rapidly in response to uncertain environments. Multi-agent systems and ML-based algorithms play a crucial role in this approach, providing increased accuracy in predicting operating times (Talmale et Shrawankar, 2021a) and facilitating dynamic optimization of production schedules (Gao, Popowski et Boerkoel, 2020). IoT technologies can significantly improve dynamic planning by collecting, analysing and using production data to forecast needs and adjust operations in real time (Kwon et Oh, 2023). Furthermore, the integration of blockchain technology with IoT guarantees the security of the exchanged data (Balon, Kalinowski et Paprocka, 2023) and optimizes the management of production resources (Mejía-Moncayo, Kenné et Hof, 2023). In addition, the use of a real-time data collection system based on a wireless data transmission platform would make it possible to track and manage energy consumption and production data (Nouinou et al., 2023). Applying these methods to LOTO strategies could optimize its implementation in operations planning by facilitating dynamic planning of safety operations. However, the safety-critical nature of LOTO makes it difficult to test these methods (Illankoon et al., 2019). Hence, DES is a promising solution for estimating possible gains of such dynamic planning of LOTO operations.

6.2.3 Dynamic planning and discrete-event simulation

Dynamic planning and DES are essential for optimizing complex systems and improving decision-making in a variety of industrial contexts (Li, Yi et Xing, 2023). Dynamic planning allows processes to be adjusted in real time in response to changes in operational conditions, while DES provides a means of modelling and analysing systems in terms of discrete events with defined effects (Vieira et al., 2022). DES techniques are relevant tools for calculating the costs and lead times of many logistics processes (Iannone et al., 2016) and transport and travel processes (Alem, 2024). From a Lean perspective, simulations are a tool for improving the performance of manufacturing processes (Islam et Ahmed, 2024). The use of software such as Arena Rockwell allows to simulate strategic scenarios and validate simulation models by comparing them with real systems (Skėrė et al., 2023). This approach is particularly useful for resource management and dynamic planning in various industrial sectors, including mining planning and supply chain management (Uhlmann et al., 2023). By integrating DES with dynamic resource changes, it is possible to improve internal resource synchronisation and optimize dynamic system planning. This ensures better management and more informed strategic decision-making, contributing to overall operational efficiency (Jajo et Matawie, 2014). Indeed, it can be concluded from literature that DES is an effective solution for testing and validating dynamic planning. Hence, it would therefore be interesting to apply it to LOTO strategies in order to optimize their deployment during lockout operations in planned shutdowns. To estimate the possible gains of such an approach, DES is an interesting tool among other solutions.

6.3 Objectives et contributions

The principal objective of this research study is to enhance LOTO procedures by integrating them into a dynamic planification model following a Lean approach. This study contributes to the existing literature by proposing a dynamic LOTO strategy that improves the efficiency of process safety management in industry. Another major contribution of this research is the development of a DES model of LOTO procedures, applicable to both conventional and dynamic LOTO. Thanks to this simulation tool, it is possible to estimate the practical benefits of dynamic LOTO, particularly in terms of reducing lockout times and improving productivity. By performing a comparative analysis of the two approaches, this research provides valuable information for the implementation of more effective LOTO strategies aligned with the principles of Industry 4.0. Thus, the specific contributions of this article are as follows:

- Definition of a dynamic LOTO strategy for process industry;
- Development of a DES model of LOTO procedures, for both conventional and dynamic lockout;
- Estimation of the benefits of dynamic LOTO using the proposed simulation tool.

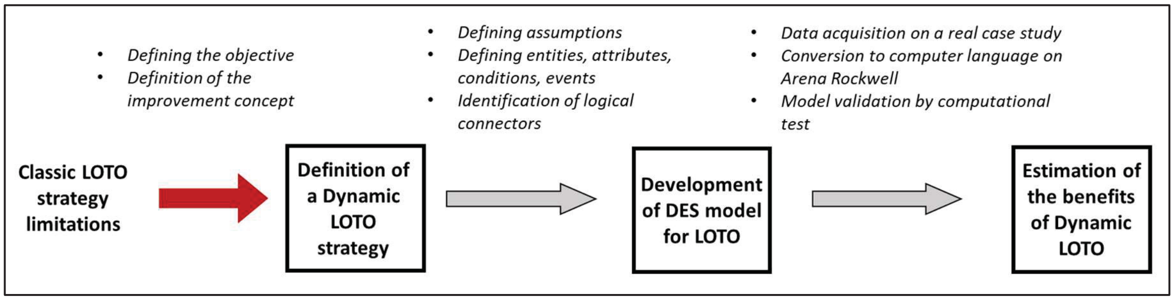


Figure 6.1 Contributions and methodology framework of this study

A structured methodological process has been adopted, incorporating transitions between the various steps. Based on the known limitations of LOTO, an operational efficiency improvement objective and a dynamic planning improvement concept, a dynamic LOTO strategy is proposed. Then, by defining assumptions, entities, attributes, events and logical connections, a DES model for both classical and dynamic LOTO is developed. Finally, using data acquired from real industrial case studies, a computational test can be carried out on Arena Rockwell Simulation to estimate the benefits of the new dynamic LOTO approach. This methodology framework is shown in Figure 6.1.

6.4 Dynamic LOTO

This article proposes a dynamic approach for LOTO in order to develop a Lean approach designed to limit non-value-added (NVA) waiting times. Consider the example presented in Figure 6.2 where two teams of workers share lockout tasks in a factory before a planned shutdown. According to the initial LOTO plan, team 1, highlighted in red color, must lock devices 1, 2 and 3. Team 2, highlighted in green color, must lock devices 4, 5, 6, 7 and 8. In this study, a scenario is considered where team 2 is unexpectedly late in locking device 5. This delay can have various origins, such as difficulty in finding the device, difficulty in deactivating it or equipment failure. Because of this delay, team 1 finishes its lockout while the green team is only in the process of locking valve 6.

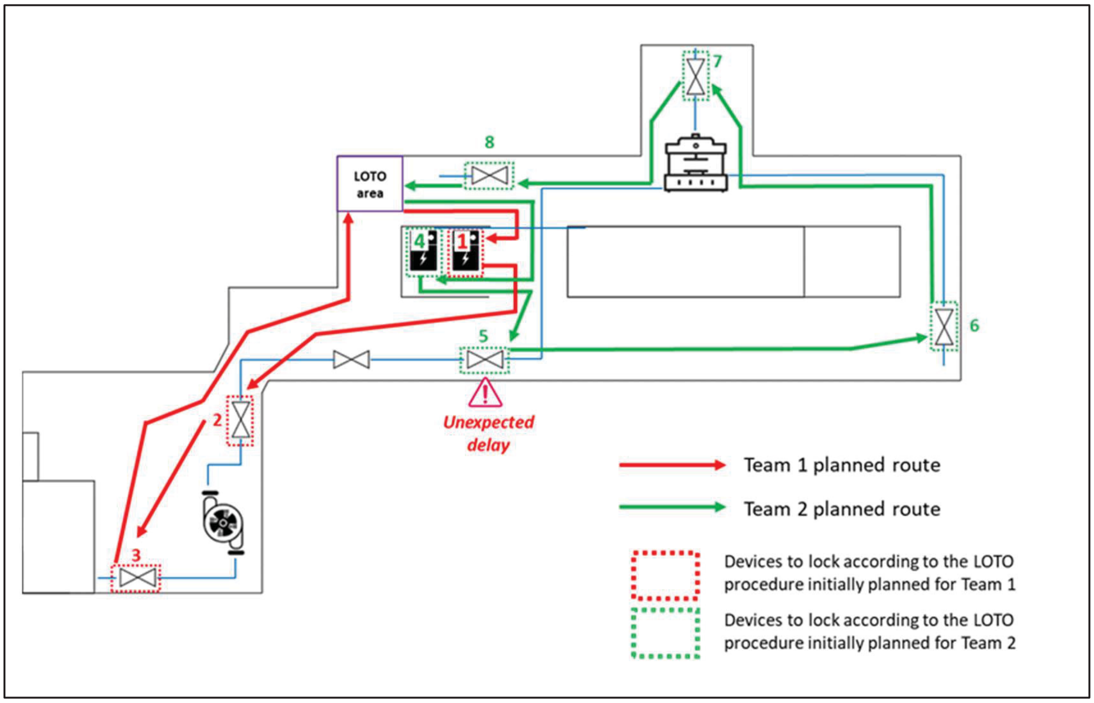


Figure 6.2 Routes of the different teams of workers in the case of classic LOTO

In the classic LOTO approach, each team has separate lockout tasks. The team 1 (red) completes its planned lockout first and must wait for team 2 (green) to complete their tasks before maintenance can begin, regardless of the delay. For example, the team 1 finishes locking devices 1, 2 and 3, while team 2 takes care of devices 4, 5, 6, 7 and 8 as originally planned. This process, although structured, can lead to delays and inefficiencies if one team is late.

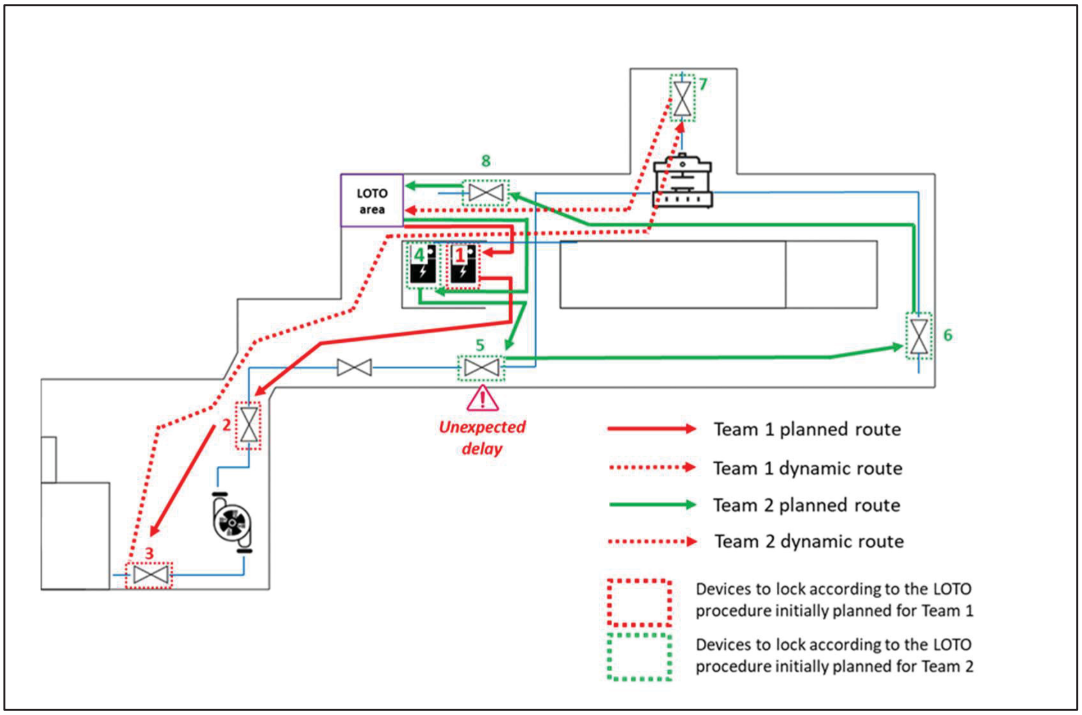


Figure 6.3 Routes of the different teams of workers in the case of dynamic LOTO

A dynamic LOTO approach introduces flexibility through the use of IoT-connected padlocks. This approach is illustrated in Figure 6.3. This approach enables real-time monitoring of lockout progress. When team 1 completes its planned lockout, it does not remain inactive but is immediately assigned a new task, such as locking valve 7. At the same time, team 2, which may be late, completes the lockout of valve 6 before moving on to valve 8. This dynamic distribution of tasks reduces downtime and optimizes the use of human resources. The dynamic LOTO strategy enables the two teams working in parallel to be more coordinated, enabled by IoT technology. Then, both teams can adjust their tasks in real time, depending on the progress of the work and any unforeseen circumstances. This method ensures seamless operations and reduces interruptions, maximising the overall efficiency of maintenance operations.

6.5 Simulation Model

In the following Section 6.5, two teams of workers operating a LOTO during a planned shutdown in a paper mill are considered. This section will define the notations, parameters and design of the simulation.

6.5.1 Notations

The simulation model notations are given in Table 6.1.

Table 6.1 Simulation model nomenclature

Indices	
i = I, II	Sets of LOTO teams/entity
n_I = *1… N_I*	Sets of LOTO(I) energy devices
n_{II} = *1… N_{II}*	Sets of LOTO(II) energy devices
Input Parameters	
P(i, n)	Precedence vector of device *(i, n)*
TIME((i, n_A),(j, n_B))	Time between the device (*i, n_A*) and the device *(j, n_B)*

The devices to be locked in the system are labelled by two numbers (i, n): i refers to the planned LOTO procedure to which the device is linked; n refers to the position of the device in the planned order of the LOTO procedure i. For example, the device (II, 3) refers to the third device to be locked according to the planned procedure LOTO(II). The precedence vectors indicate the precedence relationships that may exist between different devices in the same planned lockout. For example, a drain valve on a pump can only be locked after the pump's entry and exit valves have been locked. Thus:

$$\forall\ 1 \le n \le N_I, \exists\ 0 \le p < N_I\ /\ P(I, n) = \{y_1,\ y_2 \dots\ y_p\} \tag{6.1}$$

Equation (6.1) reflects the fact that devices $(I, y_1), (I, y_2) \dots (I, y_p)$ must necessarily be locked before device (I, n). If there are no precedence constraints, this vector will be an empty array. The same applies to the second scheduled LOTO procedure:

$$\forall\, 1 \leq n \leq N_{II}, \exists\, 0 \leq q < N_{II} \;/\; P(II, n) = \{z_1,\, z_2 \dots\, z_q\} \tag{6.2}$$

6.5.2 Assumptions

The developed model in this study considers the assumptions as described below:

- The planned locks are optimized to reduce route times.
- There are precedence conditions between the devices, and these precedence conditions are known.
- The travel times between each device are known and fixed.
- The locking time of a lockout follows a normal distribution (0.5, 0.25). This locking time is based on common observations made in the manufacturing factories used for this study.
- An unforeseen event can occur on a device, which delays its lockout. All the devices have the same probability of unforeseen events in the plant.
- Workers do not make mistakes, they perfectly follow the provided instructions and once they have passed over a piece of equipment, it is locked.
- The dynamic lockout system is reactive and instantaneous: two teams can never be assigned the same devices to lock.

6.5.3 Simulation Design

The definition of the simulation logic consists of constructing the main framework of the simulation model using logic modules, which are used to describe a series of events and movements. In order to improve the display effect, according to the simulation logic of this study, the framework, the corresponding sub-models of the simulation model are sketched using drawing software, as shown in Figure 6.4. In the logical framework of the simulation, the different nodes represent the different steps of a lockout, and the arrows between the nodes represent the directions workers take to perform the lockout. In the following sections, we describe in more detail the specific characteristics of the classic and dynamic Lockout/Tagout (LOTO) approaches. Section 6.5.3.1 outlines the general structure and initialization of the classic LOTO method, illustrating its fundamental procedures and inherent limitations. Section 6.5.3.2 presents the dynamic LOTO approach, highlighting its advanced features and improvements over traditional methods.

6.5.3.1 Classic LOTO

Section 6.5.3.1 presents the simulation model of the classic LOTO procedure. Below, the detailed sub-sections of this classic model will be examined, starting with the general structure and initialization.

6.5.3.2 General structure and initialisation

First, a simulation of a traditional lockout will be proposed. A model with two teams carrying out LOTO operations in parallel (LOTO(I) and LOTO(II)) is shown in Figure 6.4. The simulation model of traditional lockout for LOTO starts with the creation of Entity I and Entity II, representing two lockout teams. These entities move either according to the links between the blocks or between Route and Station blocks. This is done using the CREATE *LOTO(I)* and CREATE *LOTO(II)* modules. Once created, the Entity I is directed to the first device represented by the *Device(I,1)* sub-model to be locked using the ROUTE *Init_1* module to the STATION *Location(I,1)* module, where the journey time is determined by the time matrix

Time. The STATION *Location(I,1)* is located in the *Device(I,1)* submodel. The same applies to the LOTO(II) entity directed to *Device(II,1)* via the ROUTE *Init_2* module.

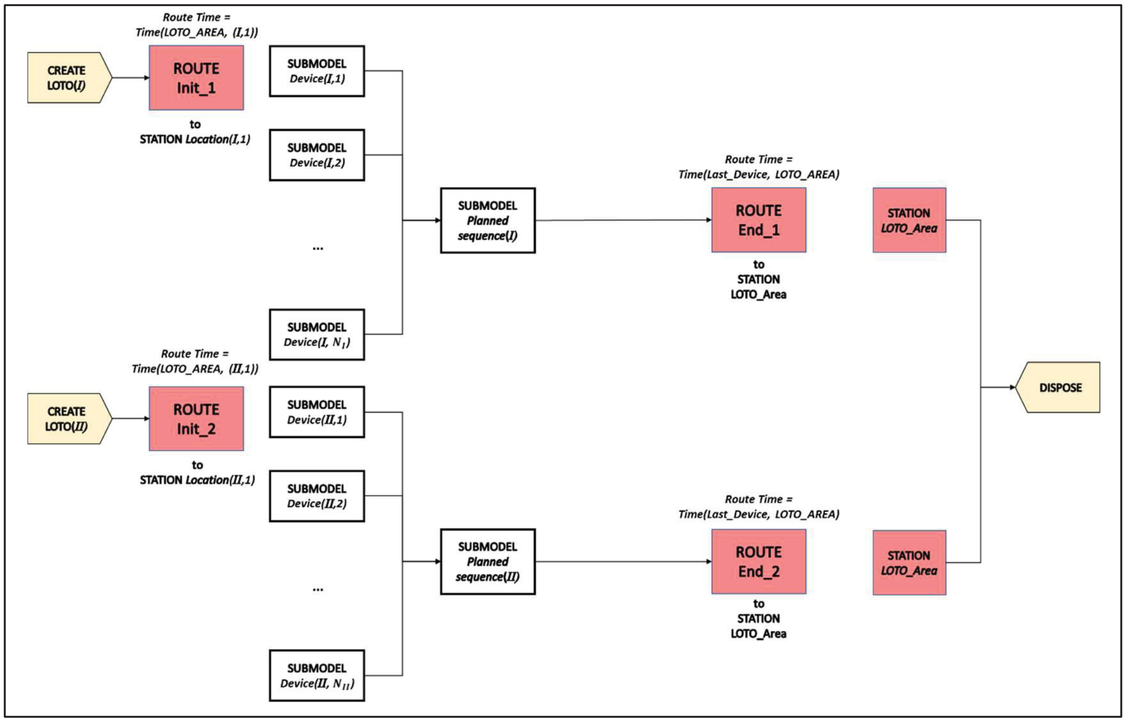


Figure 6.4 Submodels and stations of the classical LOTO simulation model

6.5.3.3 Modeling the locking of an energy device - Submodel Device(i, n)

The first device and its lockout are modelled by the submodel *Device(i,1)*. Regardless of the specific lockout or device, all devices are modeled uniformly with the same blocks. The simulation logic for all *Device(i, n)* sub-models will therefore be described and illustrated in Figure 6.5.

The *Device(i, n)* sub-model consists of the following elements:

- STATION *Location(i, n)*: representing the location of the device, to which the entity is directed;
- DECIDE *Fail(i, n)*: assessing the probability of an unexpected event with probability p.
  If an unexpected event occurs, the lockout team undergoes two delays in the DELAY modules:

- DELAY *Late* represents the time lost due to this unforeseen the unforeseen event;
- DELAY *Lock(i, n)* represents the lockout time of the device.

If there is no contingency, only the second delay occurs.

- ASSIGN *Last_Device(i, n)*: once the device has been locked, the entity is assigned the *Last_Device* attribute, indicating the last locked device. This attribute is crucial for determining subsequent travel times by indicating the matrix *TIME* indices.

The entity then leaves the submodel *Device(i, n)* via the exit point and heads for the next submodel *Planned Sequence(i)*.

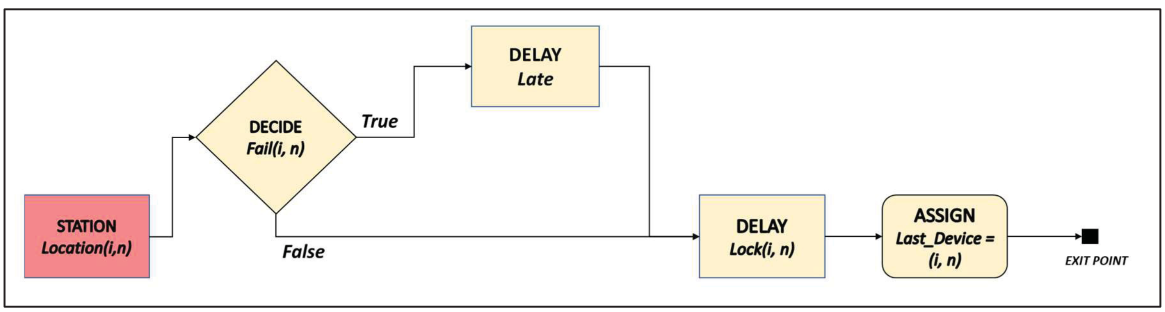


Figure 6.5 Submodel *Device(i, n)*

6.5.3.4 Modeling the planned locking sequence - Submodel Planned Sequence(i)

In the submodel *Planned Sequence(i)*, the lockout team follows the pre-established plan to get to the next device to be locked out. This submodel is shown in Figure 6.6 and consists of the following elements:

- DECIDE *Plan(i)*: this module contains a nested conditional structure, with $N_I - 1$ conditions for DECIDE *Plan(I)* and $N_{II} - 1$ conditions for DECIDE *Plan(II),* sequentially checking which device has already been locked according to the originally planned order. These conditions check the precedence constraints.

- COUNT *count_Plan(i, n)*: this module counts whether or not the entity which passes through the module has moved towards the device (i, n):

$$count\_Plan(i,n) \ = \begin{cases} 1 \ if \ \ if \ entity \ has \ moved \ to \ device \ (i,n) \\ 0 \ otherwise \end{cases} \tag{6.3}$$

Depending on the value of $count\_Plan(i,n)$, $condition(i,n)$ is as presented in Equation (6.4):

$$condition(i,n) = (count\_Plan(i,n) = 0) \tag{6.4}$$

If there are still devices to be locked, these conditions allow the entity to be sent to the first device that is not locked according to the planned order.

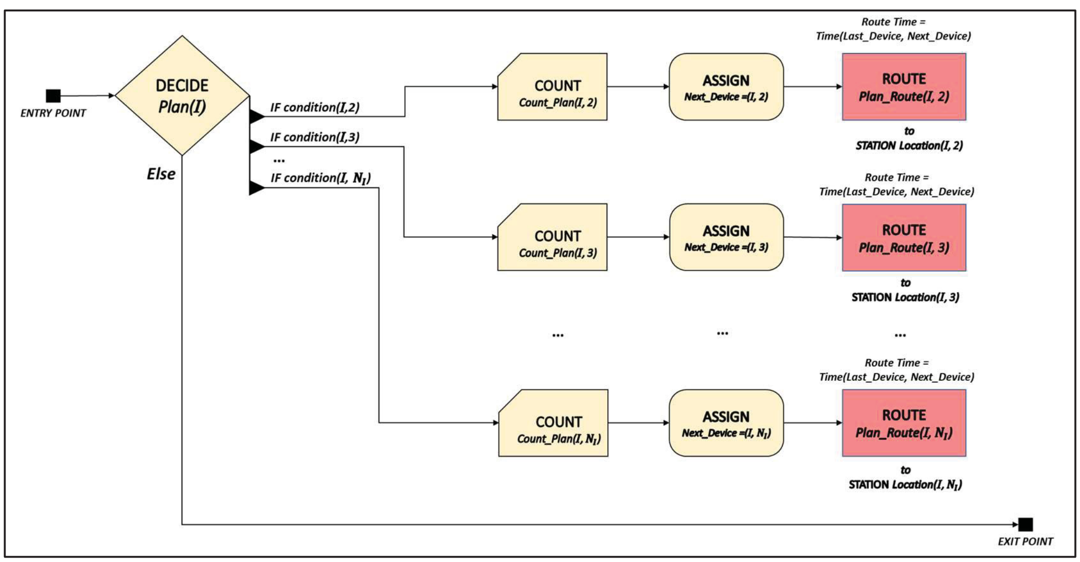


Figure 6.6 Submodel *Planned Sequence(I)*

- ASSIGN *Next_Device(i, n)*: this block is used to assign the *Next_Device* attribute to the entity, which is essential for determining future journey times using the *Time* matrix.
- ROUTE *Plan_Route(i, n)*: the entity is sent to the next device to be locked which is located at the STATION *Location(i,n)*. The entity's route time is equal to *Time(Last_Device, Next_Device)*.

Once all the devices are locked, the entity moves to the exit of the submodel.

6.5.3.5 Completion of LOTO procedure

As shown in Figure 6.4, ROUTE *End_1* and ROUTE *End_2* modules respectively guide the LOTO(I) and LOTO(II) entities to the STATION *LOTO_AREA*, with a travel time depending on the last device locked by each entity. Finally, a DISPOSE block models the end of the LOTO process. In summary, this simulation model highlights the sequence and interactions of the various stages involved in LOTO, from the creation of the worker teams to the finalisation of the process, including safety checks and contingency management.

6.5.3.6 Dynamic LOTO

After exploring the simulation model for the Classic LOTO procedure, this section presents Dynamic LOTO procedure. This model incorporates dynamic assistance mechanisms between worker teams, helping to improve the efficiency and safety of operations. The following subsections describe the structure and components of the dynamic model in detail, starting with the general structure of the simulation.

6.5.3.7 General structure

The dynamic lockout simulation model follows the structure of the traditional lockout model with the addition of a submodel *Dynamic Assistance(i)* at the output of the submodel *Planned Sequence(i)* as shown in Figure 6.7. This submodel allows the lockout team (entity) to be assigned devices from other LOTO procedures when their tasks are completed, hence providing assistance to another team. Figure 6.7 shows the new structure of the simulation with two LOTO procedures in parallel. If LOTO(I) finishes first, it will support LOTO(II), and vice versa.

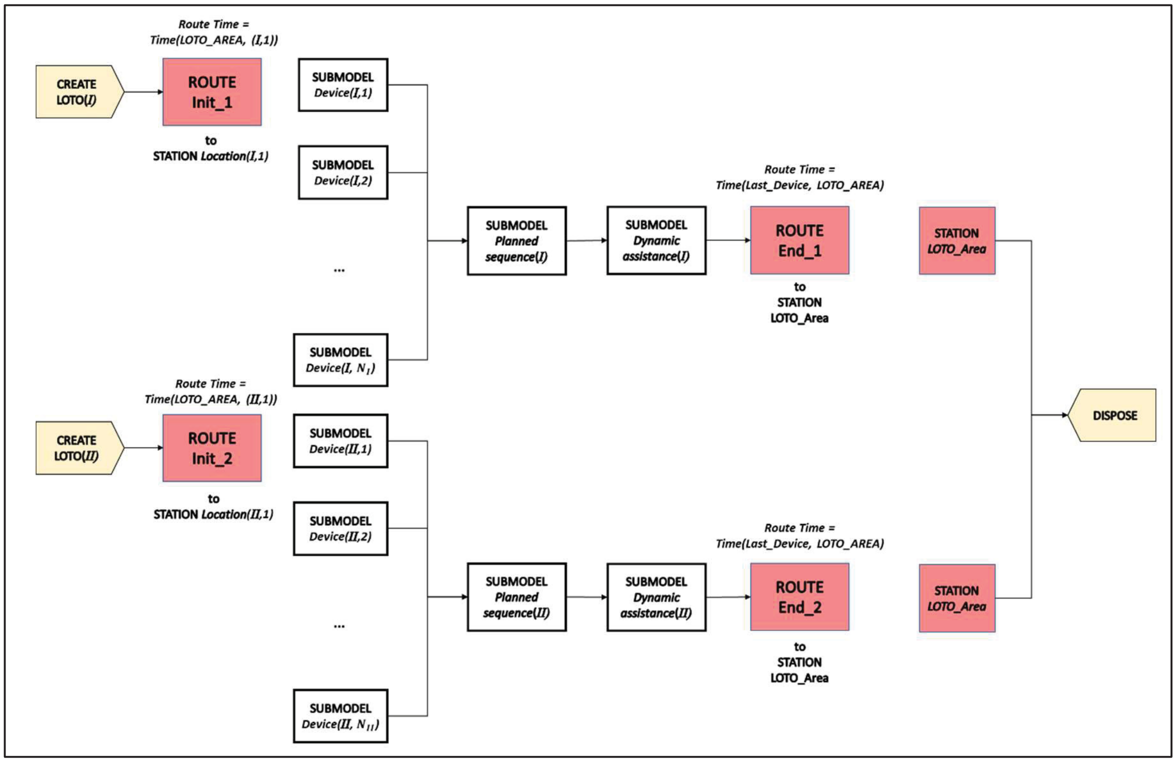


Figure 6.7 Submodels and stations of the Dynamic LOTO simulation model

6.5.3.8 Modeling assistance between worker teams - Submodel Dynamic Assistance(i)

First, for a better understanding, the construction of the simulation for the first lockout initially handled by the LOTO(I) entity is described. The simulation of the second lockout processed initially by LOTO(II) can be built in a similar way. The submodel *Dynamic Assistance(I)*, shown in Figure 6.8, is introduced at the output of the submodel *Planned Sequence(I)*. This submodel allows the lockout team to be assigned other LOTO procedures to provide additional assistance. This submodel consists of the following elements:

- DECIDE Assist(I): represents a nested conditional structure with $N_{II} - 1$ conditions, allowing sequential verification of which device has already been locked in the order originally intended for the LOTO(II) procedure. These conditions check the precedence constraints.

- COUNT *count_Assist(II, n)*: this module counts whether or not the entity which passes through the module has moved to the device (II, n):

$$count\_Assist(II,n) = \begin{cases} 1 \ if \ Entity \ I \ has \ moved \ to \ device \ (II,n) \\ 0 \ otherwise \end{cases}, \forall \, n < N_{II} \tag{6.5}$$

Depending on the value of $count\_Assist(i,n)$ and $count\_Plan(i,n)$, the conditions are defined as outlined in Equation (6.6) and Equation (6.7):

$$\begin{aligned} condition(i,n) = (count\_Assist(i,n) = 0 \ AND \ count\_Plan(i,n)) \ = 0) \\ AND \ Precedence\_constraints(i,n) \end{aligned} \tag{6.6}$$

with:

$$Precedence\_constraints(i,n) \ = (count\_Plan(i,k) = 1, \forall k \ in \ P(i,n)) \tag{6.7}$$

Thanks to these conditions, the precedence constraints are respected. When one team comes to the aid of another, it can only assist with locking devices with respected precedence constraints. According to the nested conditional structure, if there are still devices to be locked, these conditions, Equation (6.6) and Equation (6.7), allow the entity to be sent to the first device that is not locked according to the planned order. The conditions in DECIDE *Plan(I)* in the submodel *Planned Sequence(I)* have also been changed and are now identical to those in the submodel *Dynamic Assistance(I)*.

- ASSIGN *Next_Device(II, n)*: this block is used to assign the *Next_Device* attribute to the entity, which is essential for determining future travel times using the *Time* matrix.

- ROUTE *Assist_ Route(II, n)*: the entity is sent to the STATION *Location(II, n)* in a time *Time(Last_Device, Next_Device)*.

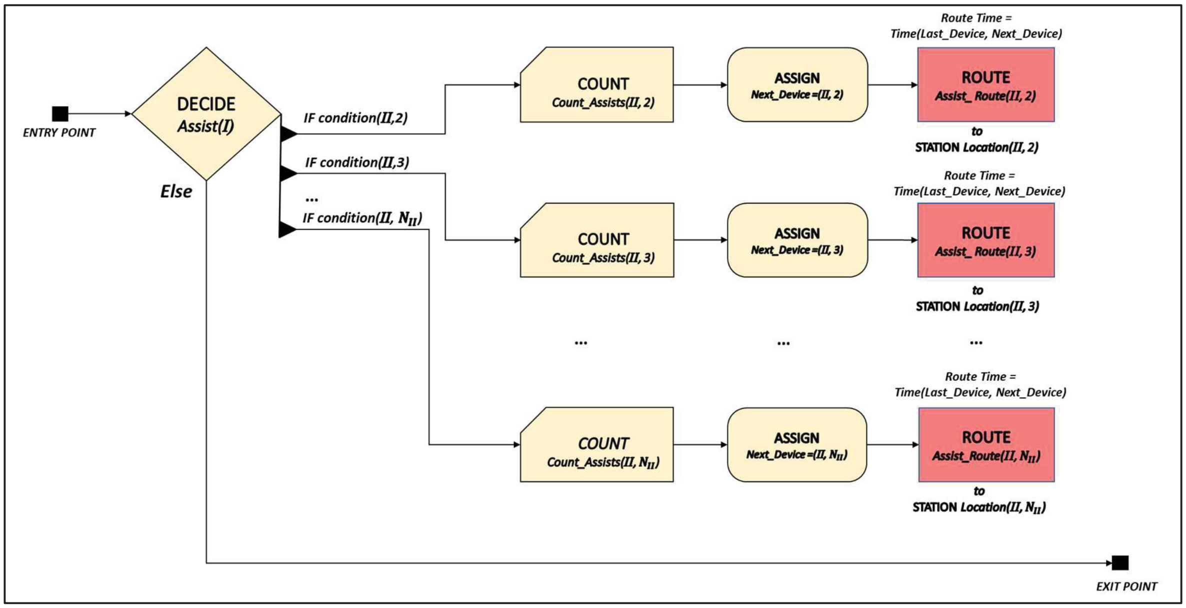


Figure 6.8 Submodel *Dynamic Assistance(I)*

By symmetry, it is possible to construct the submodel *Dynamic Assistance(II)*. The entity in charge of the LOTO(II) is sent to help complete the LOTO(I) if it completes its planned tasks first. The module DECIDE *Assist(II)* will have $N_I - 1$ conditions. If all devices are locked in the other LOTO procedure, the entity is directed to the exit of the submodel *Dynamic Assistance(i)* and then directed to the end of the procedure modeled by the DISPOSE module, as shown in Figure 6.7. In summary, this simulation model highlights the sequence and interactions of the different steps involved in dynamic lockout, incorporating dynamic assistance to improve the efficiency and safety of the process.

6.6 Computational tests

In this section 6.6, the proposed simulation models are used to carry out a comparative study between classic and dynamic LOTO procedures. A real industry case study is used for this computational test.

6.6.1 Industrial case study

This section considers the industrial case of a pulp and paper plant, with one main machine, including a large number of devices, e.g., circuit-breakers and valves, to be secured before maintenance operations. A planned shutdown is considered that requires two padlocks with two teams working in parallel. In the first stage, the teams will padlock the circuit-breakers only. Then, in a second phase, when all the circuit-breakers have been locked out, the two teams set off to lock out the system's valves, following two paths in parallel. According to the LOTO plan, the first team will lock $N_{I,1}$ = 10 circuit breakers and $N_{II,2}$ = 21 valves. The second team will lock $N_{II,1}$ = 6 circuit breakers and $N_{II,2}$ = 25 valves. Travel times between devices and precedence vectors were determined as part of the actual industrial case study. All data, such as the Time matrix, and the complete Rockwell Arena simulation models are available in a dataset on Mendeley Data (Delpla, 2024).

6.6.2 Results and discussion

The simulation, performed using Arena Rockwell Simulation, software running on a windows system with 16 GB of RAM and an Intel core 2.26 GHz processor, with 300 repetitions, compares the simulation with real time LOTO operations. Then, a comparison will be made between the classical and dynamic LOTO simulation approaches. By adopting a Lean approach to lockout (LOTO), activities are classified into value-added activities (VA), NVA activities and transportation. In this context, VA corresponds to actions directly related to making equipment safe, such as isolating energy sources and installing locking devices. These actions are essential to guarantee the safety of workers and the integrity of the equipment. NVA activities, on the other hand, represent time lost due to unforeseen events such as unplanned interruptions or errors in the lockout process. This time is a source of waste that dynamic lockout aims to minimise. Finally, transport refers to the time taken by workers to travel between different points in the plant to complete lockout operations. Dynamic lockout not only optimizes VA activities by reducing NVA activities but also by minimising transport time, thus contributing to an overall improvement in operational efficiency and a reduction in total lockout times.

6.6.3 Simulation model validation

In a first step, the expected locking time of LOTO procedures are compared with the simulation of the classic LOTO approach. The expected locking time is obtained by simple calculations using the travel times between devices and a fixed time of 0.5 minutes for the device locking time, as observed in the factories of the industrial partner in this research. The locking time of the conventional LOTO by simulation was obtained assuming a failure probability of 0%. The results of the compared locking times are presented in Table 6.2.

Table 6.2 Comparison of locking times estimated by calculation and simulation

	Expected locking time (in minutes) T_1	**Classic LOTO Simulation locking time (in minutes)** T_2	**Difference (%)** D
	Circuit breakers		
Entity I	6.51	6.55	0.61
Entity II	6.37	6.41	0.63
	Valves		
Entity I	14.65	14.78	0.88
Entity II	14.95	14.97	0.13

The results presented in Table 6.2 suggest that the locking times T_1 estimated by calculation and times T_2 obtained by simulation for the classical LOTO method are fairly close, including only very minor differences expressed as percentages. The percentage difference D is calculated as in Equation (6.8):

$$D = \frac{abs(\boldsymbol{T_1} - \boldsymbol{T_2})}{average(\boldsymbol{T_1}, \boldsymbol{T_2})} \tag{6.8}$$

The differences between the predicted locking times and the simulation results are less than 1% for all entities and devices. This low variance indicates that the estimated lockout time calculations are reasonably accurate and that the simulation model effectively captures the practicalities of the LOTO process. The differences arise from the fixed locking time of 0.5 minutes used in the calculations. This time varies slightly in the simulation, following a normal distribution centred on 0.5 minutes.

6.6.4 Comparative analysis

A comparative analysis of the simulation of the classic versus the dynamic LOTO approach is carried out. The results are detailed for different failure probabilities p (1%, 3%, 5%, 7%) and for the two types of equipment: circuit breakers and valves. For each failure probability p, for classic LOTO, the average operation time ($T_{AVG,c}$) ,and its decomposition into VA time ($T_{VA,c}$), NVA time ($T_{NVA,c}$) and Transfer time ($T_{Transfert,c}$) are given in Table 6.3 For each failure probability p, for dynamic LOTO, the average operation time ($T_{AVG,d}$), and its decomposition into VA time ($T_{VA,d}$), NVA time ($T_{NVA,d}$) and Transfer time ($T_{Transfert,d}$) are given in Table 6.4. The maximum operation times obtained from the 300 simulations for each failure probability are also given for Classic LOTO ($T_{op,max,c}$) and Dynamic LOTO ($T_{op,max,d}$).

Table 6.3 Report of results for the Classic LOTO (in minutes)

Classic LOTO						
	Failure probability (%) ***p***	$T_{AVG,c}$	$T_{VA,c}$	$T_{NVA,c}$	$T_{Transfert,c}$	$T_{op,max,c}$
	Circuit breakers					
Entity I	**1**	8.06	5.06	1.49	1.51	28.15
	3	9.44	5.06	2.88	1.51	31.59
	5	11.47	5.02	4.94	1.51	33.28
	7	13.59	5.03	7.05	1.51	50.02
Entity II	**1**	6.74	2.54	0.34	3.87	19.62
	3	7.66	2.55	1.25	3.87	30.02
	5	8.83	2.26	2.4	3.87	38.21
	7	9.7	2.56	3.28	3.87	39.61
	Valves					
Entity I	**1**	17.05	10.91	1.99	4.15	37.28
	3	21.87	10.95	6.76	4.15	43.53
	5	25.54	10.97	10.42	4.15	63.42
	7	29.03	10.91	13.97	4.15	86.3325
Entity II	**1**	17.36	12.58	2.33	2.45	37.84
	3	22.23	12.58	7.19	2.45	50.75
	5	27.16	12.54	12.16	2.45	64
	7	32.33	12.58	17.3	2.45	93.07

Table 6.4 Report of results for the dynamic LOTO (in minutes)

Dynamic LOTO						
	Failure probability (%) *p*	$T_{AVG,d}$	$T_{VA,d}$	$T_{NVA,d}$	$T_{Transfert,d}$	$T_{op,max,d}$
	Circuit breakers					
Entity I	**1**	7.96	4.59	1.78	1.58	19.02
	3	8.76	4.49	2.58	1.7	26.28
	5	10.26	4.3	4.19	1.78	31.13
	7	11.73	4.2	5.72	1.81	32.13
Entity II	**1**	7.77	3.01	0.39	4.38	23.75
	3	9.01	3.12	1.58	4.3	25.69
	5	10.54	3.29	3.03	4.22	31.69
	7	11.93	3.38	4.35	4.2	33.49
	Valves					
Entity I	**1**	17.36	11.11	2.00	4.24	33.55
	3	22.04	10.96	6.8	4.29	42.55
	5	26.93	11.22	11.38	4.33	50.58
	7	31.36	11.42	15.55	4.38	66.91
Entity II	**1**	17.36	12.34	2.28	2.74	31.27
	3	21.91	12.5	6.5	2.92	43.9
	5	26.49	12.21	11.34	2.94	52.74
	7	31.21	11.98	16.31	2.93	66.4

For circuit breakers, the average operation time using the conventional method increases with the failure probability, rising from 8.06 minutes to 13.59 minutes for Entity I and from 6.74 minutes to 9.7 minutes for Entity II. VA activities remain constant for both Entity I and Entity II. In fact, the teams of workers limited themselves to locking the devices provided in the initial plan without adapting to the delay, so the securing time remained constant. The same applies to transport time. On the other hand, NVA activities increase significantly, particularly for high failure probabilities, reaching up to 4.94 minutes for Entity I. The maximum operation time reaches 50.02 minutes for Entity I at a failure probability p of 7%. With dynamic lockout, the average operation time increases with the failure probability p, varying from 7.96 minutes to 11.73 minutes for Entity I and from 7.77 minutes to 11.93 minutes for Entity II. For Entity I, the VA activities are slightly lower than for classic lockout. Conversely, for Entity II, VA activities increased slightly, indeed Entity II assisting Entity I more often than the opposite. The average number of locked devices for Entity II is therefore higher. The same is true for NVA activities. Similarly, NVA activities decreased slightly for Entity I and increased for Entity II. In fact, Entity II locked more devices than during classic lockout, and therefore it had to deal more often with unforeseen events. Transport time is slightly higher, but remains equivalent for both approaches. There is little difference between dynamic LOTO and classic LOTO because the routes between the devices were already optimized for each LOTO, so the path followed is virtually the same. The only difference are the detours taken by Entity II to join the path taken by Entity I. For valves, the average operation time using the classic method increases sharply with the failure probability, ranging from 17.05 minutes to 29.03 minutes for Entity I and from 17.36 minutes to 32.33 minutes for Entity II. Unlike in the case of circuit breakers, it is now Entity I that assists Entity II to complete the padlocking. The time taken for VA and NVA operations decreases slightly for Entity II and increases slightly for Entity I compared with the classic LOTO. Transport times also remain similar.

From these results, the average total lockout time can be determined. As maintenance can only take place when both lockouts in parallel have been completed, the total lockout time corresponds to the time required to secure the machine. From a practical point of view, it is this time that maintenance managers seek to reduce. This is the longest average operation time between the two worker teams. This average lockout time can be determined for circuit breakers and valves for Classic LOTO ($T_c(p)$) and Dynamic LOTO ($T_d(p)$). For circuit-breaker and valve lockouts only, these times can be written as in Equation (6.9) and Equation (6.10):

$$T_c(p) = Max\left(T_{AVG,c}(Entity\ I, p),\ T_{AVG,c}(Entity\ II, p)\right) \tag{6.9}$$

$$T_d(p) = Max\left(T_{AVG,d}(Entity\ I, p),\ T_{AVG,d}(Entity\ II, p)\right) \tag{6.10}$$

The average total lockout time, i.e. the time to lock the circuit breakers and valves, is the sum of the average lockout times of the circuit breakers and valves, for the same type of LOTO and the same failure probability p. The results in Table 6.5 reveal that dynamic LOTO locking times T_d are systematically shorter than the locking times T_c of the classic method, with greater time reduction rates R as the failure probability increases. The reduction rate R is calculated as follows:

$$R(p) = \frac{T_d(p) - T_c(p)}{T_c(p)} \tag{6.11}$$

Table 6.5 Average locking times

Failure probability (%) *p*	**Dynamic LOTO time (in minutes) T_d*(p)***	**Classic LOTO time (in minutes) T_c*(p)***	**Reduction Rate (%) *R(p)***
Average Locking Times for circuit breakers			
1	7.96	8.06	-1.24
3	9.01	9.44	-4.56
5	10.54	11.47	-8.11
7	11.93	13.59	-12.21
Average Locking Times for valves			
1	17.36	17.36	0.00
3	22.04	22.23	-0.85
5	26.93	27.16	-0.85
7	31.36	32.33	-3.00
Total Average Locking Time			
1	25.32	25.42	-0.39
3	31.05	31.67	-1.96
5	37.47	38.63	-3.00
7	43.29	45.92	-5.73

Figure 6.9 illustrates these time reductions, highlighting the incremental improvements of dynamic LOTO over the traditional method.

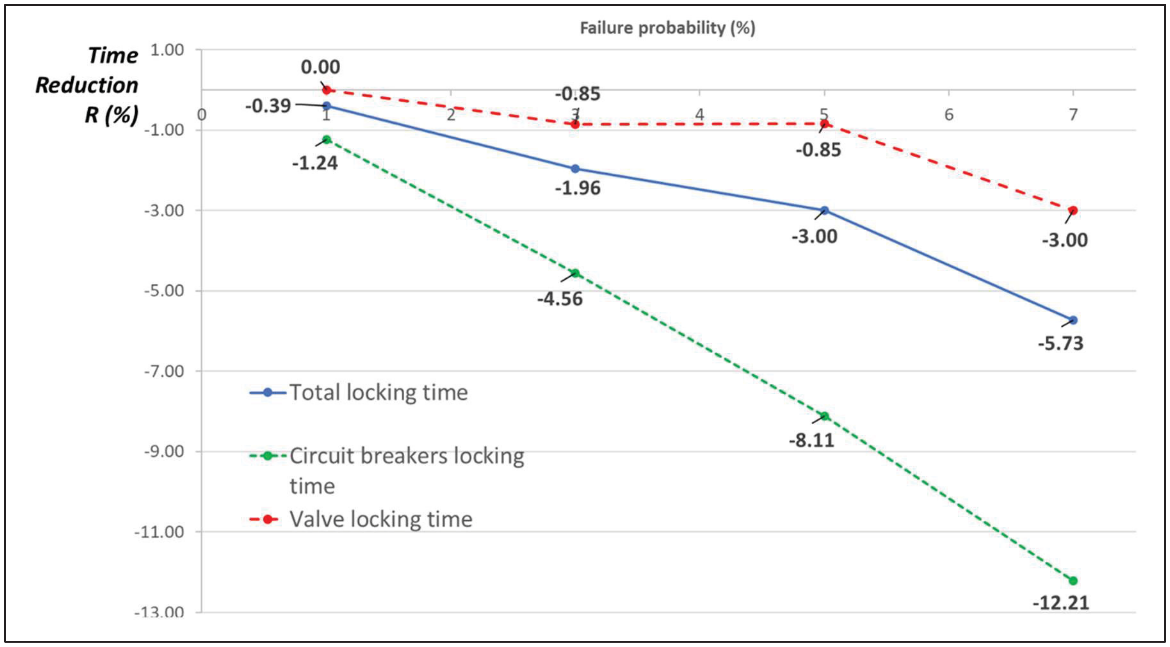


Figure 6.9 Average time reduction R with dynamic LOTO

The worst-case scenarios for workers are also interesting. Rare unforeseen events can in fact be very penalising when several of such events occur during LOTO procedures. One of the aims of dynamic lockout would be to reduce delays caused by the least advantageous scenarios. For circuit-breaker and valve lockouts only, these maximum locking times for Dynamic LOTO ($T_{d,max}$) and Classic LOTO ($T_{c,max}$) can be written as in Equation (6.12) and Equation (6.13) for any probability of failure p:

$$T_{c,max}(p) = Max\left(T_{op,max,c}(Entity\ I, p), T_{op,max,c}(Entity\ II, p)\right) \tag{6.12}$$

$$T_{d,max}(p) = Max\left(T_{op,max,d}(Entity\ I, p), T_{op,max,d}(Entity\ II, p)\right) \tag{6.13}$$

$T_{d,max}$ and $T_{c,max}$ obtained from 300 simulation repetitions are shown in Table 6.6. The reduction rate R_{max} is calculated as follows:

$$R_{max}(p) = \frac{T_{d,max}(p) - T_{c,max}(p)}{T_{c,max}(p)} \tag{6.14}$$

Table 6.6 Maximum total lockout time for both teams over 300 repetitions

Failure probability (%) p	**Dynamic LOTO maximum time (in minutes) $T_{d,max}(p)$**	**Classic LOTO maximum time (in minutes) $T_{c,max}(p)$**	**Reduction Rate (%) $R_{max}(p)$**
Circuit breakers			
1	23.75	28.15	-15.63
3	26.28	31.59	-16.81
5	31.69	38.21	-17.06
7	33.49	50.02	-33.05
Valves			
1	33.55	37.84	-11.34
3	43.9	50.75	-13.5
5	52.74	64	-17.59
7	66.91	93.07	-28.11

Figure 6.10 shows significant time savings for dynamic lockout compared to conventional lockout approaches. For valves, the maximum time reduction varies from 11.34% to 28.11% depending on the failure probability, while for circuit breakers, maximum times are reduced from 15.63% to 33.05%. These results show that dynamic interlocking reduces not only average and maximum interlocking times, but also NVA activity, thus contributing to an overall improvement in operational efficiency in the industry.

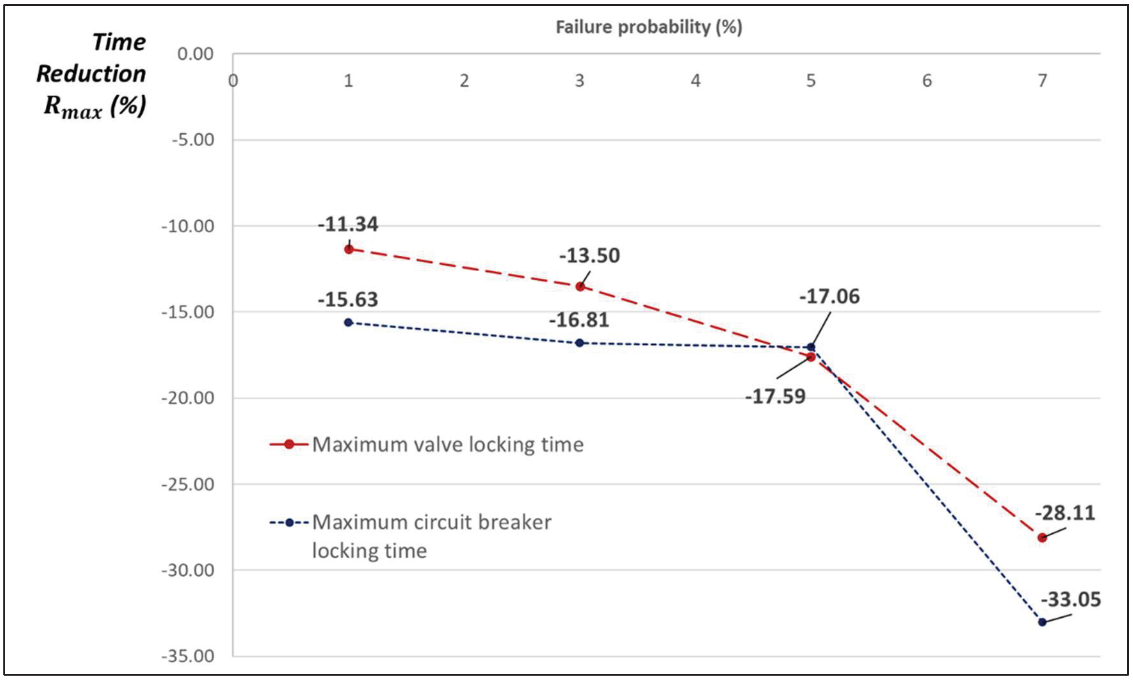


Figure 6.10 Maximum time reduction R_{max} with dynamic LOTO

The reduction in average and maximum lockout times in the case of dynamic lockout is partly explained by the fact that workloads are better balanced between the different teams of workers. In fact, in the case of classic LOTO, when one team (1) is stopped because of an unforeseen event and the other team (2) is not aware, team 1 will be able to come and help team 2 only once its initially allocated lockout procedure has been completed. Figure 6.11 shows the relative difference in operation time between Entity I and Entity II for different failure probability (see Table 6.3 and Table 6.4). In the case of dynamic LOTO, this difference remains between 0% and 3% for all failure probabilities, both for circuit breakers and valves. In the case of conventional lockout, this difference is significantly higher and will even increase dramatically with the failure probability. Hence, this analysis confirms that the proposed dynamic LOTO strategy is a promising avenue for further development towards implementation in real-world industrial plants.

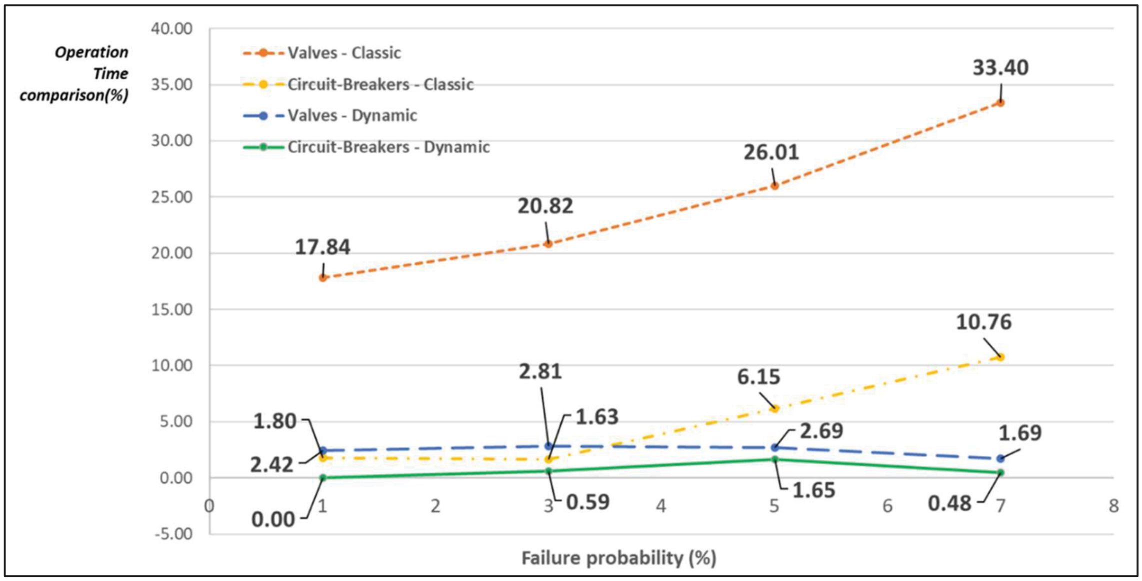


Figure 6.11 Relative difference in operation time between Team I and Team II

6.7 Managerial Insights

The managerial insights provided by this research are of particular importance to decision-makers and managers in the industrial sector. The introduction of Dynamic LOTO adds a new dimension to risk management and maintenance planning. Managers benefit from a powerful tool that improves operational efficiency, enabling a significant reduction in the costs associated with unexpected downtime and incidents. The ability to adapt lockout procedures in real-time enables more strategic allocation of human resources, optimizing staff deployment and minimizing periods of non-productivity. Additionally, the proposed Dynamic LOTO approach encourages a proactive safety culture, where priority is given to anticipating and preventing risks. This approach is in perfect harmony with the principles of modern management, which values agility and resilience.

6.8 Conclusion

This research has led to significant advances in LOTO procedures, making a specific contribution in three major directions. Firstly, the study defined a robust strategy for dynamic

LOTO, incorporating new technologies such as IoT. This strategy radically transforms traditional safe maintenance methods by incorporating a real-time adaptation capability that instantly reflects and responds to operational changes in the field. The move to a more agile system enables a faster response to unforeseen situations, boosting the efficiency of maintenance operations. Secondly, a discrete event simulation model was developed that details both classical and dynamic LOTO procedures. The simulation model predicts lockout times close to those estimated deterministically. This model offers a clear perspective on the effectiveness of current practices and suggests avenues for their improvement, thus facilitating the visualisation and analysis of safety processes in an industrial environment. Finally, using the developed simulation tool, the benefits of dynamic LOTO could be quantitatively estimated. The results of this estimation reveal a significant reduction in lockout times, attesting to the increased efficiency of this innovative approach. In particular, the reduction in lockout times of up to thirty percent for worst-case scenarios demonstrates a considerable impact on improving safety and operational efficiency. In conclusion, the Dynamic LOTO approach introduced by this study represents a step forward for industrial safety, offering better protection for workers and improving the overall efficiency of operations. These improvements, which incorporate more proactive risk management and reduced downtime, represent a crucial step towards the adoption of more intelligent and adaptive safety practices in process industry.

Data availability

The data supporting the results of this study are available on Mendeley Data at DOI:10.17632/psgwjkk5bv.1.

CONCLUSION

Les procédures de cadenassage/décadenassage (Lockout/Tagout - LOTO) sont essentielles pour assurer la sécurité des travailleurs pendant les opérations de maintenance dans l'industrie manufacturière. Elles consistent à isoler et désactiver les sources d'énergie potentiellement dangereuses pour empêcher tout démarrage involontaire des machines. Cependant, ces procédures sont souvent perçues comme une entrave à la productivité, en raison du temps nécessaire à leur mise en œuvre et de leur nature statique et manuelle. Ce contexte crée un dilemme entre la nécessité de garantir la sécurité des travailleurs et celle de maintenir une production continue et efficace. La présente thèse propose des stratégies intelligentes d'intégration du LOTO à son environnement manufacturier.

Une politique de contrôle optimal englobant la production, la maintenance et le LOTO opérationnel a été introduite comme première contribution à cette recherche. Ce problème a été formulé dans un cadre de processus de décision markovien. Une approche numérique de Kushner a été utilisé pour calculer les conditions d'optimalité de ce problème. Ces dernières ont été déterminées en appliquant les équations de Hamilton-Jacobi-Bellman. Cette politique de contrôle permet aux gestionnaires de production de savoir quand produire et quand envoyer en maintenance, en fonction du niveau de stock et de l'état de dégradation estimée de la machine. Les résultats obtenus démontrent une réduction notable des coûts engendrés par la maintenance dans le cas où des politiques de LOTO opérationnel sont mise en place, en comparaison du cas où ces dernières ne sont pas présentes.

L'assistance à la rédaction des procédures LOTO via l'utilisation du ML et du DL a été proposée. Des algorithmes de classification multi-tâches ont été utilisés, comme les algorithmiques KNN, RF et DNN, pour prédire les dispositifs à verrouiller en fonction des noms des machines. Cette automatisation permet de réduire le temps nécessaire à la rédaction des procédures et de diminuer les erreurs des travailleurs peu expérimentés. Les résultats montrent la supériorité des DNN sur les algorithmiques KNN et RF sur la précision des prédictions. Les résultats dépassent les 90% de précisions si l'on considère la top-2 précision du DNN. Ces résultats sont par ailleurs stables, peu importe le domaine industriel auquel les machines appartiennent. Toutefois, cette approche est limitée aux machines simples ; les machines complexes et peu courantes nécessitant encore une intervention humaine en raison du caractère critique des procédures LOTO en termes de sécurité.

Les échanges avec les partenaires industriels ont mis en évidence le besoin d'automatiser la fusion des procédures LOTO. Un modèle d'optimisation MINLP bi-objectifs a été développé pour planifier les trajets des équipes de maintenance en fonction des machines à sécuriser et dont on souhaite fusionner les procédures LOTO. L'algorithme NSGA-II est utilisé pour résoudre le problème d'optimisation bi-objectif et des algorithmes de résolution de problème de routage de véhicules sont utilisés pour optimiser les trajets et minimiser les temps de verrouillage. Cette contribution a ainsi permis la fusion automatisée des procédures LOTO, permettant aux gestionnaires de maintenance d'économiser plusieurs heures de travail à la réalisation de cette tâche. De plus, la réduction du temps de déplacement des cadenasseurs est estimé à plus de 30%.

Des stratégies LOTO intelligentes et adaptées à l'environnement manufacturier ont été développées pour la mise en œuvre des procédures LOTO. Ces stratégies intègrent des caractéristiques spécifiques de l'environnement, telles que la position des dispositifs énergétiques, les interconnexions entre les valves. La collaboration entre plusieurs équipes de cadenasseurs parallèles est aussi considérée.

La première approche, basée sur la position géographique des dispositifs, permet aux différentes équipes de cadenasseurs de se répartir géographiquement les dispositifs à verrouiller pour optimiser l'utilisation des ressources humaines. Cette méthode repose sur le modèle d'optimisation bi-objectifs MINLP proposé pour la fusion des procédures LOTO pour plusieurs équipes travaillant en parallèle. La différence principale vient du fait de séparer l'intégralité des dispositifs à verrouiller entre la totalité des équipes, plutôt que d'attribuer manuellement des fusions de procédures à une équipe en particulier. Cette approche permettrait de réduire le temps de verrouillage de 20 % par rapport à une fusion classique des procédures

LOTO, mais elle demanderait le développement de cadenas connecté par IoT afin d'être mis en place sur le terrain. Ce type de cadenas permettrait le découplage des opérations de maintenance et du LOTO : un cadenasseur unique ne poserait pas que tous les cadenas physiques qui sécurisent une machine. Le technicien de maintenance verrouillerait ensuite, à distance grâce à l'IoT, seulement les cadenas qui concernent la machine sur laquelle il va travailler, peu importe s'il s'agit d'un unique cadenasseur ou non qui les aient posés.

La seconde approche est une méthode dynamique du LOTO, où les procédures des équipes de cadenasseurs ajustent leurs tâches à accomplir en temps réel selon les imprévus, minimisant ainsi les retards. Une simulation à événements discrets a montré que cette approche dynamique réduit de 30 % le temps de verrouillage dans les scénarios les plus difficiles, en améliorant la coopération entre les équipes en fonction des circonstances. De même, des cadenas connectés par IoT seraient indispensables permettre au cadenasseur de poser des cadenas sur un machine qu'il ne sécurise pas en intégralité.

L'intégration de technologies, telles que l'IoT et l'IA, de nouvelles politiques d'optimisation et de nouvelles approches dans les procédures de LOTO au niveau de la planification, de la préparation et de l'exécution, peuvent considérablement améliorer la sécurité des travailleurs et le LOTO tout en cherchant l'optimisation de l'efficacité des opérations de production et de maintenance. Cette thèse a montré par différents moyens comment il était possible grâce à ces technologies et approches intelligentes d'optimiser les procédures LOTO dans le paradigme de l'Industrie 4.0. Les résultats obtenus montrent une réduction significative des temps de cadenassage, une meilleure gestion des ressources humaines et une amélioration de la continuité de la production. Cette recherche ouvre ainsi la voie à l'adoption de stratégies LOTO plus intelligentes et adaptatives dans l'industrie manufacturière. Les bases pour une transition vers des procédures LOTO s'inscrivant dans l'industrie de demain sont posés et annonce de futures recherches.

RECOMMANDATIONS ET TRAVAUX FUTURS

Suite à ce travail de recherche, plusieurs recommandations peuvent être formulées à propos du travail de recherche réalisé :

Il serait pertinent de développer des extensions du modèle proposé dans le chapitre 3 pour l'adapter à des configurations de lignes de production plus complexes. Pour cela, il serait utile de considérer l'ajout de plusieurs machines avec des interconnexions et interdépendances, ce qui permettrait de modéliser plus fidèlement les contraintes réelles rencontrées dans ce type d'industrie. Par ailleurs, l'intégration de l'incertitude pourrait améliorer la robustesse du modèle en reflétant des conditions de marché plus réalistes. Cela pourrait être réalisé en utilisant des distributions probabilistes pour la demande, ainsi qu'en explorant d'autres distributions pour modéliser les taux de défaillance des machines.

Le modèle de LOTO dynamique présenté dans le chapitre 6 pourrait bénéficier d'une exploration plus approfondie des mécanismes de réassignation et de réordonnancement des dispositifs sous des scénarios avec perturbation. Il serait aussi intéressant de simuler ces scénarios avec un nombre plus important d'équipes de maintenance et de dispositifs, afin de mieux comprendre les limites pratiques du modèle actuel et de proposer des stratégies d'amélioration.

Les approches développées dans les chapitres 3 à 6 gagneraient à être testées sur un ensemble plus large d'études de cas industriels pour évaluer leur applicabilité et leur robustesse dans divers contextes. L'élargissement du nombre de cas testés permettrait non seulement de mieux généraliser les résultats obtenus, mais aussi de démontrer la capacité des algorithmes et modèles à gérer des configurations industrielles variées. L'intégration de ces tests supplémentaires renforcerait la crédibilité des solutions proposées et faciliterait leur adoption dans l'industrie.

Il est crucial de rappeler que toute approche impliquant des procédures LOTO doit être mise en œuvre avec la plus grande précaution, en raison des risques graves pour la sécurité des travailleurs. Par conséquent, toute nouvelle méthodologie ou optimisation proposée pour les procédures LOTO doit non seulement être validée théoriquement, mais également strictement alignée avec les exigences de la norme CSA Z460. Cela garantit que ces approches, tout en cherchant à améliorer l'efficacité, ne compromettent jamais la sécurité des opérateurs sur le terrain.

De plus, cinq directions de recherche pour des travaux futurs peuvent être émises :

1) Les futures recherches devraient approfondir le principe de cadenassage opérationnel en le testant sur des équipements présentant une grande inertie d'arrêt, tels que les presses industrielles ou les machines à papier. Cela permettrait d'évaluer l'efficacité et les limites du cadenassage opérationnel dans des contextes où les temps d'arrêt sont critiques. Des simulations et des essais sur le terrain pourraient fournir des données précieuses pour affiner les procédures et améliorer la sécurité et l'efficacité des opérations de maintenance.

2) Les cadenas équipés de technologies IoT représentent une avancée significative pour les procédures LOTO. Les recherches futures devraient se concentrer sur le développement et le déploiement de ces dispositifs intelligents, qui peuvent être contrôlés et surveillés à distance. Ces cadenas IoT seraient particulièrement utiles dans les approches géographiques et dynamiques, permettant une gestion en temps réel des procédures de cadenassage. Les essais sur le terrain devraient valider leur efficacité dans divers environnements industriels et évaluer leur impact sur la sécurité et la productivité.

3) La réalité augmentée offre des possibilités prometteuses pour améliorer la formation et l'efficacité des travailleurs dans les usines. Les recherches futures devraient explorer l'utilisation de la réalité augmentée pour guider les travailleurs, en particulier ceux peu expérimentés, dans la localisation et la manipulation des dispositifs de cadenassage. La réalité augmentée pourrait fournir des instructions visuelles en temps réel sur les

manipulations à effectuer, réduisant ainsi les erreurs, les temps de formation et les retards dans l'exécution du LOTO. Des études de cas et des essais pratiques dans des environnements industriels diversifiés pourraient démontrer l'impact positif de la RA sur la sécurité et l'efficacité des procédures LOTO.

4) Une meilleure intégration des procédures de cadenassage dans les systèmes de planification des ressources d'entreprise (ERP) pourrait améliorer la coordination et l'efficacité des opérations de maintenance. Les recherches futures devraient se concentrer sur le développement de modules ERP spécifiques pour la gestion du cadenassage, permettant une planification plus fluide et une communication en temps réel entre les différents départements. L'intégration des données LOTO dans les systèmes ERP faciliterait également la maintenance prédictive et la gestion proactive des ressources.

5) L'optimisation conjointe des politiques de production, de maintenance et de LOTO, en tenant compte de la maintenance prédictive, représente un domaine de recherche crucial. Les futurs travaux devraient développer des modèles mathématiques avancés intégrant les données en temps réel des capteurs IoT pour prévoir les pannes et optimiser les interventions de maintenance. Ces modèles pourraient utiliser des algorithmes d'apprentissage machine pour analyser les données et fournir des recommandations en temps réel, améliorant ainsi la disponibilité des équipements et réduisant les coûts opérationnels.

Ces recommandations et ces travaux futurs pourront approfondir et améliorer les pratiques de cadenassage/décadenassage, en intégrant des technologies avancées et en tenant compte des besoins spécifiques des environnements industriels modernes. Ces recherches contribueront à renforcer la sécurité des travailleurs, à optimiser les opérations de maintenance et à maintenir une production continue et efficace.

ANNEXE I

ANNEXES DU CHAPITRE 3

Annex AI.A : Optimal conditions

From Equations (3.13) - (3.14), the value function can be written as follows:

$$v(\alpha(t'), x(t'), a(t'), t') = \inf_{(u,\omega)\in\Gamma^h(\alpha)} E\left\{\int_{t'}^{\infty} e^{-\rho} \,.\, g(\alpha(t), x(t), u(t))dt | x(t = t') = x, \xi(t = t') = \alpha\right\}, \forall\alpha \in B \tag{AI.1}$$

Using a perturbation $\delta t \in [0, \infty[$, we can decompose the integral of equation (A.1) as follows:

$$v(\alpha(t'), x(t'), a(t'), t') = \inf_{\substack{(u,\omega)\in\Gamma^h(\alpha)\\ 0\le\delta t<\infty}} E\left\{\int_{t'}^{t'+\delta t} e^{-\rho t}. g(\alpha(t), x(t), u(t))dt + \int_{t'+\delta t}^{\infty} e^{-\rho t}. g(\alpha(t), x(t), u(t))dt' | x(t = t') = x, \xi(t = t') = \alpha\right\}, \forall\alpha \in B \tag{AI.2}$$

We can notice that the second term of this decomposition is equal to the value function $v(\alpha(t' + \delta t), x(t' + \delta t), a(t' + \delta t), t' + \delta t)$. Thus, we find:

$$v(\alpha(t'), x(t'), a(t'), t') = \inf_{\substack{(u,\omega)\in\Gamma^h(\alpha)\\ 0\le\delta t<\infty}} E\left\{\int_{t'}^{t'+\delta t} e^{-\rho t}. g(\alpha(t), x(t), u(t))dt + v(\alpha(t' + \delta t), x(t' + \delta t), a(t' + \delta t), t' + \delta t) | x(t = t') = x, \xi(t = t') = \alpha\right\}, \forall\alpha \in B \tag{AI .3}$$

Assuming that $\delta t \rightarrow 0$ and $\nu(\alpha(t), x(t), a(t), t)$ is differentiable, then developing to the first order, according to Gerswhin (1994), we obtain:

$$
\begin{aligned}
&\nu(\alpha(t' + \delta t), x(t' + \delta t), a(t' + \delta t), t' + \delta t) \\
&\qquad = \nu(\alpha(t'), x(t'), a(t'), t') + \sum_{\beta \in B} q_{\alpha\beta}.\nu(\beta, x, \varphi(a), t')\delta t \\
&\qquad + \frac{\partial \nu(\alpha, x, a, t')}{\partial x}\delta x + \frac{\partial \nu(\alpha, x, a, t')}{\partial a}\delta a + \frac{\partial \nu(\alpha, x, a, t')}{\partial t}\delta t \\
&\qquad + o(\delta t)
\end{aligned}
\tag{AI.4}
$$

Here, we can write:

$$\delta x = \frac{dx}{dt}\delta t = (u - d).\delta t \tag{AI.5}$$

$$\delta a = \frac{da}{dt}\delta t = K_u.u.\delta t \tag{AI.6}$$

After substitution of (I.A.5) and (I.A.6) into Equation (I.A.4) we obtain:

$$
\begin{aligned}
&\nu(\alpha(t' + \delta t), x(t' + \delta t), a(t' + \delta t), t' + \delta t) \\
&\qquad = \nu(\alpha(t'), x(t'), a(t'), t') + \sum_{\beta \in B} q_{\alpha\beta}.\nu(\beta, x, \varphi(a), t')\delta t \\
&\qquad + (u - d).\frac{\partial \nu(\alpha, x, a, t')}{\partial x}\delta t + K_u.u.\frac{\partial \nu(\alpha, x, a, t')}{\partial a}\delta t \\
&\qquad + \frac{\partial \nu(\alpha, x, a, t')}{\partial t}\delta t
\end{aligned}
\tag{AI.7}
$$

Thus:

$$\nu(\alpha(t'), x(t'), a(t'), t')$$

$$= \inf_{\substack{(u,\omega)\in\Gamma^h(\alpha) \\ 0\le\delta t<}} E\left\{\int_{t=t'}^{t=t'+\delta t} e^{-\rho t}.\, g(\alpha(t), x(t), u(t))dt\right.$$

$$+ \nu(\alpha(t'), x(t'), a(t'), t') + \sum_{\beta\in B} q_{\alpha\beta}.\, \nu(\beta, x, \varphi(a), t')\delta t \qquad \text{(AI.8)}$$

$$+ (u-d)\frac{\partial\nu(\alpha, x, a, t')}{\partial x}\delta t + K_u.\, u\frac{\partial\nu(\alpha, x, a, t')}{\partial a}\delta t$$

$$\left. + \frac{\partial\nu(\alpha, x, a, t')}{\partial t}\delta t \,|x(t=t') = x, \xi(t=t') = \alpha\right\}, \forall\alpha \in B$$

If $\delta t \to 0$, we have :

$$\int_{t=t'}^{t=t'+\delta t} e^{-\rho t}.\, g(\alpha(t), x(t), u(t))dt = 0 \qquad \text{(AI.9)}$$

By developing $\frac{\partial\nu(\alpha,x,a,t')}{\partial t}$ to the first order:

$$\frac{\partial\nu(\alpha, x, a, t')}{\partial t} = \frac{\nu(\alpha, x, a, t'+\delta t) - \nu(\alpha, x, a, t')}{\delta t} + o(\delta t) \qquad \text{(AI.10)}$$

Thus Equation (I.A.3) becomes then:

$$\nu(\alpha, x, a, t') - \nu(\alpha, x, a, t'+\delta t)$$

$$= \min_{(u,\omega)\in\Gamma(\alpha)} \begin{bmatrix} \sum_{\beta\in B} q_{\alpha\beta}.\, \nu(\beta, x, \varphi(a), t')\delta t + (u-d)\frac{\partial\nu(\alpha, x, a, t')}{\partial x}\delta t + \\ K_u.\, u.\frac{\partial\nu(\alpha, x, a, t')}{\partial a}\delta t \end{bmatrix}, \forall\alpha \in B \qquad \text{(AI.11)}$$

If $\delta t \to 0$, by definition of what the discount rate ρ is and the instantaneous cost $g(\alpha, x, u, a)$, we have:

$$\nu(\alpha, x, a, t'+\delta t) - \nu(\alpha, x, a, t') = g(\alpha, x, u, a) - \rho\nu(\alpha, x, a, t') \qquad \text{(AI.12)}$$

In conclusion:

$$\rho v(\alpha, x, a) = \min_{(u,\omega)\in\Gamma(\alpha)} \begin{bmatrix} g(\alpha, x, u, a) \ + \sum_{\beta\in B} q_{\alpha\beta}.\, v\big(\beta, x, \varphi(a)\big) \\ +(u-d)\dfrac{\partial v(\alpha, x, a)}{\partial x} + K_u u.\dfrac{\partial v(\alpha, x, a)}{\partial a} \end{bmatrix}, \forall \alpha \in B \qquad \text{(AI.13)}$$

Annex AI.B : Numerical version of the developed HJB Equation

We will develop (3.15) with the Kushner approach (Kushner et Dupuis, 2001). We have:

$$\frac{\partial v(\alpha, x, a)}{\partial x} = \begin{cases} \dfrac{1}{h}\Big(v^h(\alpha, x+h, a) - v^h(\alpha, x, a)\Big) if\ (u-d) > 0 \\ \dfrac{1}{h}\Big(v^h(\alpha, x, a) - v^h(\alpha, x-h, a)\Big)\ otherwise \end{cases} \qquad \text{(AI.14)}$$

$$\frac{\partial v(\alpha, x, a)}{\partial a} = \frac{1}{h_a}\Big(v^h(\alpha, x, a+h_a) - v^h(\alpha, x, a)\Big) \qquad \text{(AI.15)}$$

By injecting Equation (AI.14) and Equation (AI.15) into Equation (3.15), we obtain:

$$\rho \nu^h(\alpha,x,u,a) = \min_{(u,\omega)\in\Gamma(\alpha)} \Bigg[g(\alpha,x,u,a) \ + q_{\alpha\alpha}.\nu^h(\alpha,x,u,a)$$

$$+ \sum_{\substack{\beta\in B\\ \beta\neq\alpha}} q_{\alpha\beta}.\nu^h\big(\beta,x,u,\varphi(a)\big)$$

$$+ \frac{|u-d|}{h}\begin{bmatrix}\nu^h(\alpha,x+h,u,a)Ind\{(u-d)\geq 0\} + \\ \nu^h(\alpha,x-h,u,a)Ind\{(u-d)<0\}\end{bmatrix} \tag{AI.16}$$

$$-\frac{|u-d|}{h}\nu^h(\alpha,x,u,a)$$

$$+ \frac{K_u u}{h_a}\Big(\nu^h(\alpha,x,u,a+h_a) - \nu^h(\alpha,x,u,a)\Big)\Bigg]$$

By isolating all the terms in $\nu^h(\alpha,x,u,a)$:

$$\left(\rho - q_{\alpha\alpha} + \frac{|u-d|}{h} + \frac{Ku}{h_a}\right)\nu^h(\alpha,x,u,a)$$

$$= \min_{(u,\omega)\in\Gamma(\alpha)} \Bigg[g(\alpha,x,u,a) \ + \sum_{\substack{\beta\in B\\ \beta\neq\alpha}} q_{\alpha\beta}.\nu^h(\beta,x,u,a)$$

$$+ \frac{|u-d|}{h}\begin{bmatrix}\nu^h(\alpha,x+h,u,a)Ind\{(u-d)\geq 0\} + \\ \nu^h(\alpha,x-h,u,a)Ind\{(u-d)<0\}\end{bmatrix} \tag{AI.17}$$

$$+ \frac{K_u u}{h_a}\nu^h(x,\alpha,a+h_a)\Bigg]$$

Hence, we obtain:

$$v^h(\alpha,x,u,a) = \min_{(u,\omega)\in\Gamma(\alpha)} \left[\frac{g(\alpha,x,u,a) + \sum_{\substack{\beta\in B \\ \beta\neq\alpha}} q_{\alpha\beta}.v^h(\beta,x,u,\varphi(a)) + \frac{|u-d|}{h}\begin{bmatrix} v^h(\alpha,x+h,u,a)Ind\{(u-d)\geq 0\} + \\ v^h(\alpha,x-h,u,a)Ind\{(u-d)<0\}\end{bmatrix} + \frac{K_u u}{h_a}v^h(\alpha,x,u,a+h_a)}{\rho - q_{\alpha\alpha} + \frac{|u-d|}{h} + \frac{K_u u}{h_a}} \right] \quad \text{(AI.18)}$$

Considering the 9 modes, the term Ω_h^{α} (see Equation (3.17)) gives the following expressions:

$$\Omega_h^1 = \omega + p + \frac{|u(1)-d|}{h} + \frac{K_u u(1)}{h_a}$$

$$\Omega_h^2 = q_{23} + p + \frac{|u(2)-d|}{h} + \frac{K_u u(2)}{h_a}$$

$$\Omega_h^3 = q_{34} + \frac{d}{h}$$

$$\Omega_h^4 = q_{45} + \frac{d}{h}$$

$$\Omega_h^5 = q_{56} + \frac{d}{h}$$

$$\Omega_h^6 = q_{61} + \frac{|u(6)-d|}{h} + \frac{K_u u(6)}{h_a}$$

$$\Omega_h^7 = q_{78} + \frac{d}{h}$$

$$\Omega_h^8 = q_{89} + \frac{d}{h}$$

$$\Omega_h^9 = q_{91} + \frac{d}{h}$$

Based on Equation (18), the term $p_x^+(\alpha)$ gives the following expressions for the 9 modes:

$$p_x^+(1) = \left\{ \begin{array}{l} \frac{u(1)-d}{h\,\Omega_h^1}\ if\ (u-d)>0 \\ 0\ otherwise \end{array} \right\}$$

$$p_x^+(2) = \left\{ \begin{array}{l} \frac{u(2)-d}{h\,\Omega_h^2}\ if\ (u-d)>0 \\ 0\ otherwise \end{array} \right\}$$

$p_x^+(3) = 0$

$p_x^+(4) = 0$

$p_x^+(5) = 0$

$$p_x^+(6) = \begin{Bmatrix} \frac{u(6)-d}{h\ \Omega_h^6}\ if\ (u-d) > 0 \\ 0\ \ otherwise \end{Bmatrix}$$

$p_x^+(7) = 0$

$p_x^+(8) = 0$

$p_x^+(9) = 0$

Based on Equation (19), the term $p_x^-(\alpha)$ gives the following expressions for the 9 modes:

$$p_x^-(1) = \begin{Bmatrix} \frac{d-u(1)}{h\ \Omega_h^1}\ if\ (u-d) \leq 0 \\ 0\ \ otherwise \end{Bmatrix}$$

$$p_x^-(2) = \begin{Bmatrix} \frac{d-u(2)}{h\ \Omega_h^2}\ if\ (u-d) \leq 0 \\ 0\ \ otherwise \end{Bmatrix}$$

$p_x^-(3) = \frac{d}{h\ \Omega_h^3}$

$p_x^-(4) = \frac{d}{h\ \Omega_h^4}$

$p_x^-(5) = \frac{d}{h\ \Omega_h^5}$

$$p_x^-(6) = \begin{Bmatrix} \frac{d-u(6)}{h\ \Omega_h^6}\ if\ (u-d) \leq 0 \\ 0\ \ otherwise \end{Bmatrix}$$

$p_x^-(7) = \frac{d}{h\ \Omega_h^7}$

$p_x^-(8) = \frac{d}{h\ \Omega_h^7}$

$$p_x^-(9) = \frac{d}{h\,\Omega_h^7}$$

Based on Equation (20), we obtain the following matrix for the terms $p^\beta(\alpha)$ of the 9 modes:

$\times$	$p^2(1) = \frac{\omega}{\Omega_h^1}$	$p^3(1) = 0$	$p^4(1) = 0$	$p^5(1) = 0$	$p^6(1) = 0$	$p^7(1) = \frac{p}{\Omega_h^1}$	$p^8(1) = 0$	$p^9(1) = 0$
$p^1(2) = 0$	$\times$	$p^3(2) = \frac{q_{23}}{\Omega_h^2}$	$p^4(2) = 0$	$p^5(2) = 0$	$p^6(2) = 0$	$p^7(2) = 0$	$p^8(2) = 0$	$p^9(2) = 0$
$p^1(3) = 0$	$p^2(3) = 0$	$\times$	$p^4(3) = \frac{q_{34}}{\Omega_h^3}$	$p^5(3) = 0$	$p^6(3) = 0$	$p^7(3) = 0$	$p^8(3) = 0$	$p^9(3) = 0$
$p^1(4) = 0$	$p^2(4) = 0$	$p^3(4) = 0$	$\times$	$p^5(4) = \frac{q_{45}}{\Omega_h^4}$	$p^6(4) = 0$	$p^7(4) = 0$	$p^8(4) = 0$	$p^9(4) = 0$
$p^1(5) = 0$	$p^2(5) = 0$	$p^3(5) = 0$	$p^4(5) = 0$	$\times$	$p^6(5) = \frac{q_{56}}{\Omega_h^5}$	$p^7(5) = 0$	$p^8(5) = 0$	$p^9(5) = 0$
$p^1(6) = \frac{q_{61}}{\Omega_h^6}$	$p^2(6) = 0$	$p^3(6) = 0$	$p^4(6) = 0$	$p^5(6) = 0$	$\times$	$p^7(6) = 0$	$p^8(6) = 0$	$p^9(6) = 0$
$p^1(7) = 0$	$p^2(7) = 0$	$p^3(7) = 0$	$p^4(7) = 0$	$p^5(7) = 0$	$p^6(6) = 0$	$\times$	$p^8(7) = \frac{q_{78}}{\Omega_h^7}$	$p^9(7) = 0$
$p^1(8) = 0$	$p^2(8) = 0$	$p^3(8) = 0$	$p^4(8) = 0$	$p^5(8) = 0$	$p^6(8) = 0$	$p^7(8) = 0$	$\times$	$p^9(8) = \frac{q_{89}}{\Omega_h^8}$
$p^1(9) = \frac{q_{91}}{\Omega_h^9}$	$p^2(9) = 0$	$p^3(9) = 0$	$p^4(9) = 0$	$p^5(7) = 0$	$p^6(9) = 0$	$p^7(9) = 0$	$p^8(9) = 0$	$\times$

Based on Equation (21), we obtain the following expressions for the term $P_a(\alpha)$ of the 9 modes:

$$P_a(1) = \frac{K_u u(1)}{h_a \Omega_h^1}$$

$$P_a(2) = \frac{K_u u(2)}{h_a \Omega_h^2}$$

$$P_a(3) = 0$$

$$P_a(4) = 0$$

$$P_a(5) = 0$$

$$P_a(6) = \frac{K_u u(6)}{h_a \Omega_h^6}$$

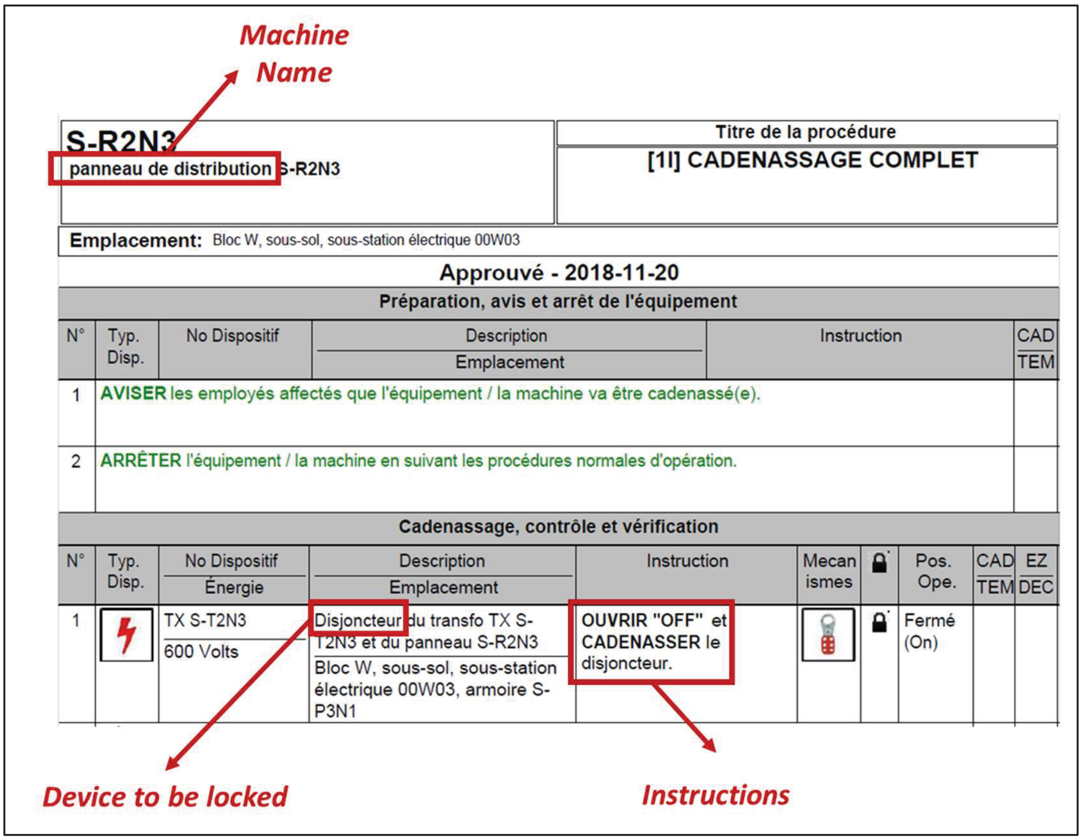
$$P_a(7) = 0$$

$$P_a(8) = 0$$

$$P_a(9) = 0$$

ANNEXE II

ANNEXES DU CHAPITRE 4



S-R2N3 panneau de distribution S-R2N3	Titre de la procédure [1I] CADENASSAGE COMPLET

Emplacement: Bloc W, sous-sol, sous-station électrique 00W03

Approuvé - 2018-11-20

Préparation, avis et arrêt de l'équipement

N°	Typ. Disp.	No Dispositif	Description / Emplacement	Instruction	CAD / TEM
1	**AVISER** les employés affectés que l'équipement / la machine va être cadenassé(e).				
2	**ARRÊTER** l'équipement / la machine en suivant les procédures normales d'opération.				

Cadenassage, contrôle et vérification

N°	Typ. Disp.	No Dispositif / Énergie	Description / Emplacement	Instruction	Mecanismes	🔒	Pos. Ope.	CAD / TEM	EZ / DEC
1		TX S-T2N3 / 600 Volts	Disjoncteur du transfo TX S-T2N3 et du panneau S-R2N3 / Bloc W, sous-sol, sous-station électrique 00W03, armoire S-P3N1	**OUVRIR "OFF"** et **CADENASSER** le disjoncteur.		🔒	Fermé (On)		

Figure AII.1 Data included in the LOTO sheets.

In Figure AII.1, a comparison is made regarding top-1 accuracy in predicting the "sectionneur" count for datasets exclusively sourced from a single industrial domain, utilizing K-Nearest Neighbors (KNN), Random Forest (RF), and Deep Neural Networks (DNN). Across all industrial domains, DNN consistently outperforms both KNN and RF in terms of accuracy.

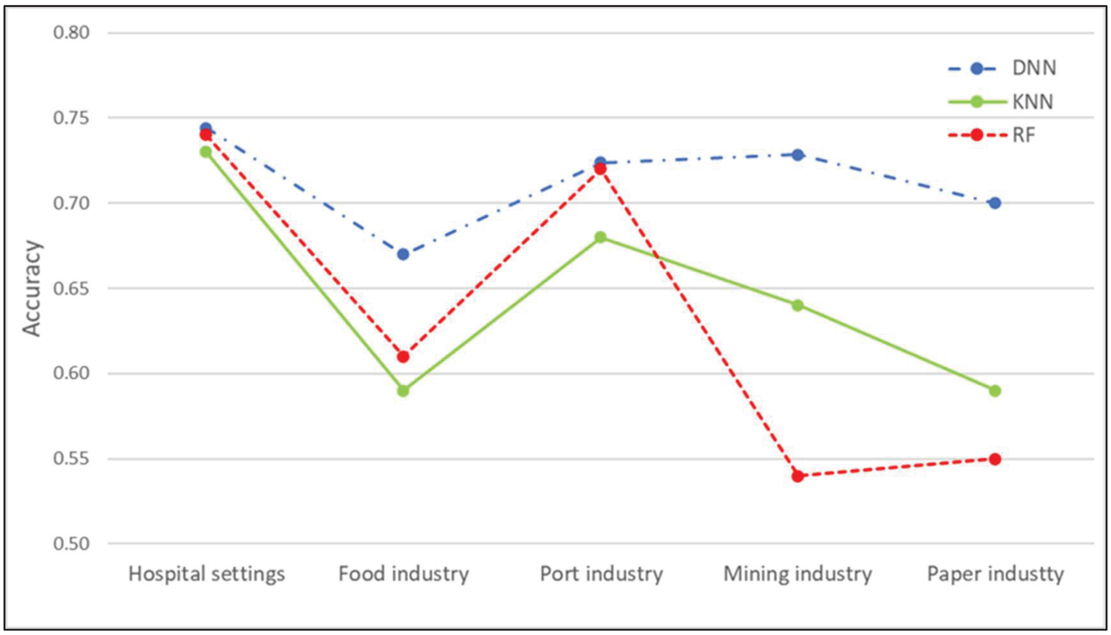


Figure AII.2 Comparison of top-1 accuracy for predicting the number of "sectionneur" for data sets exclusively included in a single industrial domain for KNN, RF and DNN

Similarly, Figure AII.3 presents a comparison of top-1 accuracy in predicting the "valve" count for datasets exclusively contained within a single industrial domain using K-Nearest Neighbors (KNN), Random Forest (RF), and Deep Neural Networks (DNN). As observed previously, the DNN provides greater precision than the KNN and RF in every area.

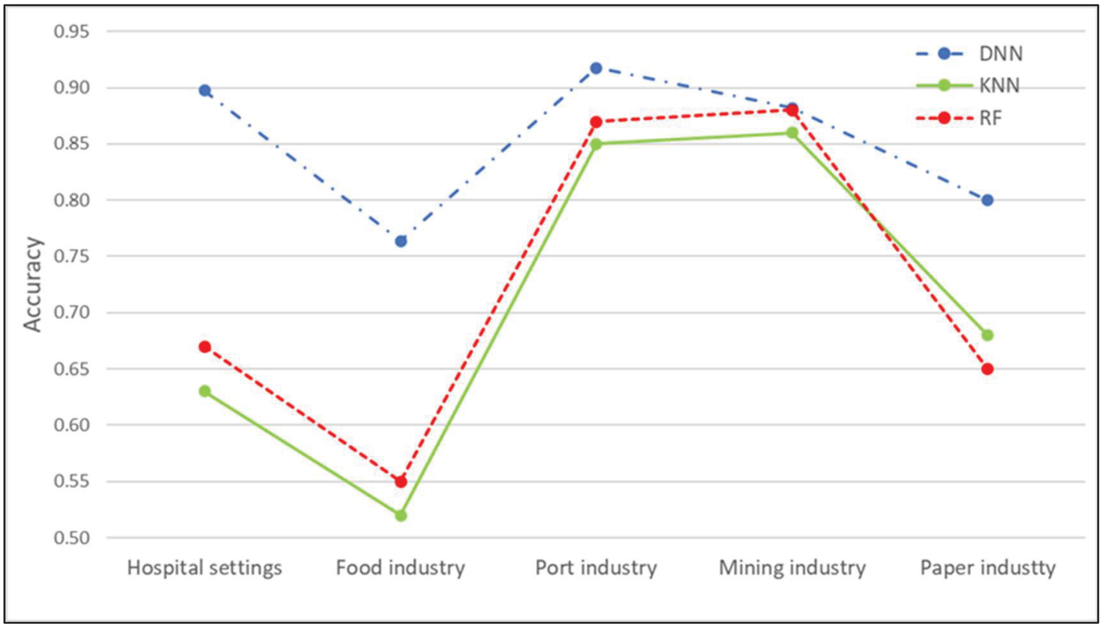


Figure AII.3 Comparison of top-1 accuracy for predicting the number of "valve" for data sets exclusively included in a single industrial domain for KNN, RF and DNN

Finally, Figure AII.4 illustrates the top-1 accuracy in predicting the " disjoncteur" count from data originating from a single industrial domain using K-Nearest Neighbors (KNN), Random Forest (RF), and Deep Neural Networks (DNN). In each field, DNN consistently achieves higher accuracy compared to both KNN and RF.

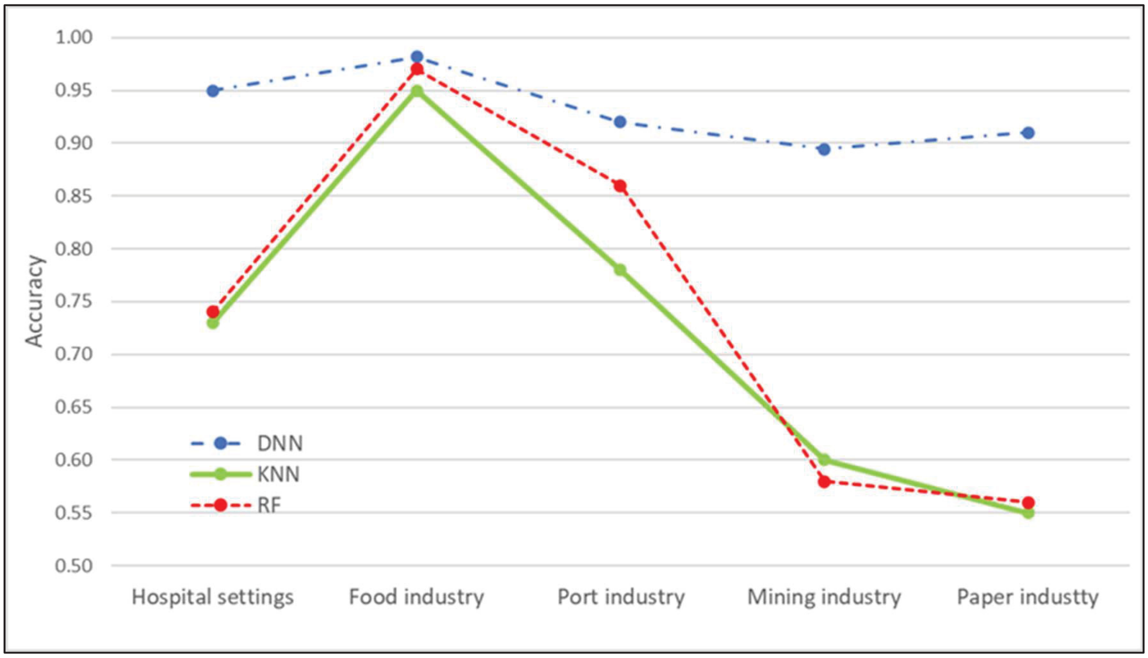
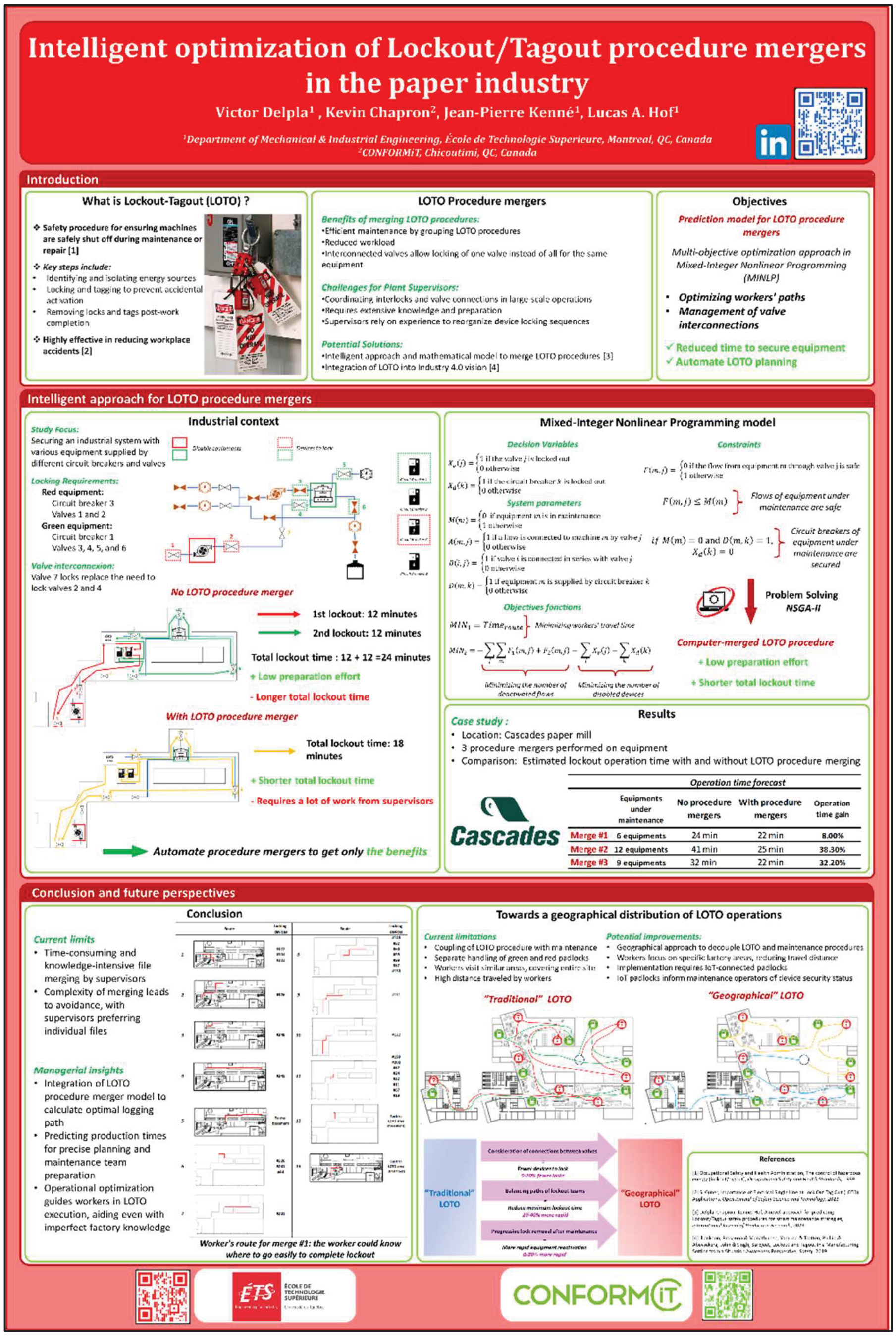


Figure AII.4 Comparison of top-1 accuracy for predicting the number of "disjoncteur" for data sets exclusively included in a single industrial domain for KNN, RF and DNN

APPENDICE I

AFFICHE PRÉSENTÉE À TAPPICON2024



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