Real-Time Data Driven Model Predictive Control for Efficient Energy Consumption in Smart Buildings

by

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MANUSCRIPT-BASED THESIS PRESENTED TO ÉCOLE DE TECHNOLOGIE SUPÉRIEURE IN PARTIAL FULFILLMENT FOR THE DEGREE OF DOCTOR OF PHILOSOPHY
Ph.D.

MONTREAL, FEBRUARY 27, 2023

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
UNIVERSITÉ DU QUÉBEC

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FOREWORD

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Quebec, Ecole de Technologie Superieure (ETS). The research described herein was conducted under the supervision of Professor Mohamed Cheriet in the Department of Automated Production Engineering and Professor Kim-Khoa Nguyen in the Department of Electical Engineering. This work is to the best of my knowledge original, except where acknowledgements and references are made to previous work. Neither this, nor any substantially similar dissertation has been or is being submitted for any other degree, diploma or other qualification at any other university. Part of this work has been presented in the following publications:

1. Mtibaa, F., Nguyen, K.-K., Azam, M., Papachristou, A., Venne, J.-S. and Cheriet, M. (2020). LSTM-based indoor air temperature prediction framework for HVAC systems in smart buildings. Neural Computing and Applications, 1–17.
2. Mtibaa, F., Nguyen, K.-K., Dermardiros, V. and Cheriet, M. (2021a). Context-aware model predictive control framework for multi-zone buildings. Journal of Building Engineering, 42, p. 102340.
3. Mtibaa, F., Nguyen, K.-K., Dermardiros, V., Venne, J.-S. and Cheriet, M. (2022). Hierarchical Multi-Agent Control Framework for Energy Efficiency and Carbon Emission Reduction in Multi-Zone Buildings. Submitted to Journal of Building Engineering (9 September 2022).
4. Mtibaa, F., Nguyen, K.-K., Dermardiros, V. and Cheriet, M. (2021b). Online Genetic-Algorithm-based Model Predictive Control Framework for Multi-Zone Buildings. 2021 European Control Conference (ECC), pp. 1011–1017.

ACKNOWLEDGEMENTS

I would like to thank my thesis director, Professor Mohamed CHERIET, for his excellent advice, his patience, his encouragement, and for having offered me an excellent atmosphere to carry out my research.

I am extremely grateful to Professor Kim Khoa NGUYEN, for his availability, his constructive criticism, and his assistance throughout my research project.

I would also like to thank the board of examiners for accepting to review and evaluate this research.

I would like to thank all my colleague at Synchromedia Laboratory and at BrainBox AI who are continuously supporting me with their best suggestions and valuable encouragements.

I acknowledge the financial support of the Mitacs Acceleration program and BrainBox AI held by professor Kim Khoa NGUYEN.

My gratitude goes out to my parents Mohamed and Fathila, and my entire family. They were always supporting me and encouraging me with their love and best wishes.

Special thanks to my grandfather Kacem who had believed in me and who had always encouraged me to push my limits.

Optimisation de contrôle prédictif orienté données en temps réel pour une consommation d'énergie et une empreinte carbone efficaces dans les bâtiments intelligents

Fatma MTIBAA

RÉSUMÉ

Le Modèle de contrôle prédictif (MPC) a reçu beaucoup d'attention ces dernières années, principalement dans le domaine du contrôle du chauffage, ventilation et climatisation (CVC) dans les bâtiments intelligents. Le MPC est un contrôle optimal qui améliore l'efficacité énergétique des systèmes CVC. Ceci est réalisé par l'utilisation d'une approche de contrôle orientée modèle qui intègre une représentation mathématique avec les facteurs les plus importants qui affectent la dynamique du bâtiment. Cependant, la conception d'un modèle précis qui modélise la dynamique du système physique est une tâche difficile dans les applications pratiques, en particulier pour les bâtiments multizone qui possèdent différents types de systèmes CVC. En outre, la non-linéarité de la dynamique thermique des bâtiments rend la prédiction de la température de l'air intérieur (IAT) plus difficile car elle est affectée par des facteurs complexes tels que les paramètres contrôlés et non contrôlés, les conditions météorologiques et l'occupation, entre autres. Les bâtiments intelligents modernes sont équipés de multiples capteurs qui collectent des données, lesquelles sont ensuite utilisées par des techniques de contrôle pour améliorer l'efficacité énergétique tout en maintenant un niveau de confort optimal. La disponibilité de données historiques offre la possibilité de développer des solutions de contrôle orienté données et basées sur des algorithmes d'intelligence artificielle. Le contrôle orienté données réduit les coûts et le temps de calcul du MPC, qui nécessite un processus de modélisation précis et complexe. Ainsi, l'objectif de cette thèse est de fournir un cadre de contrôle CVC efficace et évolutif qui minimise la consommation d'énergie, l'émission de carbone, la demande de pointe et l'inconfort pendant les heures d'occupation sous des contraintes d'auto-ajustement du point de consigne, de la rampe de température et du cycle des équipements, en intègrant un modèle de prédiction de température multi-étapes qui prend en compte la sensibilité des paramètres de contrôle.

Afin d'atteindre cet objectif, quatre questions clés doivent être adressées dans notre cadre, qui sont résumés comme suit : i) comment modéliser l'IAT dans un bâtiment intelligent multizone et pour différents types de systèmes CVC sans diminuer la précision de la prédiction ? ii) comment prédire avec précision l'IAT à plusieurs étapes dans un cadre MPC orienté données sans biaiser la décision d'optimisation? iii) comment concevoir et déployer un problème d'optimisation MPC orienté données, efficace adapté à une application de système CVC en temps réel ? iv) comment modéliser un système de contrôle oriente données plus évolutif pour le système CVC tout en réduisant la consommation d'énergie et l'empreinte carbone ?

Dans le cadre de nos contributions pour résoudre le premier problème souligné ci-dessus afin de modéliser avec précision un modèle de prédiction de l'IAT pour un bâtiment multizone possédant plusieurs types de systèmes CVC, nous proposons un nouveau modèle de prédiction de l'IAT basé sur des réseaux récurrents à mémoire court et long terme (LSTM). Deux modèles

ont été conçus, LSTM-MISO et LSTM-MIMO, soit une approche à entrées multiples et sortie unique et une approche à entrées multiples et sortie multiple, respectivement. Ces approches sont basées sur une prédiction directe séquence-à-séquence (S2S) pour prédire plusieurs étapes à la fois. En outre, une analyse de sélection des caractéristiques a été effectuée pour obtenir une structure de modèle appropriée pour les systèmes de volume d'air variable (VAV) et de volume d'air constant (CAV). Puisque le comportement de la température dépend des variables de contrôle du système CVC, on constate que la prise en compte de ces variables de contrôle par le modèle augmente la précision de la prédiction de l'IAT. La performance des différentes stratégies a été évaluée sur la base de deux études de cas sur des données opérationnelles de bâtiments intelligents réels utilisant des systèmes VAV et CAV. Pour les deux bâtiments, les résultats expérimentaux ont montré que les modèles proposés sont plus performants que les modèles de perceptrons multicouches en réduisant le pourcentage d'erreur absolu moyen de 50%.

Pour répondre au second problème, nous étendons le premier objectif de recherche et proposons un nouveau modèle de prédiction de l'IAT à plusieurs étapes basées sur un LSTM multivariable sensible au contexte (CAM-LSTM). Celui-ci est utilisé dans un cadre MPC orienté données sans biaiser la décision d'optimisation. Le CAM-LSTM est basé sur une interaction de haut niveau et de bas niveau entre les caractéristiques des paramètres d'entrée et qui tient compte de la relation sensible entre la température et les paramètres de contrôle. De plus, le CAM-LSTM utilise un réseau de neurones à double flux basé sur des séries temporelles multivariables de paramètres contrôlés et non contrôlés. En outre, un mécanisme d'attention est appliqué aux paramètres contrôlés pour leur attribuer le poids optimal afin d'améliorer la prédiction de la température de chaque zone.

Pour aborder le troisième problème, nous proposons un cadre de contrôle en temps réel efficace, basé sur un MPC orienté données utilisant l'algorithme génétique (MPC-GA). Il permet un fonctionnement optimal du système CVC validé expérimentalement dans un bâtiment commercial multizone. Le MPC-GA utilise le modèle CAM-LSTM dans le cadre MPC et il minimise : la consommation d'énergie, la demande de pointe et l'inconfort pendant les heures d'occupation sous des contraintes d'auto-ajustement du point de consigne, de la rampe de température et du cycle des équipements. Une heuristique utilisant un algorithme génétique est développée pour obtenir la combinaison optimale de contrôle du modèles MPC-GA en temps-réel pour toutes les zones sur un horizon de prédiction. Les résultats d'expérimentation ont montré que le MPC-GA surpasse les systèmes de contrôle RBC avec plus de 50% et 80% de réduction de la consommation d'énergie et de l'inconfort, respectivement.

Enfin, nous présentons une approche évolutif distribuée basée sur des multi-agents pour le contrôle optimisé d'un bâtiment intelligent multizone. L'approche utilise un ensemble d'agents locaux qui représentent les zones individuelles du bâtiment, coordonnés par un agent central. Pour chaque horizon de contrôle, le coordinateur minimise les émissions globales de carbone et attribue un budget d'énergie individuel à chaque agent local. Celui-ci minimise l'inconfort dans sa zone tout en respectant le budget d'énergie attribué par le coordinateur. Nous proposons une heuristique basée sur un algorithme génétique pour trouver les séquences de contrôle optimisées

dans chaque zone, et formulons un modèle de programmation linéaire en nombres entiers (ILP) pour le problème du coordinateur qui peut être résolu à l'aide d'un solveur ILP. Pour un jour d'essai hivernal représentatif, la méthodologie proposée a permis de réaliser des économies d'énergie de 8,8% et de réduire l'empreinte carbone de 23,4%.

Mots-clés: CVC, LSTM, Séquence-à-séquence, Prédictions multi-étapes, VAV, CAV, séries temporelles multivariées, mécanisme d'attention, MPC, algorithme génétique, contrôles optimaux, bâtiment intelligent, multi-agents, efficacité énergétique, réduction de l'empreinte carbone.

Real-Time Data Driven Model Predictive Control for Efficient Energy Consumption in Smart Buildings

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ABSTRACT

Model Predictive Control (MPC) has received a lot of attention in recent years mainly in the field of Heating, Ventilation, and Air Conditioning (HVAC) control in smart buildings. MPC is an optimal control that improves the energy efficiency of HVAC systems. This is achieved by using a model-based control approach that integrates a mathematical representation of the building with the most important factors that affect the building dynamics. However designing an appropriate controller that accurately models the dynamics of the physical system is a challenging task in real applications, especially for multi-zone building and for different HVAC system types. Moreover, the non linearity of the buildings thermal dynamics makes the Indoor Air Temperature (IAT) prediction more challenging since it is affected by complex factors such as controlled and uncontrolled points, outside weather conditions and occupancy schedule. Modern smart buildings are equipped with multiple sensors that collect data, which is then used by optimal control techniques to improve energy efficiency while maintaining comfort levels. The availability of historical data opens the opportunity to develop data-driven control solutions based on artificial intelligence algorithms. Data-driven control reduces the cost and time consuming tasks caused by MPC that requires an accurate and complex modeling processes. Thus, the goal of this dissertation is to provide an efficient and scalable data-driven HVAC control framework that minimizes energy consumption, carbon emission, peak demand and discomfort during occupied hours under self-tuned setpoint, temperature ramp and equipment cycling constraints which integrates a multi-step temperature prediction model that consider control sensitivities.

In order to meet this goal, four key issues are required to be addressed in our framework and are summarized as follows: i) how to model IAT in a multi-zone smart building and for different types of HVAC systems without decreasing the prediction accuracy?, ii) how to accurately model a multi-step IAT prediction in a data-driven MPC framework without bias on the optimization decision for the control outputs?, iii) how to design and deploy an efficient real-time data-driven MPC optimization problem suitable for a real-time HVAC system application?, and iv) how to model a more scalable data-driven control system for HVAC system while reducing energy consumption and carbon footprint?

As part of our contributions to address the first issue highlighted above and to accurately model an IAT prediction model especially for multi-zone building and for different HVAC system types, we propose a new IAT prediction model based on Long Short Term Memory (LSTM) model. LSTM-MISO and LSTM-MIMO strategies are built for multi-input single-output and multi-input multi-output, respectively. A direct prediction with sequence-to-sequence (S2S) approach has been developed to predict multi-step ahead. Furthermore, a feature selection analysis has been performed to obtain optimal model structure for both variable air volume (VAV) and constant

air volume (CAV) systems. Since the temperature behavior depends on the time of the action taken by control variables in the HVAC system, it is found that the consideration of these control variables as input increases the prediction accuracy performance. The performance of different strategies has been evaluated based on two case studies on real smart buildings operational data using VAV and CAV systems. For both buildings, experimental results showed that the proposed models outperform Multilayer Perceptrons models by reducing the mean absolute percentage error by 50%.

To address the second issue, we extend the first research objective and propose a new multi-step IAT prediction model based on a context-aware multivariate LSTM (CAM-LSTM) to be used in data-driven MPC framework without bias on the optimization decision for the control outputs. CAM-LSTM is based on high-level and low-level interaction between input features and considers the sensitive relationship between temperature and control parameters. Moreover, CAM-LSTM uses a dual-stream neural networks based on multivariate time series of controlled and uncontrolled inputs. In addition, an attention mechanism is applied on controlled parameters to give them more weight to better predict the zone temperature.

To address the third issue, we propose an efficient real-time data-driven control framework named Model Predictive Control via Genetic algorithm (MPC-GA) allowing the optimal operation of HVAC system and has been experimentally validated in a multi-zone retail building. The MPC-GA combines CAM-LSTM model with a MPC framework. The prediction model is used in the optimization model which minimizes: energy consumption, peak demand and discomfort during occupied hours under self-tuned setpoint, temperature ramp and equipment cycling constraints. A heuristic search algorithm using a genetic algorithm is used to solve the real-time data-driven MPC-GA models and obtain the future optimal combination settings of all controls for all the zones over a prediction horizon. The benchmark results showed that the MPC-GA outperforms RBC control systems with more than 50% and 80% reduction in energy consumption and discomfort respectively.

Finally, we introduce a scalable multi-agent based distributed approach for optimized control of a multi-zone smart building based on a set of local agents which represent individual zones in the building, coordinated by a central agent. For each control horizon, the coordinator minimizes the overall carbon emissions and assigns an individual energy budget to each local agent. Each local agent minimizes the discomfort in its zone while respecting the energy budget assigned by the coordinator. We propose a heuristic search based on a genetic algorithm to find the optimized control sequences in each zone, and formulate an integer linear programming (ILP) model for the coordinator problem which can be solved using an ILP solver. For a representative winter test day, the proposed methodology gave an energy savings of 8.8% and reduced the carbon footprint by 23.4%.

Keywords: HVAC, LSTM, Sequence-to-sequence, Multi-step ahead predictions, VAV, CAV, multivariate time series, attention mechanism, MPC, genetic algorithm, optimal controls, smart building, multi-agent, energy efficiency, carbon footprint reduction

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LIST OF ABBREVIATIONS

AHUs	Air Handling Units
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ARX	Autoregressive Model with Exogenous Inputs
BAD	Bypass Air Damper
CA	Coordinator Agent
CANN	Context-Aware Neural Network Model
CAV	Constant Air Volume
CCHP	Configuration of a Cooling, Heating and Power
FMI	Functional Mockup Interface
FMU	Functional Mockup Unit
E-MPC	Economic Model Predictive Control
GA	Genetic Algorithm
HVAC	Heating, Ventilation, and Air Conditioning
IAT	Indoor Air Temperature
LA	Local Agent
LSTM	Long Short-Term Memory
LSTM-Bi	LSTM-Bidirectional
MAC	Multi-Agent Control

MAD	Mixing Air Damper
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MEF	Marginal Emissions Factor
MISO	Multi-Input Single-Output
MIMO	Multi-Input Multiple-Output
MINLP	Mixed-Integer Linear Programming
ML	Machine Learning
MLP	Multilayer perceptron
MPC	Model Predictive Control
NARX	Nonlinear Autoregressive Network With Exogenous Inputs
NLP	Nonlinear Programming Algorithm
NNARX	Neural Network Autoregressive with Exogenous Input
OAT	Outside Air Temperature
PMV	Predictive Mean Vote
RBC	Rule-Based Controllers
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
RTU	Rooftop Unit
SVM	Support Vector Machine

S2S	Sequence-to-sequence
TR	Temperature Ramp
VAV	Variable Air Volume
VFD	Variable Frequency Drive

INTRODUCTION

0.1 General context

In recent years, improving energy efficiency and reducing the carbon footprint is the major concern for commercial buildings which want to make the world more sustainable. The total energy used in commercial buildings accounts for 40% of the global energy consumption (Shaikh, Nor, Nallagownden, Elamvazuthi & Ibrahim, 2014) and up to 30% of carbon dioxide emissions (Costa, Keane, Torrens & Corry, 2013). Within these large energy consumption, heating, ventilation and air conditioning (HVAC) systems are responsible for more than 50% of the energy consumption in commercial buildings (DoE et al., 2011) and it is an important producer of carbon emissions (Péan, Costa-Castelló & Salom, 2019). Moreover, it has been estimated that improving the HVAC operation can provide a potential reduction in energy consumption of between 5% and 30% (Chua, Chou, Yang & Yan, 2013).

An advanced HVAC control strategies are required to reduce the high energy consumption and improve the thermal comfort in large commercial buildings. On today's advanced HVAC systems, rule-based controllers (RBC) are generally used. However, RBC cannot generalize their rules at a building level (Privara, Cigler, Váňa, Oldewurtel, Sagerschnig & Žáčeková, 2013), due to the high complexity of managing their defined rules and continuously tuning the HVAC control signals to reduce global energy consumption while simultaneously ensure a thermal comfort. In addition, RBC are not an anticipatory controller: they operate on the basis of the current system state rather than projecting into the future and deciding on the next appropriate action (Afram, Janabi-Sharifi, Fung & Raahemifar, 2017). Model Predictive Control (MPC) has received a lot of attention in recent years mainly in the field of HVAC control in smart buildings (Serale, Fiorentini, Capozzoli, Bernardini & Bemporad, 2018). It has been proven efficient control solution for buildings by providing 17% energy savings more than RBC (Sturzenegger, Gyalistras, Morari & Smith, 2016; Shaikh *et al.*, 2014). Instead of being a reactive control,

MPC is a predictive and proactive control based on an optimization control strategy, which uses mathematical models to predict the future evolution of a dynamic system to optimise the control signal. At each time step, it solves an open loop constrained optimization problem over a finite future prediction horizon, then applied the first value of the computed control sequence to the system. When a new step starts, it gets the system state and repeats the optimization process (Camacho & Alba, 2013). Fig. 0.1 illustrates the receding horizon strategy of MPC scheme. There are several practical advantages of applying MPC to achieve energy savings and comfort in buildings. First, the disturbances affecting HVAC system. For instance, occupancy and outside weather can be predicted and integrated into the MPC. Second, MPC leads to vary the indoor temperature between a thermal comfort range by setting up the constrained optimization problem. Third, by solving the MPC problem in receding horizon, it is possible to shave the power peaks throughout the prediction horizon, thereby reduce the total electricity bill. However, MPC represents some challenges. First, it is complicated and time consuming, especially when implemented in a real case building to accurately model the dynamics of the physical system. Second, physical model has large number of states and variables. Then, many measurements are needed to use the physical model to predict the system behavior. This can require the installation of new sensors which is intrusive and expensive. Moreover, there are some measurements cannot be available from sensors, which require observers for state estimations. Thus, the user expertise, time, and associated sensor costs required to develop a model to describe the system dynamics of a single building is very high (Smarra, Jain, de Rubeis, Ambrosini, D'Innocenzo & Mangharam, 2018).

To ensure a sustainable future, new HVAC optimal control methods are being studied by researchers especially with the occurrence of data collected from multiple sensors installed in modern smart buildings. This collected data is used to build an accurate indoor air temperature (IAT) prediction model. The selection of IAT prediction models is the most important step in the development of an MPC approach, as it impacts the computation time, accuracy and efficiency

of the optimal control algorithm.

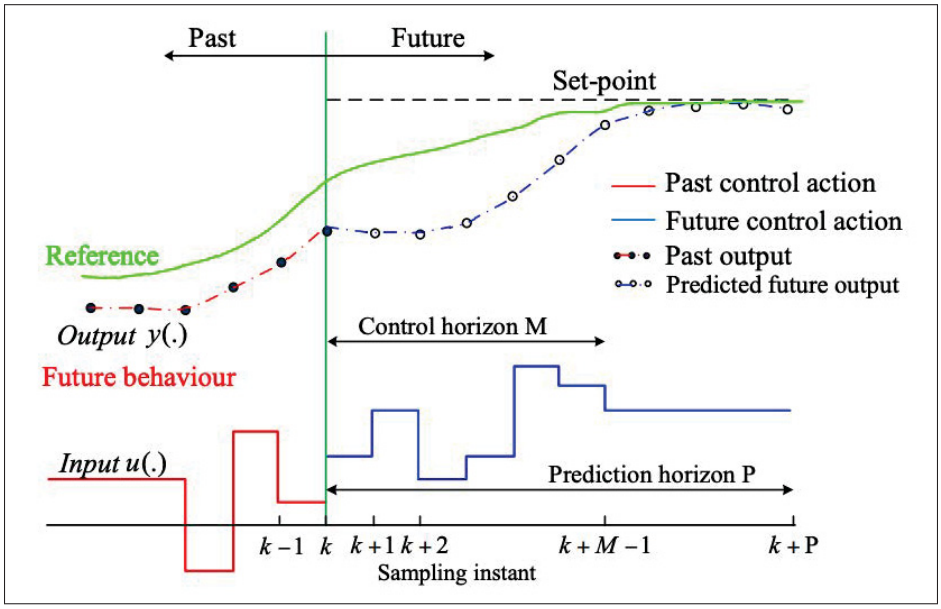

Figure 0.1 General conceptualization for model predictive control (MPC)
Taken from Yang *et al.* (2017)

Recently, data-driven control techniques based on machine learning (ML) algorithms have been proposed to model IAT and are integrated in the MPC framework to address smart building control (Chen, Wang & Srebric, 2015; Huang, Chen & Hu, 2015a). Through the availability of collected data in smart buildings, ML has a great ability to learn complex non-linear building models without depending on domain knowledge related to building physics (Kathirgamanathan, De Rosa, Mangina & Finn, 2021), which reduces costs and time associated to building modelisation caused by MPC (Serale *et al.*, 2018). Once such a prediction model is available, it will be used in the data-driven MPC to optimize energy efficiency while maintaining comfort levels. However, there is no fast and robust optimization algorithm to handle data-driven IAT prediction within the MPC framework. Moreover, the implementation of a data-driven MPC model in real building use case requires a scalable online optimization with low computation

time to generate a sequence of control signals for all the zones over a prediction horizon. The following sections present these challenges in more details.

0.1.1 Challenges of IAT modeling

0.1.1.1 IAT modeling for different types of HVAC systems

The accuracy of the building model has a high impact on the quality of the optimal control sequence generated by MPC. On the other hand, MPC optimization techniques aimed at minimizing HVAC energy consumption can influence indoor comfort. IAT is one of the essential thermal comfort parameters (Baniasadi, Habibi, Bass & Masoum, 2018). It is essential that IAT variations stay between the upper and lower boundaries of comfort. Therefore, accurately modeling IAT for HVAC systems is required. However, it is a challenging task, especially for multi-zone building which may contain different HVAC system types. Moreover, the non linearity of the buildings thermal dynamics makes the IAT prediction more difficult since it is affected by complex physical and behavioral phenomena. It is impacted by several parameters, such as controlled and uncontrolled parameters, outside weather conditions and occupancy schedule. IAT prediction might be done using physical approach which is based on mathematical equations based on Fourier's law of heat conduction which is discretized into the finite difference method and typically expressed in a resistance–capacitance analogy. However, the physical approach is a time consuming task since it requires detailed information about the building's characteristics, appliances, and occupant behavior. The availability of historical monitoring data from the panoply of sensors already deployed on smart buildings opens the opportunity to develop data-driven solutions to model IAT based on machine learning algorithms. Recently, in data-driven control, Artificial Neural Networks (ANN) and nonlinear autoregressive network with exogenous inputs (NNARX) have been extensively used to model indoor environments (Delcroix, Le Ny, Bernier, Azam, Qu & Venne, 2020; Attoue, Shahrour & Younes, 2018;

Huang, Chen & Hu, 2015b). However, prior work generally adopted a recursive prediction strategy for predicting multi-step ahead (Delcroix *et al.*, 2020; Zeng, Zhang & Kusiak, 2015; He, Zhang & Kusiak, 2014). The recursive prediction method accumulates prediction errors at each time-step, making this solution not suitable for long forecast horizon. Furthermore, the ANN method considers each input as an independent parameter. It ignores the time dependency between sequential values. Moreover, it has been shown that in most cases, the same IAT prediction model cannot be used for two different types of HVAC systems without decreasing the performance, such as the case for Constant Air Volume (CAV) and for Variable Air Volume (VAV) system.

0.1.1.2 Context-aware IAT modeling

Developing a context-aware IAT prediction model is a challenging task. The complex and non-linear inter-dependencies between multivariate time series, including control and uncontrolled parameters, make the context-aware prediction task more complicated. Moreover, since the IAT prediction results will be used in the MPC optimization problem to take informed decision for future control actions, the context-aware prediction model should consider the impact of future controls inputs on the predicted IAT results. For example, if the future steps of cooling controls are all OFF during a hot summer day, automatically the model should predict an increasing in the temperature behavior, which is not the case of models proposed by several related work (Jain, Smarra, Behl & Mangharam, 2018; Reynolds, Rezgui, Kwan & Piriou, 2018; Garnier, Eynard, Caussanel & Grieu, 2015). Previous work usually include black box models that do not take into account the physical aspect. They define a predictive model but ignore the sensitivities of control on temperature which can bias on the optimization decision for the control outputs.

0.1.2 Challenges of data-driven MPC approach

A real-time optimization is required to implement data-driven MPC model with low computation time to take the optimal control decision for all the zones over a prediction horizon. In recent years, to optimize HVAC control, an optimization procedure combining GA, MPC and artificial neural network to minimize the energy consumption has been proposed in (Reynolds *et al.*, 2018; Garnier *et al.*, 2015; Asadi, da Silva, Antunes, Dias & Glicksman, 2014). However, none of the previously mentioned approaches has been validated in real time with the building's feedback states. It is not obvious that a building operator allows to implement a data-driven controller on a real building because the error of the prediction might disturb the built environment. Implementation in real buildings can lead to undesirable results such as too hot or too cold temperatures, thus causing discomfort to the occupants. The data-driven control system should avoid these undesirable results because there is no turning back during the implementation phase. Moreover, the optimization models proposed in previous work focus mainly on energy efficiency and discomfort reduction. Others costs should be considered in the control problem. The power peak is an important cost to consider in the MPC model in order to avoid a spike in consumption. Furthermore, in order to enhance premature wear of HVAC devices, data-driven MPC problem should consider the cycling cost to achieve a more stable control decision and avoid unnecessarily cycling of equipment. In addition, in order to reduce the error between predicted temperature using control decision and the current temperature feedback, a self-tuned cost should be considered in the MPC problem. Moreover, a ramp rate cost should be included in the MPC problem in order to keep a stable temperature feedback. However, all these additional constraints make the data-driven MPC approach much more complicated to achieve the optimal control decision.

0.1.3 Challenges of centralized data-driven control

In recent years, many centralized control framework have been proposed in the literature (Tarragona, Fernández & de Gracia, 2020). However, there are many characteristics that make the centralized data-driven MPC no longer practical. First, the optimization strategies in the centralized data-driven control system can take a significant amount of time to find the optimal control variables, which is a challenge for systems with a short period of operation (Thieblemont, Haghighat, Ooka & Moreau, 2017). Centralized control framework can be computationally expensive for large scale optimization when applied to building with large number of zones, equipped by complex distribution system and influenced by various factors. In addition, online computing time can be a bottleneck for real-time applications, as the optimization problem must be solved in a short period of time. Moreover, in the centralized scheme the computational time can become a drawback due to the large amount of data to be treated. Compared with centralized control-based methods, multi-agent control (MAC) systems are more flexible and scalable (Wang, Zhang, Li & Zhao, 2021). Therefore, implementing real-time optimal control strategies for multi-zone HVAC systems using multi-agent based distributed optimization methods is a challenging research direction. Distributed optimal controls require distributed optimization methods for which convergence is not always guaranteed. Moreover, the optimization models proposed in previous work are limited to energy efficiency and discomfort minimization. More essential costs must be considered in the MAC optimization problem, such as reducing the carbon footprint.

0.1.4 Research Motivation

In order to offer an advanced control approach for HVAC systems in smart buildings, a scalable control framework based on data-driven modeling needs to be efficiently designed and implemented in real time building with low cost. IAT needs to be accurately predicted for

multi-step ahead with multi-input. Moreover, the IAT prediction model has to be general and covers both VAV- and CAV-buildings. In addition, a direct-S2S prediction instead of a recursive one, which increases the accumulation of prediction errors throughout the prediction step ahead, should be implemented. The data-driven IAT model should be used to design predictive control approaches. For this reason, the impact of controlled parameters on the prediction results should be considered. To implement data-driven control approach, an real-time optimization is required with low computation time to generate a sequence of control parameters for all the zones over the prediction horizon. The control optimization model should minimize energy, peak power and discomfort costs. Other costs should be considered in the control problem, such as the self-tuned setpoint, cycling and temperature ramp constraints in addition to energy, peak power and discomfort costs. Furthermore, the carbon footprint is an essential factor to consider in the optimization problem. The data-driven control approach should be scalable and not be limited by the number of zones in the controlled building.

As a summary, the efficiency and scalability of data-driven HVAC control approach can be achieved by:

- accurately modeling IAT prediction with multi-step ahead for VAV- and CAV-buildings.
- considering the impact of the control parameters on IAT prediction model.
- implementing an efficient HVAC control model in a real building use case which minimizes: energy consumption, peak demand and discomfort during occupied hours under self-tuned setpoints, temperature ramp and equipment cycling constraints.
- designing a scalable HVAC control model which minimizes energy consumption, discomfort and carbon footprint.

0.2 Problem statement and research questions

0.2.1 Problem statement

The research problem addressed in our work is stated as follows:

How to model and design an efficient and scalable control framework for HVAC systems in a multi-zone smart buildings that save energy and reduces carbon footprint without affecting the householder's comfort?

In order to address the above problem statement, we further detail it into four research questions (RQs) as follows:

0.2.2 Research question RQ1

RQ1 (IAT modeling): How to model IAT in a multi-zone smart building and generalize for different types of HVAC systems without decreasing the prediction accuracy?

The main issues related to RQ1 are:

- How to model IAT in a multi-zone building with multi-step prediction ahead?
- How to model IAT in a multi-zone building with multi-input single-output and multi-output?
- How to select relevant inputs for the IAT prediction model?
- How to model IAT for different HVAC systems to control inside a large-scale building without decreasing the prediction performance?

0.2.3 Research question RQ2

RQ2 (Context-aware Prediction): How to accurately model a multi-step IAT prediction in a data-driven MPC framework without bias on the optimization decision for the control outputs?

The main issues related to RQ2 are:

- How to model the high-level interaction between input features?
- How to model the low-level interaction between input features?
- How to model the sensitive relationship between temperature and control parameters?

0.2.4 Research question RQ3

RQ3 (data-driven Control): How to design and deploy an efficient real-time data-driven MPC optimization model suitable for HVAC system application?

The main issues related to RQ3 are:

- How to optimise energy, peak power and discomfort costs with considering of self-tuned setpoint, cycling and temperature ramp?
- How to integrate the multi-step IAT prediction model in the control optimization model?
- How to solve the online data-driven control model over a prediction horizon?

0.2.5 Research question RQ4

RQ4 (multi-agent data-driven control): How to model a more scalable data-driven control system for HVAC systems while reducing energy consumption and carbon footprint?

The main issues related to RQ4 are:

- How to minimize energy and carbon emission with meeting comfort in smart building?
- How to reduce execution time for the data-driven optimization problem while maintaining control performance?
- How to solve the multi-agent control model over a prediction horizon?
- How to ensure the scalability of an HVAC control system for a multi-zone building?

0.3 Outline of the thesis

This chapter describes the general context and presents the problem statement. Chapter 1 reviews the prior work related to the scope of the research problems. Chapter 2 presents the objectives of this research framework and defines the proposed methodology to address the various research questions of the problem. Then, the three next chapters present the three articles published in response to the specific research questions. The three articles are outlined as follows:

1. Chapter 3: LSTM-based indoor air temperature prediction framework for HVAC systems in smart buildings.
2. Chapter 4: Context-aware Model Predictive Control framework for multi-zone buildings.
3. Chapter 5: Hierarchical Multi-Agent Control Framework for Energy Efficiency and Carbon Emission Reduction in Multi-Zone Buildings.

Chapter 6 provides a critical discussion of some concepts of the thesis that highlight the strengths and weaknesses of the proposed methods. Finally, the general conclusion summarizes the work presented in this thesis and provides future horizons.

CHAPTER 1

LITERATURE REVIEW

This chapter presents a review of the state-of-the-art methods related to the modeling and control optimization problems for HVAC system in smart buildings. This chapter is divided into three sections that are in line with the challenges discussed in the introduction and faced by prediction modeling and optimization approaches to build and operate future efficient control system for HVAC in smart building. The first section covers the various prediction models challenges encountered to predict IAT in control system. The second section presents the different centralized data-driven control methods. The third section presents several multi-agent data-driven control approaches.

1.1 Data-driven model approaches

The main advantage of a data-driven approach is to reduce the cost and time-consumed by traditional physics-based techniques. Moreover, the data-driven approaches can deal with non-linearity, incomplete, or noisy data Serale *et al.* (2018). Machine-learning algorithms have been applied to design dynamic models of the HVAC system. For instance, the multi-step prediction of IAT can be used in a predictive control approach then leads to improving the thermal comfort and decreasing the energy consumption of buildings Xu, Chen, Wang, Guo & Yuan (2019). The key common algorithms applied in data-driven approaches that have been used extensively in the building sector for IAT modeling are regression trees Jain *et al.* (2018), random forests Smarra *et al.* (2018), nonlinear autoregressive network with exogenous inputs (NARX) Afroz, Urmee, Shafiullah & Higgins (2018b), NNARX Delcroix *et al.* (2020), ANN Attoue *et al.* (2018) and Recurrent Neural Networks (RNN) Javed, Larijani, Ahmadinia & Emmanuel (2014).

1.1.1 Machine learning algorithms to model IAT

Jain et al. Jain *et al.* (2018) combine multi-output regression trees to represent the system's dynamics. Yet, the modeling accuracy using single trees to constitute multi-step prediction

for zone temperature is strongly affected by over-fitting and high variance. The authors in Smarra *et al.* (2018) model the temperature by a set of linear regression models, which change after each time step. They model their system with regression trees to predict temperature for multi-zone using MISO structure and extend them to a random forest model. However, their model is complicated and time-consuming. Nowadays, the ANN model has been widely applied for several type of applications in HVAC sector, such as Fault Detection and Diagnostics Du, Fan, Jin & Chi (2014), thermal comfort approximation Castilla, Álvarez, Ortega & Arahal (2013) and IAT prediction Attoue *et al.* (2018); Huang *et al.* (2015b). Du et al. Du *et al.* (2014) developed ANN based tool to detect faults in the supply air temperature control loop in commercial building with VAV systems. The authors used a combined neural networks model which includes the basic neural networks and auxiliary neural networks to detect faults, and then used clustering approach for classification to diagnose the fault sources. The proposed models diagnose the faults using context information related to the monitoring parameters such as supply chilled water temperature, return chilled water temperature, chilled water flow rate and chilled water valve position. The principal component analysis is carried out to analyze the contributions of these parameters in the supply temperature control loop. The occurrence of faults is computed according to a combined relative error and its threshold. Castilla et al. Castilla *et al.* (2013) proposed a context-aware neural networks model using human and environmental variables for approximating thermal comfort evaluation for HVAC systems. Their model avoids the costs involved in calculating the classical predictive mean vote (PMV) index in terms of the computation time and the extensive sensor network size required to collect the input data. Moreover, it allows the use of PMV index within real-time model predictive control framework. Attoue and al. Attoue *et al.* (2018) developed a simple ANN-MISO model to predict indoor temperature for different forecasting time-steps. They proposed a methodology based on the selection of pertinent input parameters from a large set of features. Their experimental results show that outdoor and facade temperature data provides good forecasting results of indoor temperatures. Moreover, their results show that predictions were accurate for up to two hours. However, the predictions have unsatisfactory accuracy for more than four hours forecast ahead. Huang et al. Huang *et al.* (2015b) developed an hybrid MPC based on neural

network feedback-linearization model to predict IAT over six hours ahead. The goal of this approach is to linearize the system using the neural network through feedback to build nonlinear functions approximation. The type of HVAC system used in Huang *et al.* (2015b) is designed with constant-air volume (CAV).

Prior studies also model IAT for a VAV system Zeng *et al.* (2015); Afroz *et al.* (2018b). An indoor air temperature prediction models of multi-zone using MISO structure are proposed by He *et al.* (2014). Zeng et al. Zeng *et al.* (2015) developed an optimal control of multi-zones VAV system. They elaborated a data-driven predictive model using MLP to predict the environmental conditions of each zone and optimize energy consumption. The IAT is predicted with only one-step ahead. Moreover, multi-step prediction is necessary to lead a real-time implementation in the control phase. Moreover, only two control parameters were used as inputs in the prediction model in He *et al.* (2014); Zeng *et al.* (2015). Neither specific feature selection methodology nor model tuning approach were implemented. The context information like weather data, control parameters and other external factors might improve the future prediction. Liang et al. Liang, Ouyang, Jing, Ruan, Liu, Zhang, Rosenblum & Zheng (2019) designed a framework named UrbanFM based on deep neural networks. UrbanFM is composed of two models, an inference network component and an external factor fusion component. The inference network component generates a fine-grained flow from coarse-grained inputs by using a novel feature extraction and distributional upsampling modules. The external factor fusion component handles the context information (like the day of the week, time of the day, weather, other external factors) to capture near and distant spatio-temporal dependencies. This component plays an important role in providing a prior knowledge and improves the inference performance under sparse sampling.

A multi-zone modeling approach using the MLP-MIMO model was proposed by Huang *et al.* (2015a) to forecast two hours ahead temperature inside an open space commercial building. Afroz et al. Afroz *et al.* (2018b) predict IAT in multi-zone buildings using a different tuned model based on NARX model. The authors used MISO architecture to predict one step ahead then MIMO architecture to predict multi-step ahead for the same zone. Delcroix et al. Delcroix *et al.* (2020) predicted the behaviors of IAT using NNARX-MISO. They compared their results

with the gray-box model and the linear autoregressive model with exogenous inputs (ARX). Their comparisons show the NNARX model achieves the highest performance the alternative models. However, the authors assume that the future exogenous inputs (control parameters, outdoor temperature, etc.) are known, which cannot be true in the real case. All Afroz *et al.* (2018b), Huang *et al.* (2015a) and Delcroix *et al.* (2020), develop a one-step forecasting model, then use a recursive multi-step forecasting strategy to predict the future steps.

1.1.2 LSTM to model IAT

Generally, prior work employed artificial neural networks (ANN) as black-box models to represent HVAC building systems and combined it with an MPC optimal control framework as discussed in Finck, Li & Zeiler (2019); Reynolds *et al.* (2018). A powerful solution for modeling sequence dependency is RNN models. LSTM network is a RNN that overcomes the problem of training a recurrent network with the architecture of learnable gates. LSTM had been found suitable for electric consumption, prices forecast, and also for emission factor prediction to schedule appliances use in the smart house domain Riekstin, Langevin, Dandres, Gagnon & Cheriet (2018); Rahman, Srikumar & Smith (2018). Recently, a LSTM-RNN has been proposed in Abdel-Nasser & Mahmoud (2019) for predicting the photovoltaic power. Specifically, the authors compare the prediction accuracy of five different LSTM models. Their results show LSTM for regression with time steps and LSTM for regression using the window technique achieve the best performance. However, the authors do not take into account the context-information (such as wind speed, outside air temperature, time of day and day of week) in their models. A few studies have investigated the usefulness of LSTM for IAT multi-step predictions in the HVAC system Xu *et al.* (2019). An LSTM prediction model with MISO structure was proposed by Xu *et al.* (2019) to predict IAT until 30 minutes using a recursive prediction approach. Nevertheless, their proposed model did not show clear advantages compared to the traditional prediction model like SVM and decision tree.

1.1.3 Context-aware IAT prediction

It is obvious that the availability of an accurate multi-step prediction model is extremely important in a data-driven MPC framework. As discussed in the previous sections, several deep learning models have been proposed and integrated with MPC to define a data-driven control methodology Garnier *et al.* (2015); Jain *et al.* (2018); Reynolds *et al.* (2018). However, they usually include black box models that do not take into account the physical aspect. They define a predictive model but ignore the sensitivities of control on temperature which can bias on the optimization decision for the control outputs. For example, if the cooling controls are all OFF and it is hot outside, automatically the model should predict an increasing in the temperature behavior, which is not the case of models proposed by several related works. In general, when modeling temperature which should be used to decide the future control actions, it is essential to capture the sensitivities of the temperature output with respect to known future inputs like control commands and outside temperature. In particular, at every time t, given the known future inputs and other inputs that are only historically known, the model should correctly describe the variations of the predicted temperature output, due to variations of the command input sequence including observed and future know values. Recent deep neural networks have considered the use of transformer networks with attention-based mechanism for multi-horizon time series forecasting Lim, Arik, Loeff & Pfister (2019). In Nunez, Langarica, Diaz, Torres & Salas (2019), they use the basic structure of encoder-decoder with attention model combined with MPC to control a paste thickener systems. Although attention mechanism improve long-horizon sequence, it have difficulties handling continuous time-series data which requires a strong temporal consistency. However, temporal consistency is a requirement for temperature prediction, as the control variables should remain stable over a short period of time to avoid unnecessarily cycling equipment. In Liu, Gong, Yang & Chen (2020) and Zheng, Mukherjee, Dong & Li (2018), the attention mechanism is used to capture the spatio-temporal relationships between multivariate time series and they will be used as a reference to compare our proposed prediction model.

1.1.4 Discussion

In general, most of existing IAT prediction algorithms do not adopt a feature selection method. A feature selection investigation is required to find the exact number of control parameters that must be included as input in the predictive model to increase the accuracy. For example, the CAV system have only basic control parameters like heating stages, cooling stages and fan stages. On the other hand, the VAV systems have more parameters like supply air temperature, damper position, etc. In the literature, IAT prediction models have been proposed for either the CAV or VAV systems, but to the best of our knowledge, no prediction model has been tested or adapted on both types of systems at the same time. In addition, the development of multiple models for multi-zones are time-consuming. Yet, the size of the control problem grows rapidly as the number of air handling units (AHUs) and controlled zones increase. Furthermore, the majority of proposed models use a recursive prediction. Such recursive strategy has two major limitations. First, it accumulates prediction errors, because prediction values are used instead of real observations. This method degrades the performance of the model as the number of future steps increases. Second, it considers each input parameter as an independent parameter. Consequently, the temporal dependency among continuous variables is ignored, while the historical data collected from HVAC systems are generally time series data. These limitations can be tackled by adopting a technique that takes into account the temporal relationship among input parameters and using a direct prediction approach to avoid the problem of error accumulation. Moreover, it is important to consider the impact of controls on temperature prediction. The complex and non-linear inter-dependencies between multivariate time series, including control and uncontrolled parameters, make the prediction task more complicated. All these factors are very important to model an accurate IAT prediction model and close the control loop.

1.2 Centralized Data-driven control solutions

This section describes relevant literature research on optimization techniques used in data-driven control models in HVAC systems. To optimize HVAC control, centralized-based model predictive

control (MPC) approaches which are solved using different optimization algorithms, for instance, mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP), nonlinear programming algorithm (NLP) and evolutionary algorithms like genetic algorithms (GA), have obtained more and more attention in recent years Reynolds *et al.* (2018); Song, Liu, Liu, Jiang & Lin (2020).

1.2.1 Control optimization algorithms

Dullinger et al. Dullinger, Struckl & Kozek (2018) developed a centralized predictive HVAC controller based on a MILP approach. The proposed control system is based on two levels of operation. On the upper level, the global thermal system performance and the HVAC modes are controlled using a long prediction horizon to take care of the slow dynamics of the plant. Then, on the lower level, the system operation is optimized with a shorter horizon that corrected possible prediction deviations without increasing the computation time. Similarly, Tarragona et al. Tarragona *et al.* (2020) presented a two level centralized MPC control strategy to improve the operation of a space-heating system coupled with renewable resources. The proposed control approach is formulated as an MINLP. These double levels of control helped the system to find the optimal solution with less computation time. Raman et al. Raman, Chen & Barooah (2021) designed an NLP-based centralized control approach incorporating humidity and latent heat in the MPC optimization problem for energy-efficient HVAC control. A centralized MPC is developed in Seal, Boulet & Dehkordi (2020) aimed at occupant comfort and energy efficiency with variable cost rates. They obtained a reduction of 13% in the energy cost with the proposed control strategy compared to rule-based energy management.

1.2.2 Control optimization based on GA

Evolutionary algorithms has been widely applied to resolve the optimization problem related to MPC in HVAC systems. An optimization procedure combining GA, MPC and artificial neural network to minimize the energy consumption and it is proved to guarantee globally-bounded closed-loop stability Reynolds *et al.* (2018). They considering two different simulation scenarios

(flat and time-of-use price tariffs). According to their results, they have achieved a reduction in energy consumption by around 25% compared to a baseline heating strategy. However, this work did not consider weather and occupancy forecasting parameters in their prediction model and they only implement their approach on simulated building rather than real-world trial. Song et al. Song *et al.* (2020) proposed a GA-based centralized control method to optimize the configuration of a cooling, heating and power (CCHP) plant. A low-order ANN based models combined with MPC was developed to minimize the energy consumption of a multi-zone HVAC system Garnier *et al.* (2015). Researchers used GA to minimize the cost function. Also they used the predicted mean vote (PMV) index as a thermal comfort indicator. This strategy was compared with basic control techniques and resulted in 5.2% and 14.7% of energy saving during heating and cooling seasons respectively. However it does not include predicted weather as a model input failing to adjust control parameters in the future steps. Moreover, it was modeled using a simulation model generated in the EnergyPlus software and no real-world data was used for training or model validation. In Asadi *et al.* (2014), a GA is applied to solve a multi-objective optimization problem which trade-offs between the retrofit cost, energy consumption and thermal comfort. The authors demonstrated that GA is well suited for multi-objective problems and they showed that the simultaneous optimization of all three lead to good results in contrast to optimizing per an individual objective. However, their model is based on a simulation database that was generated from a comprehensive building model developed in TRNSYS to train and validate ANN models which is difficult to extend in real-building. Kampelis et al. Kampelis, Sifakis, Kolokotsa, Gobakis, Kalaitzakis, Isidori & Cristalli (2019) have also used GA for power optimization of HVAC systems. They studied the trade-off between minimizing energy costs and maximizing thermal comfort by integrating PMV to ensure thermal comfort requirements. The control approach they proposed is not suitable for a real-time energy and comfort management application, as it is time-consuming to execute. An adjustment of the optimization parameters is necessary to conduct the deployment in real time. An adaptive supervisory model predictive on-off control algorithm is presented in Tyukov, Shcherbakov, Sokolov, Brebels & Al-Gunaid (2017), including the predicted weather factor. The GA is used to optimize the cost function

which can save up to 20-40% of gas consumption while maintaining comfort. However, this approach has not been validated in real time with the building's feedback states.

1.2.3 Discussion

In general, most of the existing centralized control solutions are tested only on simulated environment such as EnergyPlus rather than real-world building and there are no real data used for the model validation. The time-consuming to execute existing proposed approaches requires an adjustement of the optimization parameters to conduct to the deployment in real time. Moreover, prior work focus only on minimizing energy consumption and discomfort. More factors need to be considered for instance peak demand self-tuned setpoint, temperature ramp and equipment cycling costs.

1.3 Multi-agent Data-driven control solutions

1.3.1 Energy efficiency and discomfort minimization

Different centralized control framework have been proposed in the literature Tarragona *et al.* (2020). However, there are many characteristics that make the centralized data-driven MPC less interesting. First, the optimization strategies in the centralized data-driven control system can take a significant amount of time to find the optimal control variables, which is a challenge for systems with a short period of operation Thieblemont *et al.* (2017). Centralized control framework can be computationally expensive for large scale optimization when applied to building with large number of zones and equipped by complex distribution system and influenced by various factors. For instance, in the case of using evolutionary algorithms, as the number of zones grows as the size of individuals grows, which make the convergence slower. In addition, online computing time can be a bottleneck for real-time applications, as the optimization problem must be solved in a short period of time. Moreover, in the centralized scheme the computational time can become a drawback due to the large amount of data to be treated. Compared with centralized control-based methods, Multi-agent control (MAC) systems are more flexible and

scalable Wang *et al.* (2021). MAC system, has lately caught significant attention for HVAC control systems. Su and Wang Su & Wang (2020) proposed an agent-based distributed optimal control strategy for multi-zone HVAC systems. The authors of this paper investigated different implementation issues including energy efficiency, optimization accuracy, convergence rate, computation complexities and computation loads. Results showed that the proposed control had a low computation load and a high convergence rate. Li et al. Li, Jia, Zhou & Li (2020) developed a three-layered multi-agent system based optimal control method using the chaotic search particle swarm optimization. The results demonstrated that the proposed control solution could reduce the operating cost by 1.84%. Pertzborn Pertzborn (2019) adopted an MPC and distributed optimization by using the distributed agents for optimal operation of a central chilling system combined with an ice-storage system. The distributed models divided the computational load between multiple local models and optimizations, providing an effective global control policy for the entire operating system. Joe et al. Joe, Karava, Hou, Xiao & Hu (2018) studied a distributed MPC and has demonstrated a high potential of reducing energy consumption by up to 27% within the cooling season. A real-time optimal control method is developed in Li, Wang & Koo (2021) to solve the optimization problem in a distributed manner and find the proper trade-off between maintaining thermal comfort and indoor air quality as well as minimizing energy use. Li and Wang Li & Wang (2020) designed a multi-agent based hierarchical distributed approach for the optimal control of multi-zone ventilation systems to improve indoor air quality by regulating the operation of the primary air-handling units. A centralized multi-objective optimization scheme was formulated and decomposed into different simpler distributed sub-schemes. In this way, complex control optimization problems can be solved collectively by multiple agents.

1.3.2 Carbon footprint minimization

The carbon footprint is an essential factor to consider in the optimization problem. Vogler-Finck et al. used MPC to control and optimise multi-zone operation Vogler-Finck, Wisniewski & Popovski (2018). The results show that carbon footprint and energy optimization are relevant objectives

for predictive control, while price optimization is comparatively less desirable. Carbon emission reduction is also considered in Pedersen, Hedegaard & Petersen (2017), who proposed an economic model predictive control (E-MPC) scheme for space heating operation. Simulation results showed that E-MPC increases cost savings by up to 6% and CO2 emissions by up to 3%. In Siler-Evans, Azevedo & Morgan (2012), the marginal emissions factors (MEFs) is used instead of the average emissions of the electrical grid. The MEFs also is used in Péan *et al.* (2019), which developed an MPC controller and tested within a co-simulation framework which combines an optimization software with a dynamic building simulation tool and it achieved a marginal emissions saving in the range of 19%-29%.

1.3.3 Discussion

In general, prior work demonstrate the effectiveness of using distributed optimal control approaches to improve the scalability and the energy efficiency of HVAC systems. However, operational issues when these control approaches are implemented on physical environments, for instance the convergence rate and computation load distribution have not been addressed. In addition, the scalability and robustness of the proposed distributed control systems should be improved. Therefore, implementing real-time optimal control strategies for multi-zone HVAC systems using multi-agent based distributed optimization methods is a challenging research direction. Moreover, the optimization models proposed in previous work are limited to energy efficiency and discomfort minimization. The carbon footprint reduction is an essential factor to consider in the optimization problem.

CHAPTER 2

OBJECTIVES AND METHODOLOGY

In this chapter, we explain in details the research objectives and methodology of the thesis. We describe the general methodology through four phases to achieve the objectives. Then, we present the relationship between the phases in a summary diagram to facilitate the reading of this thesis.

2.1 Research hypothesis

The research hypothesis (RH) of this thesis is defined as follows:

RH: By accurately modeling indoor air temperature, considering sensitivities of control over the prediction horizon and by optimizing the control decision, we minimize energy and carbon footprint while maintaining comfort and improve control efficiency and scalability for the HVAC system in smart buildings.

2.2 Main objective

The main objective (MO) of this thesis is defined as follows:

MO: Design an efficient and scalable data-driven HVAC control framework that minimizes energy consumption, carbon emission, peak demand and discomfort during occupied hours under self-tuned setpoint, temperature ramp and equipment cycling constraints, which integrates a multi-step temperature prediction model considering control sensitivities.

2.3 Specific Objectives

2.3.1 Specific objective SO1

SO1: Accurately model indoor air temperature prediction with multi-step in a multi-zone smart building and with different types of HVAC control systems.

In order to reduce the cost and time consuming task caused by MPC to control HVAC systems inside a large-scale building especially for multi-zone building and for different HVAC system types, we need a proper indoor air temperature model to deal with the nonlinearity of the buildings thermal dynamics since IAT is affected by complex factors such as controlled and uncontrolled points, outside weather conditions and occupancy schedule. Thus our objective is to model an accurate indoor air temperature prediction with multi-step in a multi-zone smart building and with different types of HVAC control systems.

2.3.2 Specific objective SO2

SO2: Model a multi-step IAT prediction in a data-driven MPC framework without bias on the optimization decision for the control outputs.

In order to improve the perdition accuracy and the control decision we need to consider the impact of controls on temperature in the control decision loop. Thus our objective is to build an accurate IAT prediction model based on high-level and low-level interaction between input features and consider the sensitive relationship between temperature and control parameters.

2.3.3 Specific objective SO3

SO3: Model and deploy an efficient online data-driven MPC optimization problem suitable for a real-time HVAC system application.

In order to optimise HVAC system control in smart building, we need to consider energy consumption caused by HVAC operation while preserving comfort. Thus our objective is to design, implement and deploy in real multi-zone retail building an optimized control approach which considers a self-tuned setpoint, cycling and temperature ramp constraints in addition to energy, peak power and discomfort costs.

2.3.4 Specific objective SO4

SO4: Model and deploy a scalable multi-agent online data-driven MPC framework.

In order to minimize the computation time caused by the centralized control approach, a distributed control is needed to ensure scalability that minimize computation time and support a large scale building. Thus our objective is to design and implement a multi-agent control approach that ensures energy efficiency and reduce carbon emission, while ensuring comfort as well.

2.4 General methodology

We propose four consecutive methodologies M1, M2, M3 and M4 to respectively address the requirements of the research questions RQ1, RQ2, RQ3 and RQ4 (discussed in Section 0.2) as well as the specific objective SO1, SO2, SO3 and SO4 (discussed in Section 2.3). The global framework of the thesis, as depicted in Figure 2.1, incorporates these four methodologies. The first step involves collecting historical data from HVAC systems and conducting feature selection analysis. Next, two LSTM-based temperature prediction models, MISO and MIMO, are proposed to improve the generality of HVAC systems. The CAM-LSTM model is then introduced to predict temperature while considering the sensitivity of control on the prediction. These models are discussed in more detail in the first and second methodologies, which aim to meet objectives one and two of the thesis. The prediction results are then utilized in two optimal control models, MPC-GA for centralized control, and Multi-Agent Control for distributed control, in order to achieve an efficient and scalable control model. These control models operate on a moving horizon, computing optimal solutions for a fixed prediction horizon of two hours. Only the first control signal is applied to the building, and the optimization process is executed in a closed loop as time progresses. Methodologies three and four, which address objectives three and four of the thesis, focus on these two control models.

The four methodologies are defined as follows:

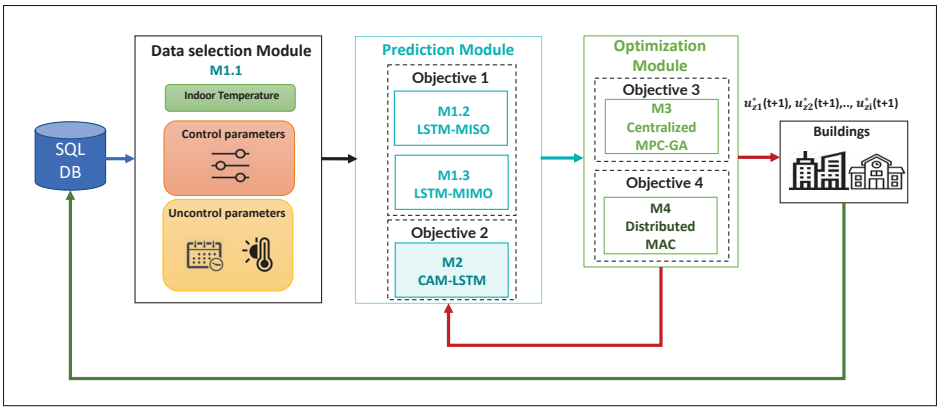

Figure 2.1 Global framework

2.4.1 Methodology M1

The methodology M1 addresses the research question RQ1 and the specific objective SO1. In this methodology, we present an accurate IAT prediction model for multi-zone building that uses LSTM and based on a direct S2S multivariate multi-step time series prediction model, instead of the recursive model, which is helpful to better control the HVAC system's operation.

The methodology M1 is summarized as follows:

- Design and implement LSTM-MISO architecture using multi-input single-output to predict the temperature for each zone based on S2S.
- Design and implement LSTM-MIMO architecture using multi-input multi-output to predict IAT for all zones simultaneously based on S2S with only one model.
- Relevance selection analysis of pertinent input parameters from a set of input parameters.
- Validate both architectures in two different types of buildings using different HVAC systems (CAV and VAV) with real industrial data.

2.4.2 Methodology M2

The methodology M2 addresses the research question RQ2 and the specific objective SO2. In this methodology, we present a new IAT prediction model based on a context-aware multivariate LSTM (CAM-LSTM) composed by dual-stream neural network with an attention mechanism which selects not only past but also future multivariate time series including controlled and

uncontrolled inputs to predict a multi-steps temperature output. This model will be integrated in the data-driven MPC framework presented in M3.

The methodology M2 is summarized as follows:

- Model the high-level interaction between input features using two dense layers with ReLU activation to build a hidden representation.
- Model the low-level interaction between input features using two 1-D convolution layers with ReLU activation functions to introduce non linearity and capture different important signal patterns.
- Model the sensitive relationship between temperature and control parameters using self-attention layers to capture the degree of relevance of control with respect to IAT.
- Model a LSTM-bidirectional layers which gives the multi-step IAT prediction of each zone for the whole prediction horizon.

2.4.3 Methodology M3

The methodology M3 addresses the research question RQ3 and the specific objective SO3. In this methodology, we design a new efficient data-driven control framework based on MPC optimization problem in multi-zone smart building.

The methodology M3 is summarized as follows:

- Propose a new optimization control model to minimize energy, peak power and discomfort costs with considering of self-tuned setpoint, cycling and temperature ramp.
- Integrate CAM-LSTM IAT prediction model in the control objective function of the control model.
- Define a new algorithm based on genetic algorithm in order to solve the online data-driven control model over a prediction horizon.

2.4.4 Methodology M4

The methodology M4 addresses the research question RQ4 and the specific objective SO4. In this methodology, we present a new scalable multi-agent control framework data-driven MPC based named MAC allowing the optimal operation of HVAC system.

The methodology M4 is summarized as follows:

- Model a local optimization control problem for the agent that minimizes discomfort during control horizon while considering a certain power budget defined by the coordinator.
- Model a global optimization problem for the coordinator that minimizes a carbon emission cost and assigns an individual energy budget to each local agent.
- Propose a new multi-agent control algorithm to solve optimization control models in parallel over a prediction horizon which ensure scalability to the control system.
- Validate the proposed MAC approach in simulation environment using Modelica.

A summary outline diagram of the thesis is presented in Fig. 2.2.

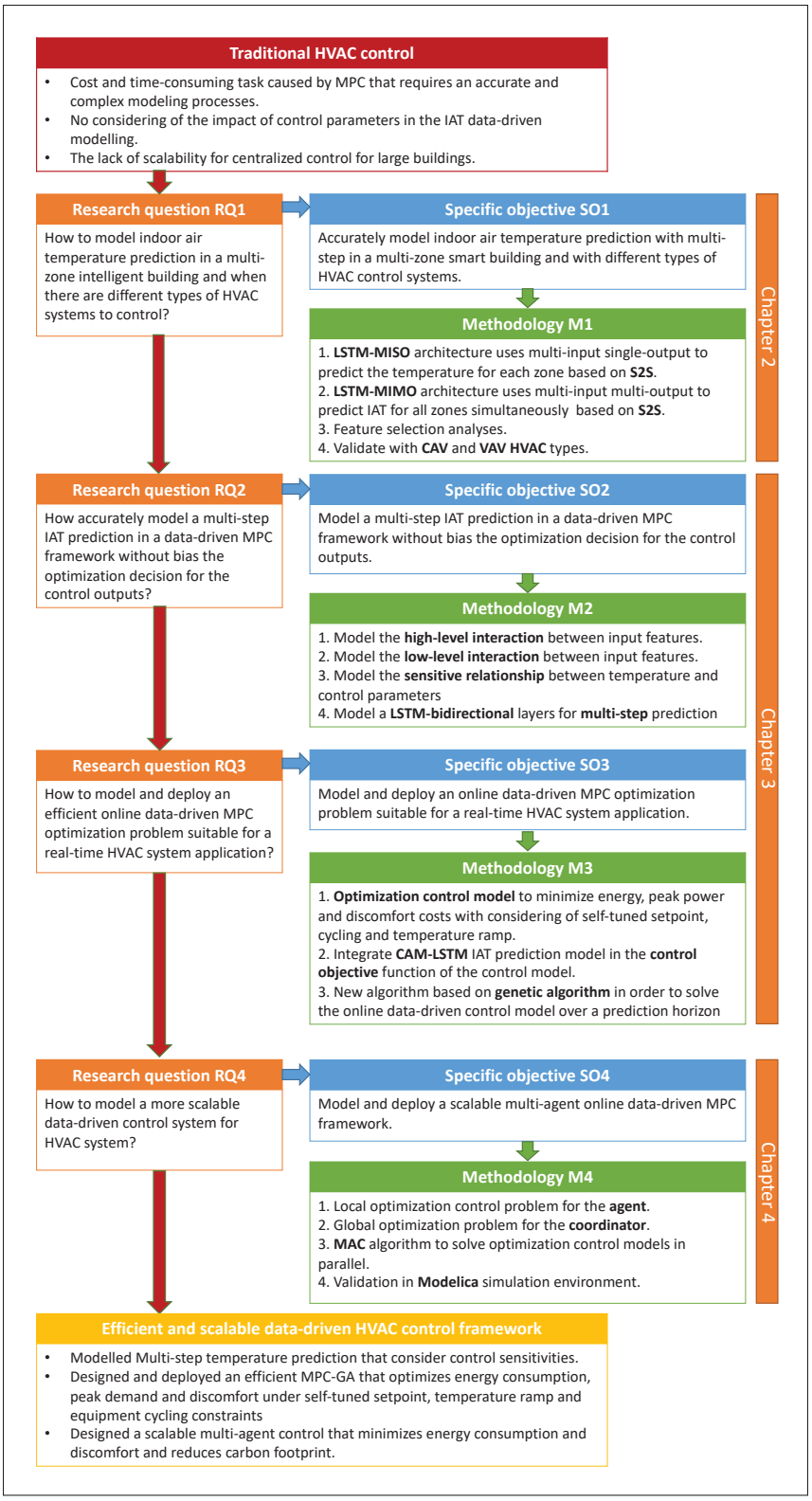

Figure 2.2 Diagram outline of the thesis

CHAPTER 3

LSTM-BASED INDOOR AIR TEMPERATURE PREDICTION FRAMEWORK FOR HVAC SYSTEMS IN SMART BUILDINGS

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Article published in *Neural Computing and Applications*, December 2020

Abstract

Accurate Indoor Air Temperature (IAT) predictions for Heating, Ventilation, and Air Conditioning (HVAC) systems is challenging, especially for multi-zone building and for different HVAC system types. Moreover, the non-linearity of the building's thermal dynamics makes the IAT prediction more difficult since it is affected by complex factors such as, controlled and uncontrolled points, outside weather conditions and occupancy schedule. This paper presents a Long Short Term Memory (LSTM) model to predict IAT for multi-zone building based on direct multi-step prediction with sequence-to-sequence approach. Two strategies, LSTM-MISO and LSTM-MIMO, are built for multi-input single-output and multi-input multi-output, respectively. The performance of these two strategies has been evaluated based on two case studies on real smart buildings using Variable Air Volume (VAV) and Constant Air Volume (CAV) systems. For both buildings, experimental results showed that the LSTM models outperform Multilayer Perceptrons models by reducing the prediction error by 50%.

Keywords: HVAC, LSTM, Sequence-to-sequence, Multi-step ahead predictions, VAV, CAV.

3.1 Introduction

The total energy used in buildings accounts for 40% of the global energy consumption and up to 30% of carbon dioxide emissions in the world Costa *et al.* (2013); Yang, Yan & Lam (2014). In building sectors, heating, cooling, ventilation and air-conditioning (HVAC) system is responsible for more than half of the energy consumed Pérez-Lombard, Ortiz & Pout (2008). The reduction of the energy consumption is crucial to enhance energy efficiency. However, the minimization of the energy consumption may influence on the indoor comfort. Indoor air temperature (IAT) is one of the essential thermal comfort parameters Baniasadi *et al.* (2018). It is necessary that IAT variations stay around the upper and lower boundaries of comfort (67 and 82°F respectively according to ASHRAE standard 55-2017 Standard (2017)). Therefore, accurately modeling IAT is required. The IAT prediction contributes to keep IAT within a comfortable range. Hence, the IAT prediction model helps to offer a future boundary setting and detects any contradiction between estimated and actual conditions. The IAT prediction can be achieved using physics-based or data-driven methods. Physics-based models are based on Fourrier's Law of heat conduction which is discretized into the finite difference method and typically expressed in an resistance-capacitance analogy Rojas, Kunusch, Ocampo-Martinez & Puig (2015). However, the IAT model varies from one zone to the others and is nonlinear since it is affected by complex factors, for instance, controlled and uncontrolled points, outside weather conditions, occupancy schedule, etc. These factors make the IAT prediction modeling using physical approach more challenging and time consuming Afroz *et al.* (2018b), especially for multi-zone building and when there are different types of HVAC systems to control Sturzenegger *et al.* (2016). Data-driven models is based on the data generated from a large number of sensors and thermostats already deployed. Data-driven approaches, to model IAT, have been studied in different previous studies Chen *et al.* (2015); Huang *et al.* (2015a). The first advantage to use data-driven approaches is to eliminate the cost and time-consuming task to build IAT physics-based models. Besides, IAT model is easy to implement for a multi-zone system using Artificial Intelligence (AI) techniques since it can deal with non-linearity in the system Serale *et al.* (2018).

Recently, Artificial Neural Networks (ANN) and nonlinear autoregressive network with exogenous inputs (NNARX) have been extensively used to model indoor environments Huang *et al.* (2015b); Attoue *et al.* (2018); Delcroix *et al.* (2020). However, prior work generally adopted a recursive prediction strategy for predicting multi-step ahead He *et al.* (2014); Zeng *et al.* (2015); Delcroix *et al.* (2020). For instance, the model predicts time t and uses the predicted value to predict $t + 1$, and recursively until $t + p$, where p is the time horizon. This method accumulates prediction errors at each time-step. Furthermore, the ANN method considers each input as an independent parameter. It ignores the time dependency between sequential values. Unlike many studies which used ANN with Multilayer Perceptrons (MLP) models or NNARX, this paper investigates a time series approach for multi-step prediction model using Long Short-Term Memory (LSTM) which is shown to be an accurate forecasting method for time series data Xu *et al.* (2019); Riekstin *et al.* (2018). In this paper, two prediction structures are used to model IAT in multi-zone with multi-step prediction: the LSTM-MISO architecture uses multi-input single-output to predict the temperature for each zone; the LSTM-MIMO architecture uses multi-input multi-output to predict IAT for all zones simultaneously with only one model. This strategy shows clear advantages compared to prediction models presented in prior work Huang *et al.* (2015b); Liang *et al.* (2019); Delcroix *et al.* (2020). The proposed LSTM framework is based on a direct sequence-to-sequence (S2S) multivariate multi-step time series prediction model, instead of the recursive model, which is helpful to better control the HVAC system's operation.

The key problem to be addressed in this paper is an IAT prediction model used for a CAV system cannot be applied to a VAV system or vice versa without decreasing the performance. Therefore, a general modeling process consider different properties of both systems are required to save time and cost particularly when there are many HVAC systems to control inside a large-scale building. Our proposed models have been tested in two different types of buildings: the first floor of a hotel in Montreal with five VAVs systems and a small retail store with three zones supplied by three CAVs systems. A general framework with specific feature selection approaches which

can adapt to VAV and CAV types has been defined. Furthermore, we evaluated the effect of tuning model hyperparameters in both systems to increase the accuracy of the prediction model.

The contributions of this paper are: 1) a data-driven framework for modeling IAT with LSTM-MISO and LSTM-MIMO models based on the S2S approach; 2) different settings of previous time-step and input parameters to increase the performance of multi-step prediction models; 3) the validation of the proposed framework in two real cases with the industrial data;

This paper is structured as follows: Section 2 summarizes the prior work related to our research. Section 3 describes the two types of buildings used in this study. Section 4 illustrates the detailed methodology of our proposed data-driven framework for modeling IAT for both MISO, and MIMO architectures using S2S approach. Section 5 discusses the experimental results and compares the performance of the proposed models. Finally, we conclude key findings and present future research directions.

3.2 Related Work

The main advantage of a data-driven approach is to reduce the cost and time-consumed by traditional physics-based techniques. Moreover, the data-driven approaches can deal with non-linearity, incomplete, or noisy data Serale *et al.* (2018). Machine-learning algorithms have been applied to design dynamic models of the HVAC system. For instance, the multi-step prediction of IAT can be used in a predictive control approach then leads to improving the thermal comfort and decreasing the energy consumption of buildings Xu *et al.* (2019).

The key common algorithms applied in data-driven approaches that have been used extensively in the building sector for IAT modeling are regression trees Jain *et al.* (2018), random forests Smarra *et al.* (2018), nonlinear autoregressive network with exogenous inputs (NARX) Afroz *et al.* (2018b), NNARX Delcroix *et al.* (2020), ANN Attoue *et al.* (2018) and Recurrent Neural Networks (RNN) Javed *et al.* (2014). Table 3.1 summarizes state-of-the-art of data-driven approaches. Jain et al. Jain *et al.* (2018) combine multi-output regression trees to represent the system's dynamics. Yet, the modeling accuracy using single trees to constitute multi-step

prediction for zone temperature is strongly affected by over-fitting and high variance. The authors in Smarra *et al.* (2018) model the temperature by a set of linear regression models, which change after each time step. They model their system with regression trees to predict temperature for multi-zone using MISO structure and extend them to a random forest model. However, their model is complicated and time-consuming.

Table 3.1 Comparison of models prediction

References	Data-driven model	HVAC type	Prediction horizon	Type of model	Tuning Model
Du *et al.* (2014)	ANN - Clustering	VAV	-	MISO	Yes
Castilla *et al.* (2013)	ANN - MLP	Solar cooling	60 s	MISO	Yes
Liang *et al.* (2019)	UrbanFM	-	-	-	No
Huang *et al.* (2015a)	ANN - MLP	CAV	2 hours	MISO and MIMO	No
Attoue *et al.* (2018)	ANN - MLP	CAV	1 to 4 hours	MISO	Yes
Xu *et al.* (2019)	RNN - LSTM	CAV	5 to 30min	MISO	No
Abdel-Nasser & Mahmoud (2019)	RNN - LSTM	-	1 hour	MISO	No
Afroz *et al.* (2018b)	RNN - NARX	VAV	28 days	MISO and MIMO	Yes
Delcroix *et al.* (2020)	RNN - NNARX	CAV	1 hour	MISO	Yes
Huang *et al.* (2015b)	RNN - NNFL	CAV	6 hours	MISO	No
He *et al.* (2014)	ANN - MLP	VAV	15 min	MISO	No
Zeng *et al.* (2015)	ANN - MLP	VAV	15 min	MISO	No
Jain *et al.* (2018)	Regression Trees	CAV	6 hours	MISO	No
Smarra *et al.* (2018)	Random forests	CAV	6 hours	MISO	No

Nowadays, the ANN model has been widely applied for several type of applications in HVAC sector, such as Fault Detection and Diagnostics (FDD) Du *et al.* (2014), thermal comfort approximation Castilla *et al.* (2013) and IAT prediction Attoue *et al.* (2018); Huang *et al.* (2015b). Du et al. Du *et al.* (2014) developed ANN based tool to detect faults in the supply air temperature control loop in commercial building with VAV systems. The authors used a combined neural networks model which includes the basic neural networks and auxiliary neural networks to detect faults, and then used clustering approach for classification to diagnose the fault sources. The proposed models diagnose the faults using context information related to the monitoring parameters such as supply chilled water temperature, return chilled water temperature, chilled water flow rate and chilled water valve position. The principal component analysis is carried out to analyze the contributions of these parameters in the supply temperature control loop. The occurrence of faults is computed according to a combined relative error and its threshold. Castilla et al. Castilla *et al.* (2013) proposed a context-aware neural networks model using human and environmental variables for approximating thermal comfort evaluation

for HVAC systems. Their model avoids the costs involved in calculating the classical predictive mean vote (PMV) index in terms of the computation time and the extensive sensor network size required to collect the input data. Moreover, it allows the use of PMV index within real-time model predictive control framework. Attoue and al. Attoue *et al.* (2018) developed a simple ANN-MISO model to predict indoor temperature for different forecasting time-steps. They proposed a methodology based on the selection of pertinent input parameters from a large set of features. Their experimental results show that outdoor and facade temperature data provides good forecasting results of indoor temperatures. Moreover, their results show that predictions were accurate for up to two hours. However, the predictions have unsatisfactory accuracy for more than four hours forecast ahead. Huang et al. Huang *et al.* (2015b) develop an hybrid MPC based on neural network feedback-linearization model to predict IAT over six hours ahead. The goal of this approach is to linearize the system using the neural network through feedback to build nonlinear functions approximation. The type of HVAC system used in Huang *et al.* (2015b) is designed with constant-air volume (CAV).

Prior studies also model IAT for a VAV system Zeng *et al.* (2015); Afroz *et al.* (2018b). An indoor air temperature prediction models of multi-zone using MISO structure are proposed by He *et al.* (2014). Zeng et al. Zeng *et al.* (2015) developed an optimal control of multi-zones VAV system. They elaborated a data-driven predictive model using MLP to predict the environmental conditions of each zone and optimize energy consumption. The IAT is predicted with only one-step ahead. Moreover, multi-step prediction is necessary to lead a real-time implementation in the control phase. Moreover, only two control parameters were used as inputs in the prediction model in He *et al.* (2014); Zeng *et al.* (2015). Neither specific feature selection methodology nor model tuning approach were implemented. The context information like weather data, control parameters and other external factors might improve the future prediction. Liang et al. Liang *et al.* (2019) designed a framework named UrbanFM based on deep neural networks. UrbanFM is composed of two models, an inference network component and an external factor fusion component. The inference network component generates a fine-grained flow from coarse-grained inputs by using a novel feature extraction and distributional upsampling modules. The external

factor fusion component handles the context information (like the day of the week, time of the day, weather, other external factors) to capture near and distant spatio-temporal dependencies. This component plays an important role in providing a prior knowledge and improves the inference performance under sparse sampling. A feature selection investigation is done to find the exact number of control parameters that must be included as input in the predictive model to increase the accuracy. For example, the CAV system have only basic control parameters like heating stages, cooling stages and fan stages. On the other hand, the VAV systems have more parameters like supply air temperature, damper position, etc. In the literature, IAT prediction models have been proposed for either the CAV or VAV systems, but to the best of our knowledge, no prediction model has been tested or adapted on both types of systems at the same time. In addition, the development of multiple models for multi-zones are time-consuming. Yet, the size of the control problem grows rapidly as the number of air handling units (AHUs) and controlled zones increase. A multi-zone modeling approach using the MLP-MIMO model was proposed by Huang *et al.* (2015a) to forecast two hours ahead temperature inside an open space commercial building. Afroz et al. Afroz *et al.* (2018b) predict IAT in multi-zone buildings using a different tuned model based on NARX model. The authors use MISO architecture to predict one step ahead then MIMO architecture to predict multi-step ahead for the same zone. In this paper we use MIMO atchitecture to predict multi-zone with multi-steps ahead. Delcroix et al. Delcroix *et al.* (2020) predicted the behaviors of IAT using NNARX-MISO. They carried out their experiments with the same type of CAV building used in this paper, and they compared their results with the gray-box model and the linear autoregressive model with exogenous inputs (ARX). Their comparisons show the NNARX model achieves the highest performance the alternative models. However, the authors assume that the future exogenous inputs (control parameters, outdoor temperature, etc.) are known, which cannot be true in the real case. All Afroz *et al.* (2018b), Huang *et al.* (2015a) and Delcroix *et al.* (2020), develop a one-step forecasting model, then use a recursive multi-step forecasting strategy to predict the future. Such recursive strategy has two major limitations. First, it accumulates prediction errors, because prediction values are used instead of real observations. This method degrades the performance of the model as the number of future steps increases. Second, it considers each input parameter as an independent parameter. Consequently, the

temporal dependency among continuous variables is ignored, while the historical data collected from HVAC systems are generally time series data. These limitations can be tackled by adopting a technique that takes into account the temporal relationship among input parameters and using a direct prediction approach to avoid the problem of error accumulation. A powerful solution for modeling sequence dependency is RNN models. LSTM network is a RNN that overcomes the problem of training a recurrent network with the architecture of learnable gates. LSTM had been found suitable for electric consumption, prices forecast, and also for emission factor prediction to schedule appliances use in the smart house domain Riekstin *et al.* (2018); Rahman *et al.* (2018). Recently, a LSTM-RNN has been proposed in Abdel-Nasser & Mahmoud (2019) for predicting the photovoltaic power. Specifically, the authors compare the prediction accuracy of five different LSTM models. Their results show LSTM for regression with time steps and LSTM for regression using the window technique achieve the best performance. However, the authors do not take into account the context-information (such as wind speed, outside air temperature, time of day and day of week) in their models. A few studies have investigated the usefulness of LSTM for IAT multi-step predictions in the HVAC system Xu *et al.* (2019). An LSTM prediction model with MISO structure was proposed by Xu *et al.* (2019) to predict IAT until 30 minutes using a recursive prediction approach. Nevertheless, their proposed model did not show clear advantages compared to the traditional prediction model like SVM and decision tree. Indeed, the use of recursive prediction can decrease the prediction performance. This paper systematically investigates the performance of direct multi-step prediction approach using LSTM-MISO and LSTM-MIMO architectures in CAV and VAV HVAC systems.

3.3 Smart Building Models

3.3.1 CAV-building

CAV systems supply air at a constant volume and variable temperature Yan, Luh & Pattipati (2017). Fig. 3.1 (a) illustrates one of three zones of retail store with a CAV system. The fresh air entering from outside is mixed with the return air to produce fresher air to the fan

ventilation. The speed of the fan is fixed, and it is controlled by an (ON/OFF) switch. Thus, even for part-load conditions, the fans use the maximum energy that leads to wasting energy. The mixed air is conditioned by the heating/cooling coils, and then distributed to the zones through different diffusers. There is no controllable terminal damper in the conditioned area zone. The terminal is set at a fixed opening level and cannot be actively controlled. The air returns from the zone to the roof top unit then it can be rejected outside or mixed with the fresh air. The IAT and humidity are monitored by sensors. There is significant thermal coupling between the three zones and with the neighbor spaces. The CAV system uses five controlled points for each zone i, to maintain the IAT at the comfort value, the Fan Ventilation Stage (FVS), two Heating Stages (HS_1 and HS_2) and two Cooling Stages (CS_1 and CS_2) as described in Table 3.2, and enumerated by 1, 2 and 3 respectively in Fig. 3.1 (a). The fan, cooling, and heating stages of the CAV are controlled by the heating and cooling set-points versus the zone's temperature. The total power use of each CAV system in monitoring time Δt is calculated according to the stages of control parameters, and it is stated as:

$$P_i(t) = \sum_{j=1}^{2} \sum_{t=0}^{\Delta t} (CS_{ji}(t).C^c + HS_{ji}(t).C^h) + \sum_{t=0}^{\Delta t} FVS_i(t).C^f, \forall i \tag{3.1}$$

Where $P_i(t)$ represent the total amount of power at time t for zone i, $CS_{ji}(t) = \{0, 1\}$ is the stage j of the cooling unit of zone i at time t, $HS_{ji}(t) = \{0, 1\}$ is the stage j of the heating unit of zone i at time t, $FVS_i(t) = \{0, 1\}$ is the stage of the fan unit of zone i at time t, C^c is the capacity in kW of the cooling equipment i, C^h is the capacity in kW of the heating equipment i and C^f is the capacity in kW of the fan unit. The total amount of power $P_i(t)$ have a positive influence on the prediction model as described in Table 3.5 and will be used as input to the model.

3.3.2 VAV-building

Figure 3.1 (b) shows a VAV system deployed in the ground floor of a hotel. It has one air handling unit (AHU), AC1 which serves a conditioned area with five zones. The main components of the AHU are cooling/heating coils and an air supply fan represented by system components number

12, 6, and 13 in Fig. 3.1 (b), respectively. Each zone has a Variable Air Volume (VAV) box and a duct heater controlled by the control parameters, heating/cooling stage 1 and 2, defined by the system components number 8 and 9, respectively. The AHU circulates the air in its zones by supplying fresh air from outside that is passed by the fresh air damper to control how much fresh air is needed. The fresh air damper and exhaust air are modulated together to maintain the fluidity of the pressure of the circulating air in the system ducts. The fresh air is then conditioned by heating or cooling as per the zone demand by the heating/cooling coils in the supply duct. Since the system's fan is controlled by a binary switch, not by a Variable Frequency Drive (VFD), the pressure in the ducts is regulated by the bypass air damper (BAD). The BAD manage the change in air pressure that would occur due to the different VAVs damper discrete opening levels in each zone $D_i(t)$ (from 0 to 100%). If a specific zone demands more cooling/heating, the cooling/heating coils in that respective VAV's zone will operate to meet the required temperature set-point Yan *et al.* (2017). The Mixing air damper (MAD) is used as a form of energy recovery mechanism since the returning air has already been conditioned when it was in the supply duct. The MAD is modulated if the return temperature is within the desired range, whether it is cooling or heating season when compared to the fresh air temperature to precondition the fresh air before it is exposed to the cooling/heating coils so that achieving the desired temperature will cost less. The VAV system can save more energy compared to CAV Yao, Lian, Liu, Hou & Wu (2007). However, it is difficult to accurately model the IAT variations in VAV systems regarding the complex dependencies of the elements in the AHU system and the high number of control parameters as described in Table 3.2. The action taken by each control parameter can change the IAT value.

The VAV system is controlled by eleven control points, to ensure the heating/cooling demand and satisfy the thermal comfort. As described in Table 3.2, six control points in AC1 are represented by the set of system components numbered from 1 to 6 and the other five control points in each zone i are numbered from 7 to 11. The damper position of each zone i has a direct impact on energy load, calculated by equation 3.2, where $D_i(t)$ represents the opening level of each VAV box damper of each zone i and ρ is the fan demand in (kW) of the air handling unit AC1.

In other words, this equation gives the power used by each opening action for each VAV box damper. This parameter is an uncontrolled variable and will be used as input to the prediction model as described in Table 3.3.

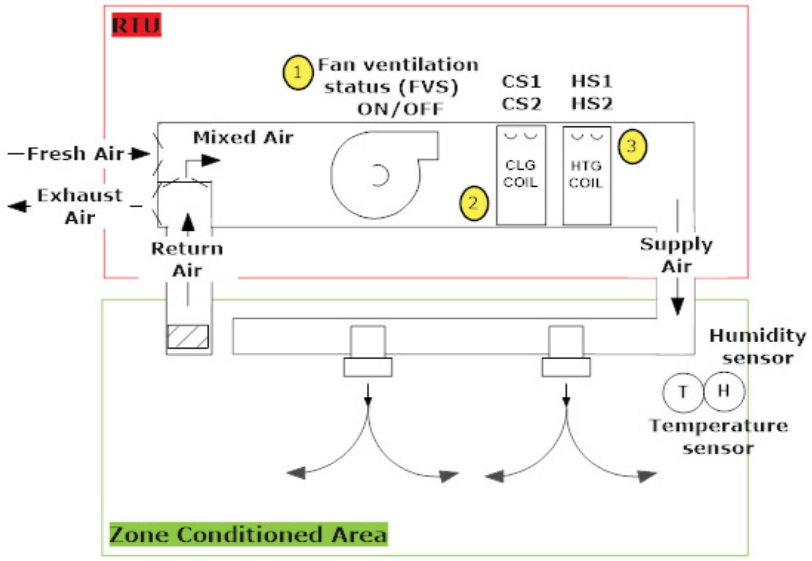
$$P_i(t) = \left(\frac{D_i(t)}{\sum_{i=1}^{N} D_i(t)} \right) * \rho, \forall t \tag{3.2}$$

Table 3.2 Control points parameters

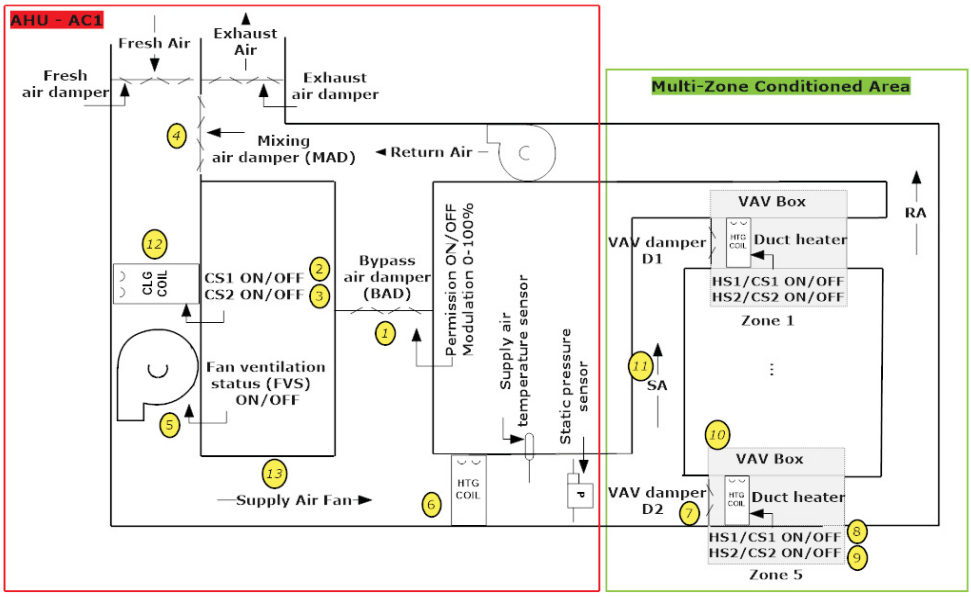
CAV building	VAV building	Control parameters	Description	Unit value
	X	BAD	Bypass air damper	%
	X	CS_1	Cooling stage 1 for AC1	b
	X	CS_2	Cooling stage 2 for AC1	b
	X	MAD	Mixing air damper	%
X	X	FVS	Fan ventilation stage	b
	X	HO	Heating output	%
	X	D_i	Damper position opening level	%
X	X	HS_{1i}/CS_{1i}	Heating/Cooling stage 1 for zone i	b
X	X	HS_{2i}/CS_{2i}	Heating/Cooling stage 2 for zone i	b

Table 3.3 Multivariate inputs variables

VAV-Building			CAV-Building		
Inputs	Description	Unit	Inputs	Description	Unit
Controlled variables, $v_i(t)$			Controlled variables, $v_i(t)$		
$v_i(t)$	The controlled vector at time t of zone i	-	$v_i(t)$	The controlled vector at time t of zone i	-
Uncontrolled variables, $u_i(t)$			Uncontrolled variables, $u_i(t)$		
h	Hour of day	Integer	h	Hour of day	Integer
d	Day of week	Integer	d	Day of week	Integer
S_i	Supply air temperature of each zone i	°C	H_i	Indoor humidity of the zone i	%
S_{ac1}	Supply air temperature of AC1	°C	T_i^{out}	Outdoor air temperature	°C
Hd_i	Heating demand of zone i	CFM	T_{i+p}^{out}	Predicted Outdoor air temperature	°C
T_i^{out}	Outdoor air temperature	°C	P_i	Power use of zone i	kW
T_{i+p}^{out}	Predicted Outdoor air temperature	°C			
P_i	Impact of damper position on temperature value	kW			
Target Variables, $y_i(t)$			Target Variables, $y_i(t)$		
T_i^{in}	Indoor temperature of zone i	°C	T_i^{in}	Indoor temperature of zone i	°C



(a) CAV system for one zone.



(b) Air handling unit AC1 with VAV type of HVAC system.

Figure 3.1 Schematic diagram of air handling unit in both buildings with CAV and VAV systems
(a) represent CAV-building, and (b) represent VAV-building

3.4 Data-driven framework for modeling IAT

3.4.1 Pre-processing methodology

3.4.1.1 Data collection and feature selection

The data was collected from November 1st, 2018, at 12 a.m. to March 31, 2019, at 11:59 p.m. with 10-minutes sampling intervals. Since not all the sensors are sending the data at the same time step, we developed pre-processing algorithms to sample and interpolate the data every 10 minutes.

A feature selection process is executed to obtain a set of principal variables using Extra Trees classifier and correlation techniques. We apply this method to each buiding datasets. Significant features are selected as input to predict the IAT and they are summarized in Table 3.3. In order to build predictive models, the selected features include context-information are categorized into three groups:

- Controlled features: Includes current control actions that impact HVAC system operations. The set $v_i(t)$ is the vector of the control variables at time t for each zone i as depicted in Table 3.2. The set of control variables depends on the type of building as shown in section 3.3.
- Uncontrolled features: The set $u_i(t)$ is the vector of the measurable input variables at time t for each zone i (e.g. the supply air temperature, the outdoor air temperature, the impact of damper position on temperature value, etc.).
- Target features: The set $y_i(t)$ is the vector $T_i^{in}(t)$ of IAT for each zone i.

We add the hour of day and day of the week as inputs. The hour input leads to know the difference between temperature profile during occupancy and unoccupancy time. The day input leads to distinguish between business and weekend days. All selected features are normalized between 0 and 1 before they are used for training, to prevent the dominant effect of particular variables. The equation in (3.3) is used to scale the variables into [0,1].

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3.3}$$

Where x_{scale} represent the scaled variable, x define the variable value before scaling, x_{min} and x_{max} are the minimum and maximum values of the dataset to be scaled, respectively.

3.4.1.2 Model training organization for multi-step prediction

After data pre-processing steps, the dataset was split into randomly sampled training (60 % of the data), validation (20 % of the data) and testing (20 % of the data) sets from five months of data. Models are developed using the training and validation datasets and the prediction results are from the test dataset. The IAT can be easily predicted in short term with only 10 minutes ahead prediction since they follow a slow dynamic process. However, a long-term prediction is needed for optimal operational of the HVAC system. To create the dataset to train the multi-step prediction model, we test different configurations, with a different number of previous time steps and future time steps. In this paper, we looked at multivariate inputs for multi-step time series forecasting model. The multivariate multi-step time series forecasting is a challenging task, especially in the preparation of time series data and the definition of the shape of multiple inputs and multi-step outputs for the model. Therefore, the time series data are transformed into a supervised learning problem. Each dataset of each building was manipulated and re-scaled in such a way that it can feed the prediction model. The multivariate time series dataset for each zone i is defined as:

$$X_i^l(t) = \begin{bmatrix} v_i(t-l+1) & u_i(t-l+1) & Y_i(t-l+1) \\ v_i(t-l+2) & u_i(t-l+2) & Y_i(t-l+2) \\ v_i(t-l+3) & u_i(t-l+3) & Y_i(t-l+3) \\ \vdots & \vdots & \vdots \\ v_i(t-1) & u_i(t-1) & Y_i(t-1) \\ v_i(t) & u_i(t) & Y_i(t) \end{bmatrix} \tag{3.4}$$

Each row of the matrix $X_i^l(t)$ represents the input vector given to the network at each time step. The sliding window algorithm is applied to define the shape of training data sets and predicted vectors. Window method leads to the use of a set of recent last time steps to predict the next time step. The window length l represents the number of past time steps used before the predicted horizon p, and it defines the length of the data over which the algorithm train the data. The window moves as the new data comes in, sample by sample, over the data used for training. In fact, the algorithm uses the recently measured data samples to replace the previous data frame. Consequently, the model can be retrained and updated using the newest dataset. For instance, to predict p time-steps, we use a window of l size which include l prior input vectors. The size of the window is a parameter that can be tuned according to past and future steps to predict. For example, if six prior input vectors (l=6=60min) of each of three inputs time series are used, and there are three-time steps (p=3=30min) of temperature must be predicted, then the input at a time t can be represented as:

$$X_i^6(t) = \begin{bmatrix} v_i(t-5) & u_i(t-5) & T_i^{in}(t-5) \\ v_i(t-4) & u_i(t-4) & T_i^{in}(t-4) \\ v_i(t-3) & u_i(t-3) & T_i^{in}(t-3) \\ v_i(t-2) & u_i(t-2) & T_i^{in}(t-2) \\ v_i(t-1) & u_i(t-1) & T_i^{in}(t-1) \\ v_i(t) & u_i(t) & T_i^{in}(t) \end{bmatrix} \tag{3.5}$$

And the output will be:

$$Y_i^3(t) = \begin{bmatrix} T_i^{in}(t+1) \\ T_i^{in}(t+2) \\ T_i^{in}(t+3) \end{bmatrix} \tag{3.6}$$

The input data is two-dimensional matrix, with six-time steps of samples including controlled, uncontrolled and target features. And, the output data is two dimensional matrix. For each sample of $X_i^6(t)$, three-time steps $Y_i^3(t)$ will be predicted for each zone i.

3.4.2 Data driven LSTM-based framework for multi-step IAT prediction

The predictive model of the IAT of each zone i has the form shown in equation 3.7.

$$T_i^{in}(t+k) = f(T_i^{in}(t), v_i(t), u_i(t)), \forall i \in [1, N] \tag{3.7}$$

The historical data collected from buildings have many features such as IAT, relative humidity, heating demand, damper positions, heating/cooling stages, etc. The interaction between these features is complicated and nonlinear. Therefore, it might be difficult to build a linear or polynomial regression, and it can provide a poor prediction accuracy. This is why nonlinear models like neural network models are used. To construct the predictive models we will use two types of neural network models, LSTM and MLP, which will be discussed in details in the next sections. We use direct-S2S forecasting models to predict different horizon for MISO and MIMO structure. This approach involves a heavier computational load than recursive forecasting used by Huang *et al.* (2015b). These models will be used in future work, to construct the optimization model for control purpose.

3.4.2.1 LSTM Model Definition

Few previous steps data can lead to getting an accurate predictive model; however, in some cases, older data can lead to recognizing general trends that recent data fail to show. This problem is called Long-Term Dependencies. The characteristic of MLP and basic RNN cannot solve this problem. On the one hand, MLP does not consider the dataset as a time series. Moreover, RNN fails to consider recent with distant past data in the learning phase. To deal with long terms dependencies in time series data, we use the LSTM model introduced by Schmidhuber et al. Gers, Schraudolph & Schmidhuber (2002). LSTM is one of many variations of the RNN. The ability of LSTM to reduce the vanishing and exploding gradient problems efficiently makes such an approach more appropriate for contexts having a long-term dependency problem. Since the HVAC data is sequential, and future outputs depend not only on the current values of inputs but

also on the previous information; hence a model based on LSTM is a good choice to predict IAT in the HVAC system. The main advantage of LSTM is the use of gates Hochreiter & Schmidhuber (1997) to manage its own memory by choosing to update or not the information goes through the cell. In fact, LSTM network is able to learn long-term dependencies from an input sequence thanks to its internal memory cells. An example of LSTM cell is described in Fig. 3.2.

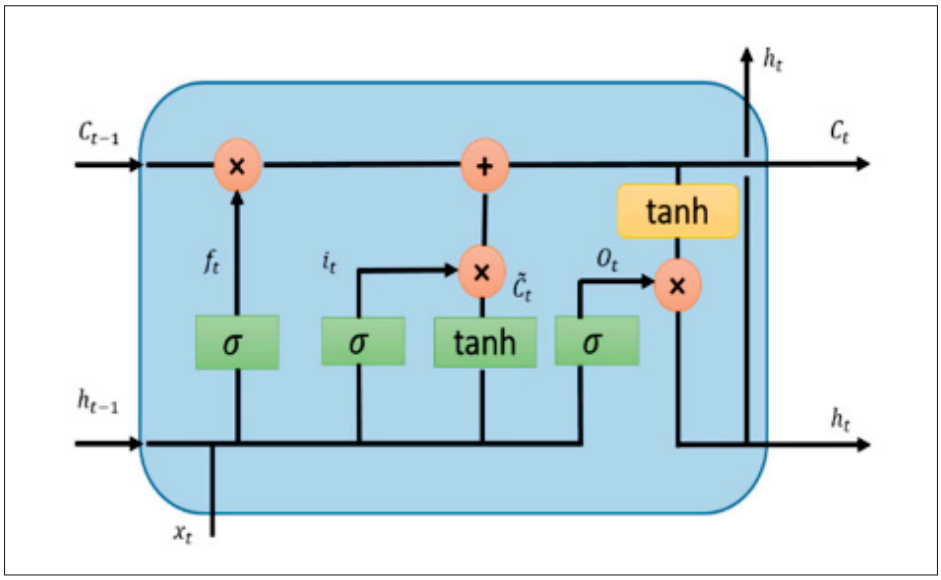


Figure 3.2 Diagram for LSTM cell
Taken from Alom *et al.* (2019)

The information will be added or removed according to the cell state defined by three different gates. The input gate i_t is responsible for the process of controlling the input activation and adding new information to the cell state. The forget gate f_t is responsible for deciding if the memory cells require to remember or forget its former status. The output gate o_t controls the output activation and determines if the information from the current cell states needs to be sent or not to the next layer. The equations for the input gate i_t, forget gate f_t and output gate o_t can be expressed by:

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t + b_i\right]\right) \tag{3.8}$$

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t + b_f\right]\right) \tag{3.9}$$

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t + b_o\right]\right) \tag{3.10}$$

Where W_i, W_f and W_o are the weight matrices, b_i, b_f and b_o are the biases for the input gate, forget gate and output gate, respectively; h_{t-1} is the previous hidden state and x_t is the input at current time step. The σ operator is the logistic sigmoid function and it is used as an activation function in the hidden layer which range from 0 to 1 and it is described by (3.11).

$$\sigma(x) = (1 + e^{-x})^{-1} \tag{3.11}$$

3.4.2.2 LSTM-based direct Sequence to Sequence (S2S) prediction architecture

LSTM is useful for different types of applications, which need various architecture according to the studied problem. In this paper, the problem can be formulated as, given a time series of observations as input, predict a sequence of observations as output for a range of future time steps.

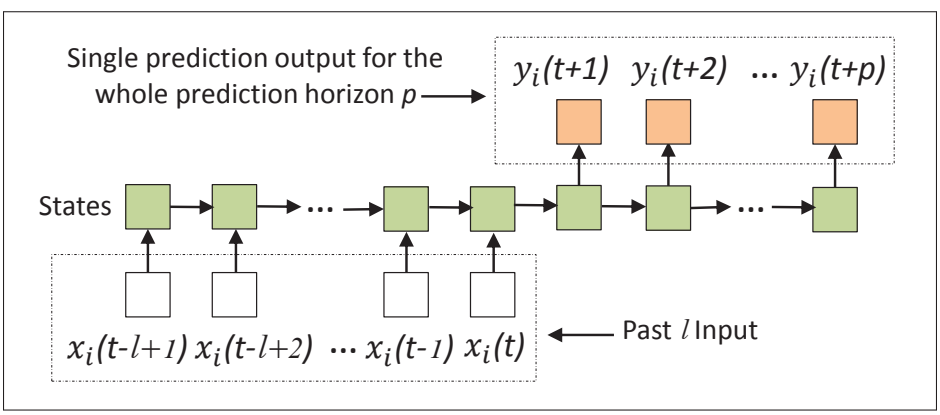


Figure 3.3 LSTM-based direct-S2S for MISO architecture

In order to further improve the flexibility of the temperature forecasting methodology, an LSTM based direct sequence to sequence (direct-S2S) architecture is investigated to solve the defined problem. This method was used in the video classification problem, which takes video frames as

input and tries to label each frame of the video with the consideration of the temporal evolution of the features for each time-step Lipton, Kale, Elkan & Wetzel (2015).

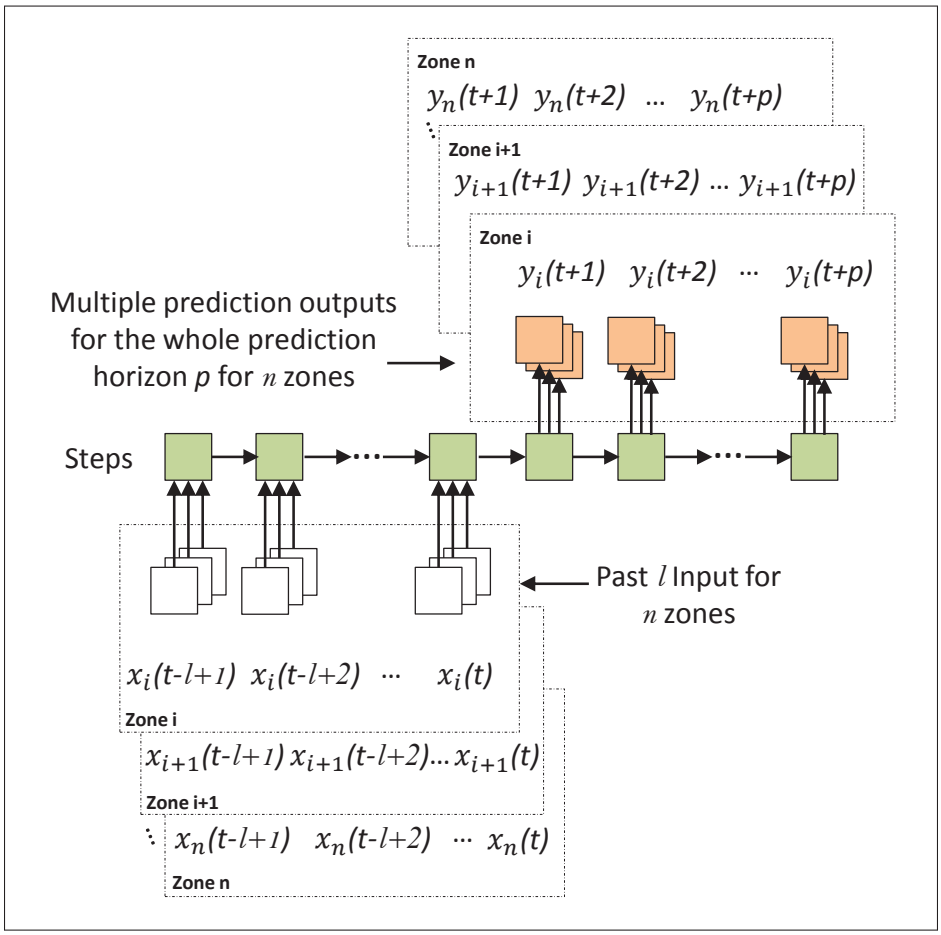


Figure 3.4 LSTM-based direct-S2S for MIMO architecture

Two direct-S2S models are developed for MISO and MIMO architectures. The direct-S2S for LSTM-MISO architecture uses the input matrix $X_i^l(t)$ with l past time steps to predict the output vectors $y_i(t+1), y_i(t+2), ..., y_i(t+p)$ with p time steps ahead, as shown in the Fig. 3.3. For the MISO architecture, one model is developed for each zone i. However, in the case of direct-S2S for the LSTM-MIMO architecture, one model is developed for all the zones, as shown in the Fig. 3.4. It includes as input all n zones feature vectors, $x_i, x_{i+1}, ..., x_n$ with all l past time steps of each feature vector. All controlled variables of all n zones are included in the input vectors. Moreover, this architecture has n output prediction vectors, $y_i, y_{i+1}, ..., y_n$ with p future steps

each. The two time steps, l and p, have a variable length. The main advantage of direct-S2S architecture is that it allows tuning l to have the best prediction performance of p steps. As discussed in section 3.5, we set a time step ahead to 2 hours and we tune l to 5, 10 and 12 hours, then choose the l giving the best prediction performance.

3.4.3 Data driven predictive models deployment

3.4.3.1 Baseline models deployment

The proposed models are compared with relevant past studies' models as baselines and there are as follows:

- MLP Huang *et al.* (2015a): MLP is a class of feedforward artificial neural network. MLP connects multiple layers in a directed graph. In this paper, the MLP model implemented includes three layers. The first layer is fed by a set of input features presented in Table 3.3. The second layer is a hidden layer, containing 200 neurons. The third layer is the output layer with p linear neurons. A direct MLP-MISO and MLP-MIMO models are implemented for VAV and CAV system cases.
- NNARX Delcroix *et al.* (2020): this network is implemented using a recursive prediction method. The exogenous inputs contain the controlled variables $v_i(t)$ and uncontrolled variables $u_i(t)$. We used the forecasted weather data available online, and the real observations for $v_i(t)$. The number of hidden layers and neurons are set to 2 and 200 respectively. The activation function is ReLU and the solver is Adam. The NNARX-MISO architecture is implemented for VAV and CAV system use cases.
- CANN Liang *et al.* (2019): The context-aware neural network model (CANN) is based on the model proposed in Liang *et al.* (2019), named UrbanFM. CANN uses two components: 1) the external factor fusion component to integrate context information and 2) the inference network component to include the IAT target feature. The inputs of the first components are the controlled variables $v_i(t)$ and uncontrolled variables $u_i(t)$. The embedding external factors vector concatenate the continuous features like outdoor temperature $T_i^{out}(t)$ and

categorical features include the hour of day h, the day of the week d, the on/off controlled variables $v_i(t)$. This vector is fed into the feature extraction module of the first component to design the complicated interaction. The inputs of the second components concatenates the context features extracted from the first component and the target information (IAT). Then the output of the first and second component are concatenated to fit a convolution layer and predict the future steps of IAT.

3.4.3.2 LSTM models deployment

To consider a direct-S2S architecture, LSTM model might transform the input sequence into the correct output sequence representation in the learning phase. Therefore, we design the LSTM model with four fully connected layers used repeat vector and time distributed layers to form the LSTM model for MISO and MIMO architectures. For the case of LSTM-MISO model, the vector-matrix $x(t)$ represents the input for the first LSTM layer, which consists of 200 LSTM cells. The repeat vector, repeats one time for each time step p the incoming 1D inputs vector from the previous LSTM layer to create 2D matrix output in order to include multiple future time steps in the model. For instance, if the shape of the input was (32), and we want to predict three times ahead, so the output shape of the repeat-vector layer would be (3, 32). The output 2D matrix from the repeat vector layer, passes as the input to the LSTM layer. At each moment, the output of the LSTM layer is connected to the fully connected Dense layer. Then, time distributed layer applies a specific layer such as Dense layer to every sample it receives as an input to get the final output y_{t+1} with p time steps ahead. The exact architecture for direct-S2S LSTM-MISO model is as follows:

1. Input $(x_i(t-l), x_i(t-l+1), ..., x_i(t))$
2. LSTM layer (N=200, activation function=ReLU)
3. Repeat vector layer (N=1)
4. LSTM layer (N=200, activation function=ReLU)
5. Time distributed layer (N=100, activation function=ReLU)
6. Fully connected (N=1, activation function=linear)

7. Output $(y_i(t+1), y_i(t+2), ..., y_i(t+p))$

The main differences between MISO and MIMO deployment architecture are the input and output data. The exact architecture for direct-S2S LSTM-MIMO model is as follows:

1. Input ($x_i, x_{i+1}, ..., x_n$ with all l past time steps of each vector)
2. LSTM layer (N=200, activation function=ReLU)
3. Repeat vector layer (N=p)
4. LSTM layer (N=200, activation function=ReLU)
5. Time distributed layer (N=100, activation function=ReLU)
6. Fully connected (N=p, activation function=linear)
7. Output ($y_i, y_{i+1}, ..., y_n$ with p future steps each)

3.4.3.3 Modeling Error

To evaluate the performance of proposed predictive models, three metrics in 3.12, 3.13 and 3.14 are used to evaluate the models: the mean absolute percentage error (MAPE), the root mean square error (RMSE) and the mean absolute error (MAE). The MAPE measures the size of the error in percentage terms, and a lower result indicates better performance. A high MAPE score indicates a high error range. The RMSE penalizes more larger error values, and can be bigger than MAE for outliers. MAE is a commonly used metric to evaluate forecast accuracy, and corresponds to the mean value of the sum of absolute differences between actual and forecast values.

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{3.12}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (y_k - \hat{y_k})^2} \tag{3.13}$$

$$MAE = \frac{1}{n} \sum_{k=1}^{n} |y_k - \hat{y_k}| \tag{3.14}$$

Where y and $\hat{y}$ define the real and predicted outputs respectively, and n is the total observation number.

3.5 Results and discussion

The performance of multi-step IAT prediction models is evaluated on LSTM, NNARX and MLP models applied on real data collected from hotel and retail store in Montreal with VAV and CAV system respectively. Five zones are investigated for a VAV-building and three zones for a CAV-building. Only winter season data is considered in this study, but the same models can be applied to other seasons in further studies. The choice of the number of previous steps for the training model is not obvious and it can affect the performance of the prediction. An example of the effect of using a different number of previous time steps to predict two hours in zone 1-2 in VAV-building is showed in TABLE 3.4. It is observed that the use of ten hours to predict two hours gives the best performance. More experiments have been executed on different zones to find the optimal number of previous steps for different number of prediction steps ahead. Finally, we used last 1 hour and 5 hours to predict 30 minutes and 1 hour ahead, respectively. Furthermore, we consider ten previous hours to predict 2 hours, 4 hours, and 6 hours ahead. In the following, we present the feature selection procedure and then we evaluate the performance of multi-step prediction models for MISO and MIMO architectures.

Table 3.4 Effect of the number of previous steps to predict two hours in zone 1-2 in VAV building

Model	Previous steps (h)	Future steps (h)	MAPE (%)	RMSE (°C)	MAE (°C)
1	5	2	0.4880	0.0225	0.1077
2	10	2	**0.4264**	**0.0173**	**0.0941**
3	12	2	1.0651	0.1187	0.2354

Table 3.5 Datasets and feature selection

Datasets	Feature selection	MAPE (%)			RMSE (°C)			MAE (°C)		
	VAV-Building	MLP	NNARX	LSTM	MLP	NNARX	LSTM	MLP	NNARX	LSTM
VF1	T_i^{in}, P_i,Hd_i, T_i^{out}, h, d	**0.8346**	0.5145	0.7502	0.0851	0.0865	0.0615	**0.1842**	0.1142	0.1666
VF2	T_i^{in}, S_i,P_i,Hd_i, T_i^{out}, h, d , D_i, HS_{1i}, HS_{2i}	0.8775	0.5385	0.6708	0.0868	0.0911	0.0527	0.1939	0.1193	0.1487
VF3	T_i^{in}, S_i,P_i, Hd_i,T_i^{out}, h, d , D_i, MD_a,SF_a, H_a	0.8465	0.5165	0.8633	**0.0807**	0.0821	0.0796	0.1871	0.1146	0.1921
VF4	T_i^{in}, S_i,P_i, Hd_i,T_i^{out}, h, d , D_i, HS_{1i}, HS_{2i},MD_a,SF_a, H_a	0.8431	**0.4989**	**0.5694**	0.0853	**0.0803**	**0.0380**	0.1861	**0.1108**	**0.1262**
	CAV-Building	MLP	NNARX	LSTM	MLP	NNARX	LSTM	MLP	NNARX	LSTM
CF1	T_i^{in}, H_i^{in}, T_i^{out}, h, d	0.7857	0.5819	0.5740	0.0565	0.0608	0.0293	0.1617	0.1198	0.1181
CF2	T_i^{in}, H_i^{in}, T_i^{out}, h, d, P_i	0.7743	0.5737	0.5606	0.0545	0.0595	0.0285	0.1593	0.1181	0.1155
CF3	T_i^{in}, H_i^{in}, T_i^{out}, h, d, P_i, HS_{1i}, HS_{2i}	0.7585	0.5335	0.5505	0.0493	0.0525	0.0245	0.1561	0.1099	0.1140
CF4	T_i^{in}, H_i^{in}, T_i^{out}, h, d, P_i, HS_{1i}, HS_{2i}, F_i	**0.7375**	**0.4822**	**0.5043**	**0.0479**	**0.0476**	**0.0208**	**0.1519**	**0.1042**	**0.1**

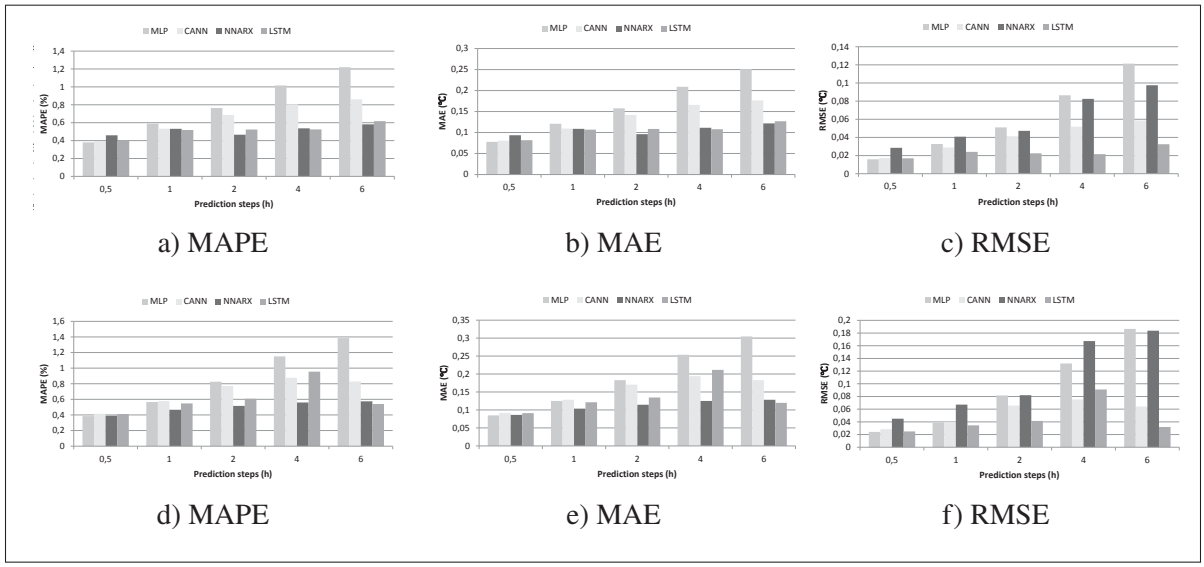


Figure 3.5 MISO-Model prediction error for two buildings
(a) (b) (c) represent zone 2 in CAV-building , and (d) (e) (f) represent zone 1-2 in VAV-building

3.5.1 Feature selection experiments

Since we predict from 30 minutes to 6 hours, we assume that two hours of future time steps prediction can give a good understanding of what features must be used to improve the prediction performance. Experiments have been done with three datasets having no HVAC control parameters (VF1, CF1 and CF2), and five datasets having controls (VF2, VF3, VF4, CF3, and CF4). These datasets are built from existing VAV and CAV datasets by adding or removing some features. With each dataset, we evaluate the performance of LSTM and two baseline (MLP and NNARX) models using different metrics.

TABLE 3.5 shows, in the case of zone 1-2 in VAV-building, some features have positive impacts on the LSTM and NNARX models, but no impact on the MLP model. We notice that adding input features of control parameters for the VAV (VF2) and for the AC1 (VF3) separately, have negative impacts on MLP, NNARX and LSTM. Furthermore, models using dataset including input features of control parameters for both AC1 and VAV (VF4) provides the best prediction performance for LSTM and NNARX. However, MLP gives the best performance when control parameters are not included in the dataset (VF1), but it achieves the lowest performance comparing to VF4. We notice that the missing of control features in the dataset CF1 in the case of CAV-building, decreases the prediction. Moreover, adding control variables to the model CF4 for CAV buildings increases the prediction performance of LSTM and NNARX models. The temperature behavior depends on the time of the action taken by the control parameters. Unlike MLP, the LSTM model takes into account the sequence of time behavior, so including the control variables as inputs in the LSTM model increases the performance of the long-term prediction accuracy. Similarly, NNARX includes the future control parameters to predict future steps, so the consideration of these data makes the prediction more accurate. Therefore, 13 features used in VF4 and the 9 features used in CF4 have a significant impact on the multi-step prediction model of IAT for both single-zone in VAV and CAV buildings.

3.5.2 Performance evaluation of multi-step prediction models

3.5.2.1 Single-zone prediction results

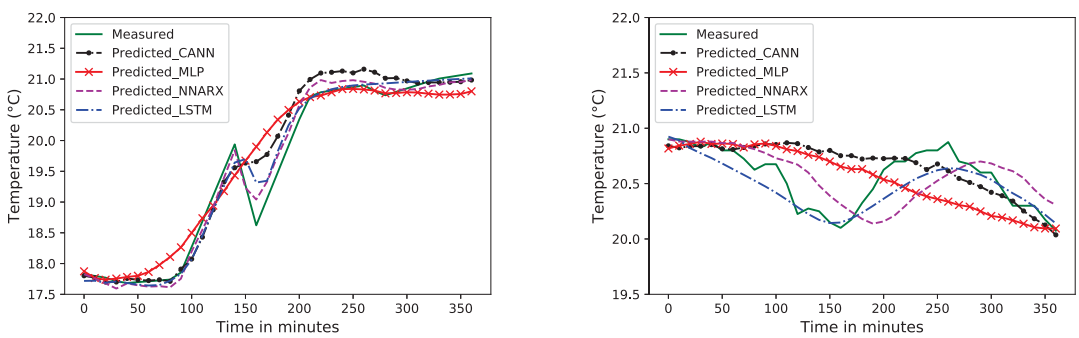
This section discusses the prediction performance of LSTM-MISO model. We used MLP, CANN, NNARX with MISO stucture as a baseline models. The prediction accuracy of the all models is evaluated by comparing three metrics, MAPE, RMSE and MAE. The numerical results of LSTM-MISO and baseline models and the different steps used are shown in details in Fig. 3.5. The Fig. 3.5 (a), (b) and (c) represent the MAPE, the MAE and the RMSE results respectively, to predict 30 minutes, 1 hour , 2 hours, 4 hours and 6 hours for the zone 1-2 in CAV-building. Fig. 3.5 (d), (e) and (f) represent the MAPE, the MAE, and the RMSE results, respectively,

to predict 30 minutes, 1 hour, 2 hours, 4 hours and 6 hours for the zone 2 in VAV-building. We notice that, in the two cases of building, for a short period the improvement by applying LSTM is not noticeable compared to baselines, but as soon as we go further in time (2, 4 and 6 hours) the improvement by LSTM gets more and more important. The MAPE and MAE scores of NNARX and LSTM models are quite similar, especially for 6 hours prediction. In the case of CAV buildings, the NNARX for 6h prediction model gives the best MAPE and MAE scores, as shown in Figures 3.5 (a) and (b). It is because NNARX uses the measured/real values of exogenous inputs (control parameters and outdoor temperature) to predict multi-step ahead Delcroix *et al.* (2020). NNARX performs the multi-step prediction by feeding back the IAT prediction output and the future exogenous input information as the input for the next prediction. Indeed, we observe that RMSE of the NNARX model is higher than RMSE of LSTM and CANN models because of the error propagation over time caused by the recursive prediction method used, since RMSE penalizes large error values. The Figures 3.5 (a), (b) and (c), indicate that the error of LSTM-MISO model increase according to the time prediction steps in the CAV-building. However, it is not the case for VAV-building, as shown in Figures 3.5 (d), (e) and (f) where the largest error occurs when the LSTM-MISO model tries to predict 4 hours ahead in VAV-building. The performance of MISO-LSTM to predict 6 hours ahead is better than to predict 4 hours ahead in VAV-building. Fig. 3.6 presents the results of 6-hour ahead prediction of indoor temperature for zone 2 and zone 1-2 in CAV and VAV building respectively, using the LSTM-MISO and baseline approaches. It can be seen that LSTM-MISO and NNARX models work reasonably well for both types of buildings and they are close to real measurements. However, for MLP and CANN models, the prediction variability follows the real measures, but the predicted values move around the real values. The high prediction error is due to the neglect of time sequence dependencies. Although CANN model tries to capture the sequential relationship among inputs by using the external factor fusion component, it is less powerful than the gates mechanism used in LSTM model. Due to the proximate results of NNARX and LSTM models, we study further the standard deviation of error and prediction efficiency of both models.

Standard deviation of error

Figures 3.7 (a), (b), (c) and (d) show the mean error in terms of temperature for each time step

predicted on the 20% of testing data and the standard deviation of this error for LSTM-MISO and NNARX-MISO models in CAV and VAV building. We notice the error of LSTM-MISO in under 0.35 °C for both types of buildings. In the same time, the error of NNARX is over 0.45 °C. In reality, the precision of temperature sensors is often ±0.5 °C, this value is considered as an appropriate benchmark for the accuracy of models ASHRAE (2002). Although the error of NNARX is within the error benchmark, it is less accurate than LSTM. An important remark is the performance of NNARX-MISO deteriorates along with an increasing prediction horizon compared to LSTM-MISO. In other words, the estimated values of NNARX-MISO generally deviate from measured values for long-term prediction due to error accumulation overtime. On the other hand, Figures 3.7 (c) and (d) clearly show LSTM model performance over a 6-hour period is very similar to that of 30-minute period. Consequently, the increasing number of advanced time steps does not deteriorate the prediction performance of LSTM-MISO model due to the direct prediction method.



a) Zone 2 in CAV-building

b) Zone 1-2 in VAV-building

Figure 3.6 Results for 6 hours ahead for indoor temperature prediction in (a) zone 2 in a CAV-building, and (b) zone 1-2 in a VAV-building

Prediction efficiency

We compare the prediction efficiency of LSTM and NNARX in terms of execution time. As depicted in Table 3.6, the execution time of NNARX is significantly higher than LSTM for both types of buildings.

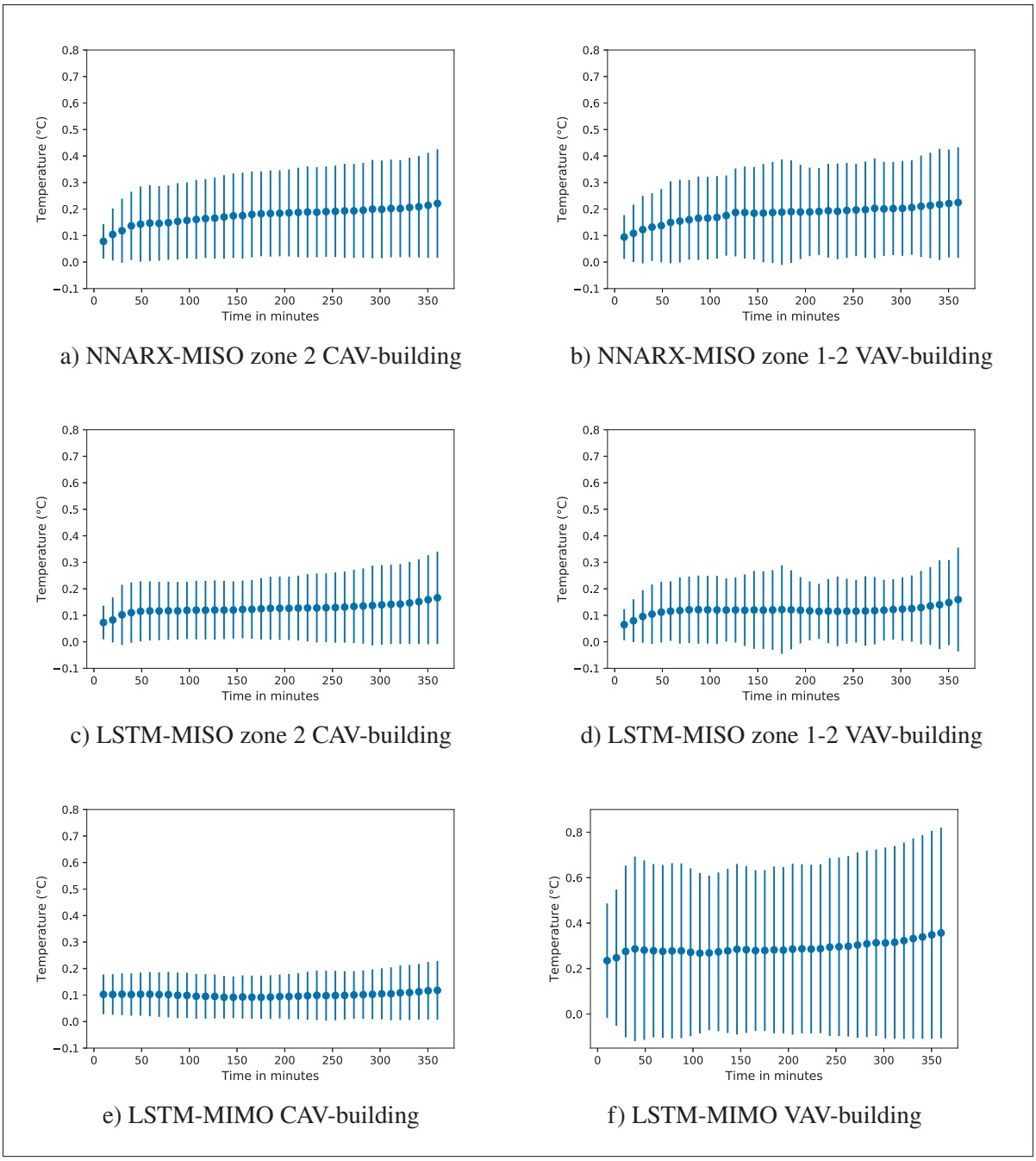


Figure 3.7 The standard deviation of Error for MISO and MIMO models for CAV and VAV buildings for 6 hours prediction ahead
(a) (c) (e) CAV-building, and (b) (d) (f) VAV-building

In a predictive control system, if the control horizon is 5 minutes and the prediction horizon is 4 hours, the execution time of IAT prediction could not exceed the control horizon to be

included in the predictive control system. As shown in Table 3.6, for 4 hours prediction, the execution time of NNARX is higher than 5 minutes. In this case, NNARX is not appropriate for a predictive control system against LSTM should be used because its execution time is 15 seconds only.

Table 3.6 Execution time (in seconds) of NNARX and LSTM models for CAV-building and VAV-building

	CAV-Building		VAV-Building	
	NNARX-MSIO	LSTM-MSIO	NNARX-MSIO	LSTM-MSIO
30 min	80,71	4,97	83,59	4,83
1 h	182,13	10,20	186,06	8,84
2 h	203,19	15,25	287,31	14,45
4 h	472,29	14,88	379,22	16,79
6 h	550,21	17,54	565,80	17,41

3.5.2.2 Multi-zone prediction results

In this section, we implement a multi-zone model which predicts the IAT for all the zones in the building using all control parameters vectors as input. Fig. 3.8 shows a comparison of experimental results between LSTM-MISO models and LSTM-MIMO models. It describes the mean errors of all investigated zones of each building for single-zone and multi-zone prediction models. It shows that in the case of CAV-building, the MAPE for LSTM-MIMO model is better than LSTM-MISO model. Furthermore, the MAPE, MAE and RMSE errors for all three zones decreased after the LSTM-MIMO model is used for 30 minutes and 6 hours prediction. For instance, it can be observed that, the MAPE reduces with more than 0.3% on average to 6 hours prediction ahead. We notice that in Fig. 3.7 (e), the mean error with its standard deviation in terms of temperature for each time step predicted for LSTM-MIMO in the case of CAV-building is better than for LSTM-MISO model (Fig. 3.7 (c)) and it does not exceed 0.2 °C which is less than the accuracy value of temperature sensor (±0.5 °C) ASHRAE (2002). However, the error in LSTM-MIMO model for VAV-building case is worse than LSTM-MISO and NNARX-MISO. As the CAV-building is an open space, and it is a light-weight structure, the thermal interaction among all adjacent zones influences the temperature prediction results. So, the consideration of

all parameters as inputs in the model, and the exchanged information among zones increases the accuracy of the LSTM-MIMO model.

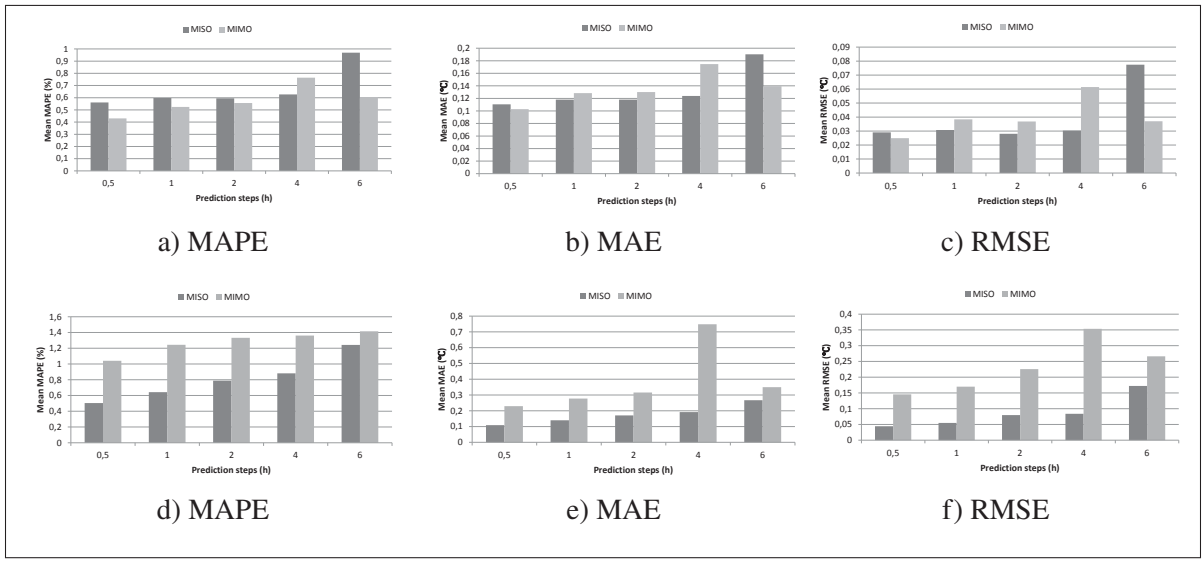


Figure 3.8 Comparison between MIMO and MISO Model prediction error for two buildings
(a) (b) (c) represent CAV-building, and (d) (e) (f) represent VAV-building

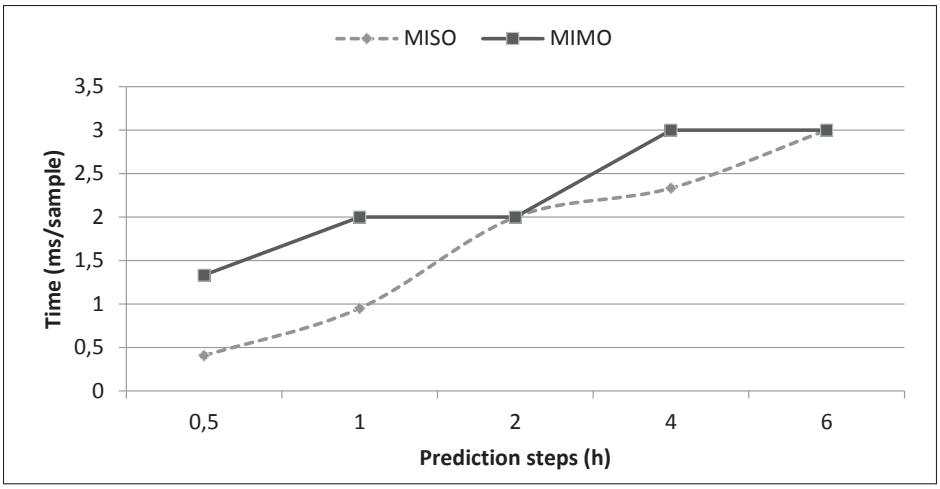


Figure 3.9 Prediction time execution for CAV-building

On the other hand, in the VAV-building with heavy-weight building structure, the interaction among adjacent zones does not influence the prediction performance. The size of VAV-Building

zones is not all uniform, and there is no significant heat transfer from zone to zone. For these reasons, LSTM-MISO model performs better for the VAV-building use case. Predicting a MIMO model is more expensive in terms of time compared to a MISO model, as expected. For example, as shown in Fig. 3.9, it takes 1.33 ms/sample using a MIMO model while only 0.4 ms/sample using a MISO model to predict 30 minutes, which can be explained by the large amount of input in the MIMO model. However, in Fig. 3.9 we notice that the execution time for predicting two hours and six hours using LSTM-MIMO model is comparable to the time using LSTM-MISO models. Moreover, as shown in Fig. 3.8, the prediction error for MIMO models is lower than MISO models for two and six hours ahead. As a result, executing LSTM-MIMO model for online prediction, for two and six hours-ahead is more computationally efficient than LSTM-MISO models.

3.6 Conclusion

This paper presents an LSTM-MISO and LSTM-MIMO framework based on direct-S2S architecture to predict multi-step ahead of IAT for two real-world cases on different buildings. While most of prior work only investigate a specific type of HVAC system, the modeling framework proposed in this study covers both VAV and CAV buildings. The consideration of control variables as the input increases the prediction accuracy of the LSTM models. The proposed framework considers a direct-S2S prediction instead of a recursive one, which increases the accumulation of prediction error throughout the prediction step ahead. This study showed that LSTM-MISO model is efficient for VAV buildings. However, since there is an effect of thermal coupling between adjacent zones in CAV building because of its open space area, it is found that the overall prediction accuracy increases using the MIMO model. We can conclude that LSTM-MIMO is a valuable method for modeling IAT in a light-weight building with CAV type of HVAC system. In future work, the proposed LSTM-based data-driven framework for multi-step prediction ahead of IAT will be used to design predictive control approaches in order to decrease energy consumption, e.g. load shifting control, demand-limiting control or optimal start-stop time control.

CHAPTER 4

CONTEXT-AWARE MODEL PREDICTIVE CONTROL FRAMEWORK FOR MULTI-ZONE BUILDINGS

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Article published in *Journal of Building Engineering*, October 2021

Abstract

Today, Model predictive control (MPC) has largely been used to optimize energy consumption and maintain thermal comfort in buildings. However, to build an online MPC model in building, the dynamics of the physical system must be accurately modeled, which is a time-consuming and costly task. Neural network models help to overcome the modeling problems especially with the availability of historical data. This research presents a novel online data-driven control framework named Model Predictive Control via Genetic algorithm (MPC-GA) allowing the optimal operation of the heating, ventilation, and air conditioning system and has been experimentally validated in a multi-zone retail building. The MPC-GA combines an attention-based neural network time series multivariate prediction model with a MPC framework. The prediction model used a dual-stream neural networks based on multivariate time series of controlled and uncontrolled inputs. The attention mechanism is applied on controlled parameters to give them more weight to better predict the zone temperature. The prediction model is used as input for the optimization framework which minimizes: energy consumption, peak demand and discomfort during occupied hours under self-tuned setpoint, temperature ramp and equipment cycling constraints. A heuristic search algorithm using a genetic algorithm is used to solve the

online data-driven MPC-GA models and obtain the future optimal combination settings of all controls for all the zones over a prediction horizon. The benchmark results showed that the MPC-GA outperforms RBC control systems with more than 50% and 80% reduction in energy consumption and discomfort respectively.

Keywords: HVAC, multivariate time series, neural network, attention mechanism, MPC, genetic algorithm, optimal controls.

4.1 Introduction

The total energy used in commercial buildings accounts for 40% of the global energy consumption Shaikh *et al.* (2014) and up to 30% of carbon dioxide emissions Costa *et al.* (2013). A survey conducted in the United States has shown that in buildings, more than 50% of the energy consumed is related to heating, cooling, ventilation and air conditioning (HVAC) systems, while lighting accounts for about 9% DoE *et al.* (2011). The main question that should be addressed is, what are the best approaches to cool or heat buildings in order to save energy and reduce carbon footprint without affecting the householder's comfort? On today's advanced HVAC systems, rule-based controllers (RBC) are generally used. However, RBC cannot generalize their rules at a building level Privara *et al.* (2013), due to the high complexity of managing their defined rules and continuously monitoring and tuning the HVAC control signals to reduce global energy consumption while simultaneously ensure a thermal comfort. In addition, RBC are not anticipatory controller: they operate on the basis of the current state of the system rather than projecting into the future and deciding on the next appropriate action Afram *et al.* (2017). Model predictive control (MPC) is an optimal control that can improve energy efficiency in HVAC systems. It has been proven efficient control solution for buildings by providing 17% energy savings more than RBC Shaikh *et al.* (2014); Sturzenegger *et al.* (2016). Instead of being a reactive control, MPC is a predictive control that uses weather forecast and occupancy data over a prediction horizon and executes the appropriate control signals at the present time. The major challenge with MPC is to accurately model the dynamics of the physical system, which requires tuning of the system controller parameters and deploying new sensors in the

building Sturzenegger *et al.* (2016). This task is complicated, requires expertise to use and time-consuming especially when there are many types of buildings to control. Modern smart buildings are equipped with a variety of sensors, such as temperatures and humidity probes, power meters, air-pressure transducers, and so on. The availability of historical monitoring data from this panoply of sensors already deployed opens the opportunity to develop data-driven solutions based on Artificial Intelligence (AI) algorithms Chen *et al.* (2015); Huang *et al.* (2015a). The main advantage to use data-driven control is to reduce the cost and time consuming task caused by MPC that requires an accurate and complex modeling processes Serale *et al.* (2018). To implement MPC model, real-time optimization is needed with low computation time to generate a sequence of control signals for all the zones over prediction horizon.

Evolutionary algorithms like genetic algorithms (GA) have been widely applied to resolve the optimization problem related to MPC in HVAC systems. An optimization procedure combining GA, MPC and artificial neural network to minimize the energy consumption has been proposed in Reynolds *et al.* (2018), Garnier *et al.* (2015) and Asadi *et al.* (2014). However, none of the previously mentioned approaches has been validated in real time with the building's feedback states. It is not obvious that a building operator allows to implement a data-driven controller on a real building because the error of the prediction might disturb the built environment. Implementation in real buildings can lead to undesirable results such as temperatures that are too cold or too hot and drop the security of the controls. The data-driven control system should avoid these undesirable results because there is no turning back during the implementation phase. Moreover, the optimization models proposed in previous work focus mainly on energy efficiency and discomfort reduction. In this paper, the control problem considers a self-tuned setpoint, cycling and temperature ramp constraints in addition to energy, peak power and discomfort costs, and it has been implemented online in real building use case.

Unlike some prior work Reynolds *et al.* (2018); Garnier *et al.* (2015) that do not consider weather and occupancy forecasting parameters, past and future weather conditions, occupancy and controlled values are all included in our prediction model to improve the perdition accuracy and the control decision. The main challenge is developing a prediction model to consider the

impact of controls on temperature and close the control loop. The complex and non-linear interdependencies between multivariate time series, including control and uncontrolled parameters, make the prediction task more complicated. The typical LSTM models with an attention mechanism Lim *et al.* (2019); Nunez *et al.* (2019) failed to capture temporal patterns across multiple time steps. In this paper, we propose a context-aware multivariate LSTM (CAM-LSTM) based on dual-stream neural network with an attention mechanism which selects not only past but also future multivariate time series including controlled and uncontrolled inputs to predict a multi-steps temperature output. Firstly, the control and uncontrolled multivariate time series are fed independently into two parallel streams. The first stream includes one high-level and one low-level feature extraction components to model the complex mixtures of temporal patterns. The second stream includes the same components as the first one, in addition to an attention component which learns the dependencies among various controls and target features. To the best of our knowledge, this is the first work that uses attention with dual stream network in predictive control mechanism.

The proposed MPC-GA control system combines CAM-LSTM models based on an attention mechanism learned in offline mode and GA to generate the control sequence for the whole prediction horizon. The GA leads to find the optimal sequence combination of control signals, which minimize the cost function. The CAM-LSTM model uses this optimal combination as input to predict the future indoor air temperature (IAT). Experiments on real-world demonstrate the accuracy and robustness of the proposed MPC-GA control method.

The contributions of this paper are: 1) a CAM-LSTM models based on dual-stream neural network including attention mechanism which include past and future controlled and uncontrolled inputs; 2) an optimization model to minimize energy, power peak and discomfort that considers a self-tuned setpoint, cycling and temperature ramp as constraints; 3) The validation of the closed-loop MPC-GA control framework in a real multi-zone retail building.

This paper is structured as follows: Section 2 summarizes the prior work related to our research. Section 3 describes the use case used in this study and the global methodology of our proposed

data-driven optimization framework. Section 4 illustrates in details the CAM-LSTM model. The control design of MPC-GA framework is introduced in Section 5. Section 6 discusses the experimental results and compares the performance of the proposed models. Finally, we conclude key findings and present future research directions.

4.2 Related Work

This section describes relevant literature research on machine learning and optimization techniques used in data-driven control models in HVAC systems.

4.2.1 Machine learning approaches

Generally, prior work employed artificial neural networks (ANN) as black-box models to represent HVAC building systems and combined it with an MPC optimal control framework as discussed in Finck *et al.* (2019); Reynolds *et al.* (2018). Nevertheless, LSTM has been shown to outperform ANN in HVAC systems by as much as 50% of accuracy especially for time series data Mtibaa, Nguyen, Azam, Papachristou, Venne & Cheriet (2020). LSTM uses historical data and future instances, taking into account the inertia of the system. A preliminary work has been reported in Mtibaa *et al.* (2020), wherein we have modeled a multi-step temperature prediction in HVAC systems using an LSTM model and compared the performance of multi-input single-output (MISO) and multi-input multi-output (MIMO) architectures. However, only past controlled and uncontrolled parameters are used for the prediction. Additionally, a Neural Network Autoregressive with Exogenous Input (NNARX) model is proposed by Delcroix *et al.* (2020) which predicts the behaviors of the indoor air temperature. The experiments are performed with the same type of use-case building used in this paper. The accuracy results are very close to the LSTM-MISO used in Mtibaa *et al.* (2020). However, the authors in Delcroix *et al.* (2020) develop a one-step forecasting model, then use a recursive multi-step forecasting strategy to predict the future steps. Such recursive strategy degrades the performance of the model as the number of future steps increases, because prediction values are used instead of real observations and the error is compounded. In addition, the temporal dependency among

continuous variables is ignored, while the historical data collected from HVAC systems are generally time series data.

In this paper, we add context-aware attention component to the LSTM model to consider the sensitive relationship between temperature and control parameters. Liang et al. Liang *et al.* (2019) designed a framework named UrbanFM based on deep neural networks. An external factor fusion component is added to handle the context information (like the day of the week, time of the day, weather, other external factors) and capture near and distant spatio-temporal dependencies. This component plays an important role in providing a prior knowledge and improves the inference performance under sparse sampling. This module is integrated in the high-level feature extraction used in this paper to model the complex high-level interaction between input features. A data-driven control model was proposed in Jain *et al.* (2018) which combine multi-output regression trees with MPC. The proposed approach was applied to trade-off peak power reduction against thermal comfort in buildings. Yet, the modeling accuracy using single trees to represent multi-step prediction is strongly affected by overfitting and high variance. The authors in Smarra *et al.* (2018) replace the model dynamic in MPC by a set of linear regression model which changes from time step to time step. A regression model was used then extended to a random forest model. The proposed control model was applied to design the optimal ON/OFF scheduling for the heating system in order to save energy.

It is obvious that the availability of an accurate multi-step prediction model is extremely important in a data-driven MPC framework. As discussed in the previous paragraph, several deep learning models have been proposed and integrated with MPC to define a data-driven control methodology Garnier *et al.* (2015); Jain *et al.* (2018); Reynolds *et al.* (2018). However, they usually include black box models that do not take into account the physical aspect. They define a predictive model but ignore the sensitivities of control on temperature which can bias the optimization decision for the control outputs. For example, if the cooling controls are all OFF and it is hot outside, automatically the model should predict an increasing in the temperature behavior, which is not the case of models proposed by several related works. In general, when modeling temperature which should be used to decide the future control actions, it is essential

to capture the sensitivities of the temperature output with respect to known future inputs like control commands and outside temperature. In particular, at every time t, given the known future inputs and other inputs that are only historically known, the model should correctly describe the variations of the predicted temperature output, due to variations of the command input sequence including observed and future know values. Recent deep neural networks have considered the use of transformer networks with attention-based mechanism for multi-horizon time series forecasting Lim *et al.* (2019). In Nunez *et al.* (2019), they use the basic structure of encoder-decoder with attention model combined with MPC to control a paste thickener systems. Although attention mechanism improve long-horizon sequence, it have difficulties handling continuous time-series data which requires a strong temporal consistency. However, temporal consistency is a requirement for temperature prediction, as the control variables should remain stable over a short period of time to avoid unnecessarily cycling equipment. In Liu *et al.* (2020) and Zheng *et al.* (2018), the attention mechanism is used to capture the spatio-temporal relationships between multivariate time series and they will be used as a reference to compare our proposed prediction model. The use case demonstrated in this paper includes historical target parameters, historical and future known control and uncontrolled parameters. To model an appropriate data-driven control model, we propose a CAM-LSTM prediction model based on attention mechanism that considers the contribution of both control and uncontrolled parameters to dynamically model temperature behavior in the future. This prediction model is used in the core of the MPC process in the optimization problem.

4.2.2 Optimization approaches

Evolutionary algorithms has been widely applied to resolve the optimization problem related to MPC in HVAC systems. An optimization procedure combining GA, MPC and artificial neural network to minimize the energy consumption and it is proved to guarantee globally-bounded closed-loop stability Reynolds *et al.* (2018). They considering two different simulation scenarios (flat and time-of-use price tariffs). According to their results, they have achieved a reduction in energy consumption by around 25% compared to a baseline heating strategy. However, this

work did not consider weather and occupancy forecasting parameters in their prediction model and they only implement their approach on simulated building rather than real-world trial. A low-order ANN based models combined with MPC was developed to minimize the energy consumption of a multi-zone HVAC system Garnier *et al.* (2015). Researchers used GA to minimize the cost function. Also they used the predicted mean vote (PMV) index as a thermal comfort indicator. This strategy was compared with basic control techniques and resulted in 5.2% and 14.7% of energy saving during heating and cooling seasons respectively. However it does not include predicted weather as a model input failing to adjust control parameters in the future steps. Moreover, it was modeled using a simulation model generated in the EnergyPlus software and no real-world data was used for training or model validation. In Asadi *et al.* (2014), a GA is applied to solve a multi-objective optimization problem which trade-offs between the retrofit cost, energy consumption and thermal comfort. The authors demonstrated that GA is well suited for multi-objective problems and they showed that the simultaneous optimization of all three lead to good results in contrast to optimizing per an individual objective. However, their model is based on a simulation database that was generated from a comprehensive building model developed in TRNSYS to train and validate ANN models which is difficult to extend in real-building. Kampelis et al. Kampelis *et al.* (2019) have also used GA for power optimization of HVAC systems. They studied the trade-off between minimizing energy costs and maximizing thermal comfort by integrating PMV to ensure thermal comfort requirements. The control approach they proposed is not suitable for a real-time energy and comfort management application, as it is time-consuming to execute. An adjustment of the optimization parameters is necessary to conduct the deployment in real time. An adaptive supervisory model predictive on-off control algorithm is presented in Tyukov *et al.* (2017), including the predicted weather factor. The GA is used to optimize the cost function which can save up to 20-40% of gas consumption while maintaining comfort. However, this approach has not been validated in real time with the building's feedback states. In this research, we use GA strategy with low computation time to solve the online MPC optimization problem which minimize energy, peak power and discomfort costs and consider a self-tuned setpoint, cycling and temperature ramp constraints.

4.3 Smart Building Model

4.3.1 System description

The proposed control solution can be applied to any HVAC system with a rooftop unit (RTU). Consider an example of a retail building with an open space of around 1000 m^2 located in Montreal, QC, Canada. The building has three zones equipped with a RTU each and controlled by a separate thermostat per zone. Each RTU contains a fan with two heating and two cooling coils stages as described in Fig. 4.1. We assume that the speed of the fan is fixed and it is controlled by an ON/OFF switch. We assume that there is significant thermal coupling between the three zones since there are no walls between them. Given a zone i, it is controlled by a vector $\hat{u}$ including five control parameters $\hat{u}_{c1i}$, $\hat{u}_{c2i}$, $\hat{u}_{fi}$, $\hat{u}_{h1i}$ and $\hat{u}_{h2i}$ which represent cooling stage 1, cooling stage 2, fan ventilation stage, heating stage 1 and heating stage 2. The control signal is binary: 0 signifying OFF and 1, ON. The set of valid operation combinations contain six possibilities: $\hat{u}_i = \{\{0,0,0,0,0\},\{0,0,1,0,0\},\{1,0,1,0,0\},\{1,1,1,0,0\},$
$\{0,0,1,1,0\},\{0,0,1,1,1\}\} = \{0,1,2,3,4,5\}$, which indicate: that all control parameters are OFF, only fan is ON, cooling stage 1 and fan are ON, all cooling control parameters with fan are ON, heating stage 1 and fan are ON and all heating control parameters with fan are ON, respectively. The system is operated with a capacity of $P_{c,s1} = 18.5$ kW for the first cooling stage, $P_{c,s2} = 37$ kW for the second cooling stage, $P_{h,s1} = 39.8$ kW for first heating stage and $P_{h,s2} = 59.8$ kW for second heating stage and $P_f = 1.5$ kW for fan stage. The heating/cooling stage 1 can operate alone, however the stage 2 always works with the stage 1. The fan can activate alone, or whenever the heating/cooling system is ON. We assume that at least one fan is ON during occupancy time to avoid that one fan is over used and another is never used. We assume that the same fan is always ON during one day then next one the following day and so on. The energy efficiency of a building can be achieved by tuning the sequence of switch ON/OFF control signals across the prediction horizon while respecting the constraint operation of the system. The system operates following a tiered utility rate. Energy is charged at 0.05303 \$/kWh if the energy consumption is less than the maximum energy supplied per month $E_{max} = 210000$

kWh/month and 0.0373 $/kWh otherwise. The power-peak rate is 14.58 $/kW and charged on the maximum power demand during the month.

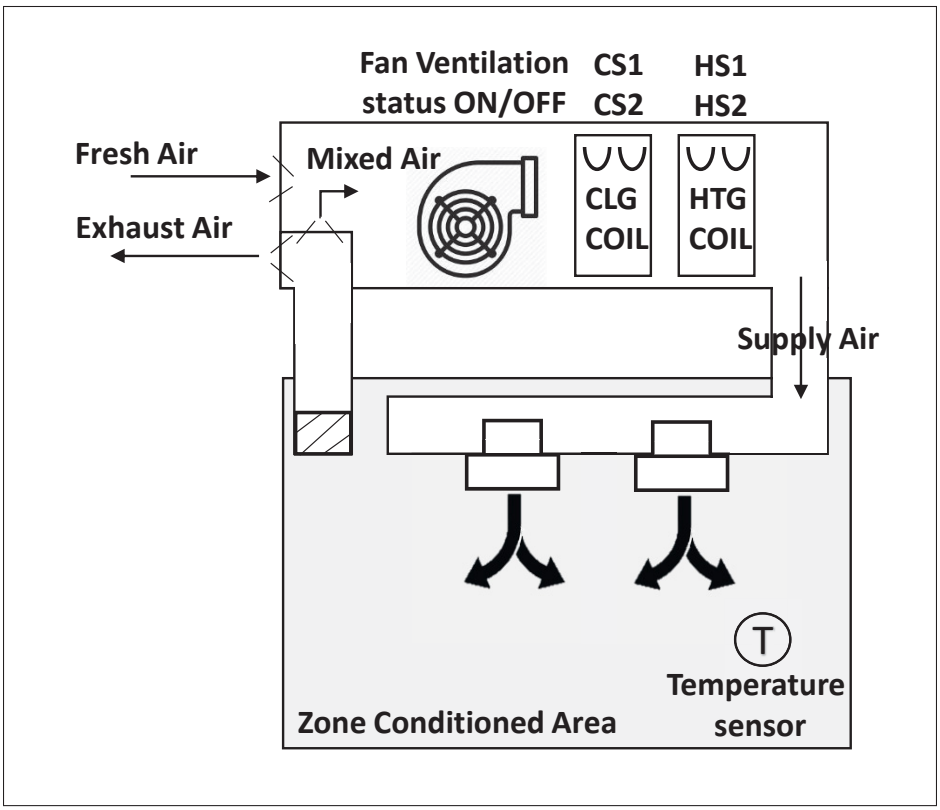


Figure 4.1 Schematic diagram of RTU for one zone

4.3.2 Data-driven control framework

In this paper we propose a new data-driven control framework allowing the HVAC operation in retail building to be optimized by determining an optimal control (on/off) operation status of the subsystems. The data-driven control framework is composed by three modules; data extraction module, prediction module and optimization module. The extraction module gets time dependent input features at each time step from the database. These data will feed the prediction module which will be described in detail in the section 4.4. This module contains the prediction model for each zone in order to predict the temperature over a control horizon. The prediction data will feed the optimization module (section 4.5) in order to compute the optimal

control sequence using MPC-GA. The MPC-GA operates on a receding horizon by solving for a fixed prediction horizon (2 hours in our case) from the current timestep t. The first control signal $u^*_{z1,2,3}(t+1)$ is applied to the building. All this process is executed as a closed-loop over the time progress.

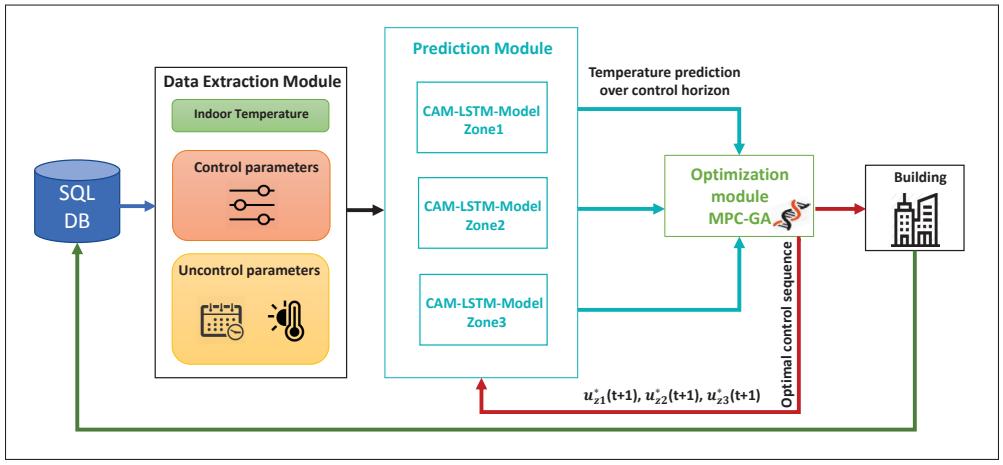


Figure 4.2 Data-driven control design

4.4 Context-aware multivariate LSTM framework for modeling IAT

4.4.1 Data organization

The data was collected from August 1st, 2019 to August 31, 2020. with 5-minute sampling intervals. TABLE 4.1 summarizes all features used in this work. In order to build predictive models, the selected features include observed and known inputs are categorized into three groups:

- Controlled features: Includes past observed and future known control actions that impact HVAC system operations. The set $u_{i,t-l:t}$ are the vectors of the past observed control variables for each zone i. The set $u_{i,t+1:t+p}$ is the future known controlled variables which represent the outputs of MPC-GA model discussed in section 4.5.2.

- Uncontrolled features: The set $v_{i,t-l:t}$ are the vectors of the past observed measured variables for each zone i (e.g. the outdoor air temperature, the day of the week and the hour of the day). The set $v_{i,t+1:t+p}$ are the vectors of the future known measured variables.
- Target features: The set $y_{i,t-l:t}$ is the vector T_i^{in} of IAT for each zone i.

We add the hour of day and day of the week as inputs. The hour input helps differentiate temperature profiles during occupied and unoccupied times. The day input helps identify business days and weekends. All selected features are normalized between 0 and 1 before they are used for training, to prevent the dominant effect of particular variables. The equation (4.1) is used to scale the variables into [0,1].

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4.1}$$

Where x_{scale} represents the scaled variable, x defines the variable value before scaling, x_{min} and x_{max} are the minimum and maximum values of the dataset to be scaled, respectively.

Table 4.1 Feature description

Feature	Description	Unit
Controlled variables, u_i		
u_{c1i}	cooling stage 1 of zone i	Binary
u_{c2i}	cooling stage 2 of zone i	Binary
u_{fi}	Fan stage of zone i	Binary
u_{h1i}	heating stage 1 of zone i	Binary
u_{h2i}	heating stage 2 of zone i	Binary
Uncontrolled variables, v_i		
h	Hour of day	Integer
d	Day of week	Integer
T^{out}	Outdoor air temperature	°C
Target Variables, y_i		
T_i^{in}	Indoor air temperature of zone i	°C

After data pre-processing steps, the dataset was divided into randomly sampled training (60 % of the data), validation (20 % of the data) and testing (20 % of the data) sets from one year of data.

The dataset has been randomly sampled for training instead of using k-folds cross validation because the dataset is large enough (i.e., one year of data with 5-minute sampling intervals) and time-dependent. The historical data is used to train a predictive model for the future behavior. Models are developed using the training and validation datasets and the prediction results are derived from the test dataset. The operation of HVAC controls leads to maintain the comfort in the building. So it is important to learn/capture the effect of the HVAC system on the evolution of the indoor temperature. The prediction model will be used in an optimal control framework where HVAC controls minimizing operation costs while maintaining thermal comfort need to be determined. Consequently, the prediction model must be sensitive to HVAC control profile.

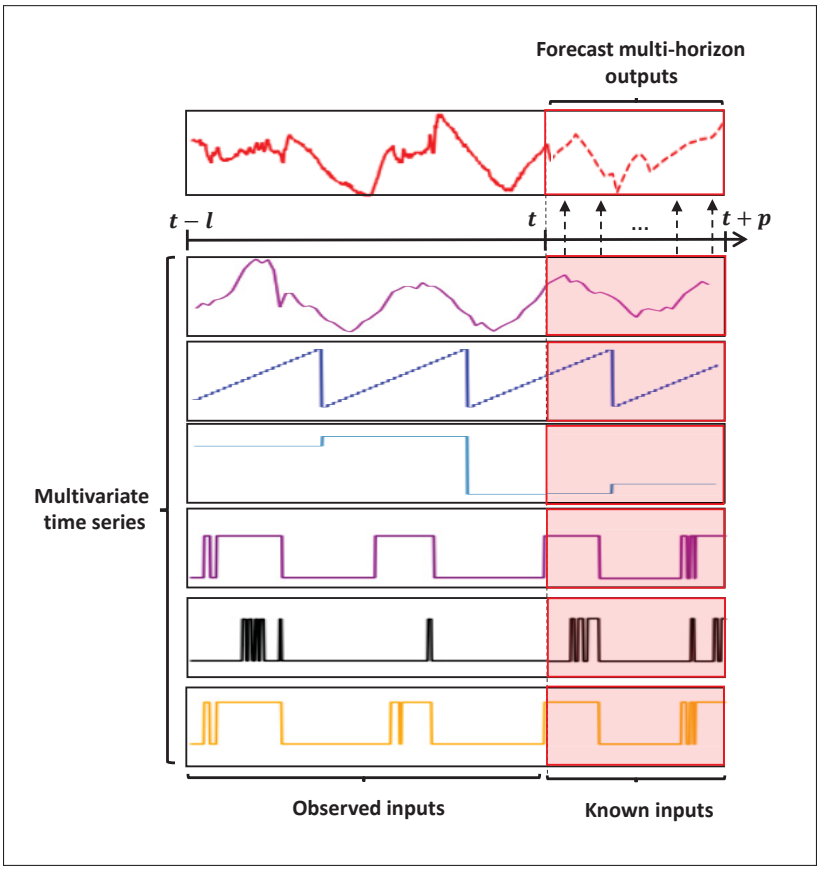


Figure 4.3 Multi-horizon forecasting with multi-variate time series composed by past observed and known future inputs

For example, if the heating control inputs of the model are OFF during a cold winter days, the IAT prediction must decrease. In this paper, the main prediction problem can be formulated as, given a past time series of observations of temperature, past and future uncontrolled and controlled data as input, predict a sequence of temperature as output which can be influenced by control parameters as illustrated in Figure 4.3. The Figure 4.4 defines the detailed structure of a data sample for one zone i to predict a horizon of p future steps with l previous steps. The input of the model includes the future known variables of uncontrolled and controlled parameters. The future controlled parameters over control horizon from time $t + 1$ to $t + p$ represents the output of MPC-GA model. The prediction model of the temperature of each zone i has the form shown in 3.1.

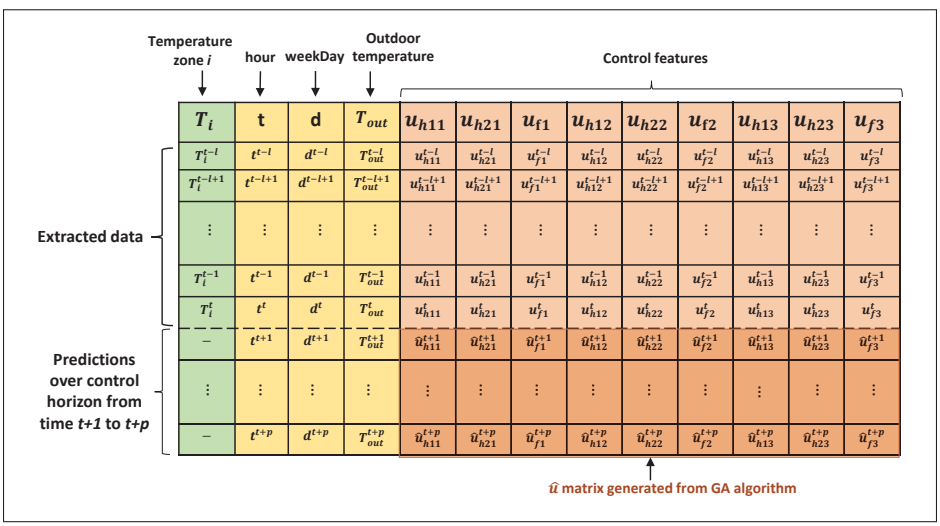


Figure 4.4 Input data sample description

4.4.2 CAM-LSTM model

The control signals have a complicated influence on temperature behavior. The proposed CAM-LSTM model leads to capture the complex impact of control signals on prediction. The CAM-LSTM model is composed by three main component: the high-level feature extraction component, the low-level feature extraction component and the attention networks component as shown in Figure 4.5. The multivariate time series data are separated into three groups, uncontrol,

control and target features. The model follow dual-stream network. The first branch treats uncontrol parameters and the second one is dedicated to control parameters. The control and uncontrol parameters are fed as input into a first feature extraction component separately. The outputs of these two modules are concatenated with the target feature and fed as input into a second feature extraction using convolution layers separately. In the second branch, the attention networks takes as inputs the extracted features from control parameters. The self-attention layers capture the degree of relevance of control with respect to IAT. The outputs of first branch and attention networks is concatenated and fed into LSTM-bidirectional layers which gives the multi-step IAT prediction of each zone for the whole prediction horizon p as output. In this section, we describe the key components of the main three components.

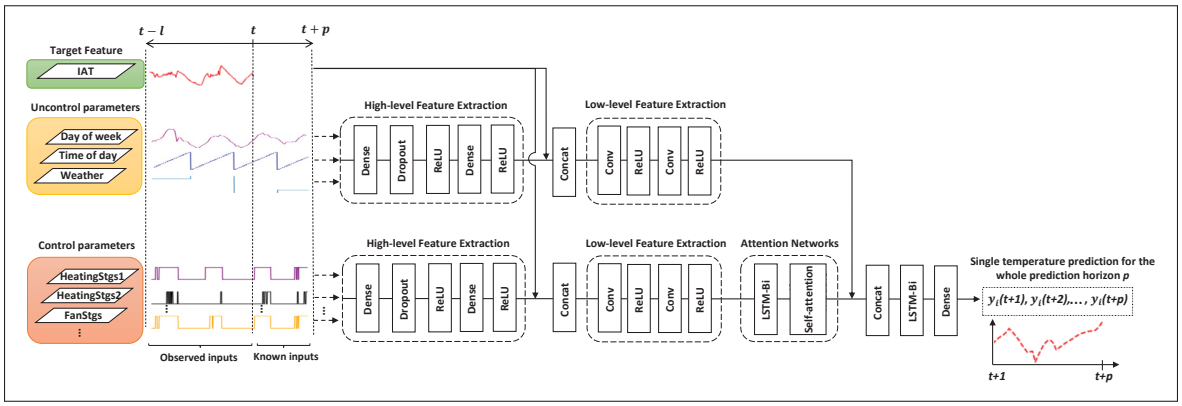


Figure 4.5 Schematic diagram of dual-stream neural networks model for temperature prediction

4.4.2.1 High-level feature extraction

This component is structured with two dense layers with ReLU activation. The dense layers leads to combine the several external impacts to build a hidden representation, that models the complex high-level interaction between features Liang *et al.* (2019). The first feature extraction is applied for control u_i and uncontrol v_i parameters separately. This module provides one output for each branch H_{u_i} and H_{v_i}. These two outputs carries the uncontrol and control information until the end of network and thus prevents the information from disappearing into the deep network. H_{u_i}

and H_{v_i} are then concatenated with the target feature y_i to construct two augmented features H_{y,u_i} and H_{y,v_i}. These two augmented features are fed into the low-level feature extraction.

4.4.2.2 Low-level feature extraction

We use two 1-D convolution layers with ReLU activation functions to introduce non linearity. The convolution filters are applied on both controlled feature fused H_{y,u_i} and uncontrolled feature fused H_{y,v_i}. The first convolution layer take the fused high level features as input and construct a low-level view H'_{y,u_i} and H'_{y,v_i} for control and uncontrol branch separately. The convolution layers are the ability to capture different important signal patterns. It is important to note that the 1-D convolution is applied to create a multi-dimensional representation of each time step. Therefore, if the initial time series contains n steps, it will always contain n steps.

4.4.2.3 Attention networks

The attention networks focus on certain parts of the control input when predicting temperature. The prediction of the next p hours of temperature should be based on the action taken by controls in the past and in the future. There are two scenarios. In the first scenario, we assume that the cooling controls $u_{i,t+1:t+p}$ are ON and outside is warm. In the second scenario, we assume that cooling $u_{i,t+1:t+p}$ are OFF and the outside is warm. If we want to predict the indoor temperature from $t+1$ to $t+p$, for the first scenario the prediction should be between setpoints range, however for the second scenario the prediction should exceeds the higher setpoint. The model should be given more weights on control status which will help to better predict the temperature. The attention mechanism in our model play an essential role to simply looking for the good features of control parameters u_i that help a best prediction of $\hat{T}_i^{t+k|t}$. The rest of the features will simply be ignored. This mechanism was applied horizontally across the feature time-series instead of expand the dimensions of the attention mechanism. The LSTM-Bi layer take as input the augmented features extracted from controlled parameters H'_{y,u_i}. The output of the LSTM-Bi layer is represented as follows, $\left\{h_{1,t'}, h_{2,t'}, ..., h_{n,t'}\right\}$ where $h_{t,t'} = \left[\overrightarrow{h_{t,t'}}, \overleftarrow{h_{t,t'}}\right]$. The $\overrightarrow{h_{t,t'}}, \overleftarrow{h_{t,t'}}$ are subsequently concatenated and fed into an attention layer, where self-attention weights $\{\alpha_t\}_{t=1}^{n}$

are computed. The attention weights indicates the importance of the input time series sample at time-step t to predict the output value at time-step $t+1$. In general the self-attention use a softmax function to normalize the vector e_i over the input time series sequence. However this method leads to pick one single input variable and ignore other multivariate inputs. In this paper we use a sigmoid function to compute the weights, as we work with multivariate inputs and we assume that more than one input variable are used for prediction.

$$e_t = \sigma\left(h_{t,t'} W_t + b_t\right) \tag{4.2}$$

$$a_t = sigmoid\left(e_t\right) \tag{4.3}$$

Where $\sigma(.)$ represents the sigmoid activation function and W_t are the weights specific to the input feature representation $h_{t,t'} = \left[\overrightarrow{h_{t,t'}}, \overleftarrow{h_{t,t'}}\right]$.

Each self-attention weight represents the relevance of one or more control parameters within all controls. Indeed, relevant parameters should be assigned the most higher weight values. The output of the attention networks component is computed by performing a weighted aggregation of the LSTM-Bi output and the self-attention weights as follows,

$$l_{t'} = \sum_t a_t h_{t,t'} \tag{4.4}$$

This output is augmented by the first uncontrolled stream network. The concatenation of both outputs is then fed into LSTM-Bi layer. At the end, a dense layer generates a prediction of a single temperature for the whole prediction horizon p.

4.5 Control design

4.5.1 Formulation of optimization problem for the MPC

Based on CAM-LSTM models described in section 4.4.2 and the HVAC operational constraints, a general optimization problem with the three objectives, minimization of the total energy

consumption, the peak power and the discomfort during occupancy time is formulated in (4.5). Energy, power and discomfort are normalized to $[0, 1]$ using minimum and maximum values that are calculated from existing data in the database. The predictive controller solves at each time step the problem defined in (4.5) according to the constraints defined in (4.6) to (4.19).

$$\min_{\hat{u}} \alpha \cdot Energy(\hat{u}) + \beta \cdot Power(\hat{u}) + \gamma \cdot Discomfort(\hat{u}) \tag{4.5}$$

$s.t.$

$$Energy(\hat{u}) = \sum_{t=1}^{N_p} \sum_{i=1}^{N_z} E_i^{t+k|t}(\hat{u}) \cdot p_{energy}^{t+k|t} \tag{4.6}$$

$$Power(\hat{u}) = \sum_{t=1}^{N_p} \sum_{i=1}^{N_z} \max p_i^{t+k|t}(\hat{u}) \cdot p_{power}^{t+k|t} \tag{4.7}$$

$$Discomfort(\hat{u}) = \sum_{t=1}^{N_p} \sum_{i=1}^{N_z} \max\left\{0, \hat{T}_i^{t+k|t}(\hat{u}) - \overline{T}_{sp}\right\} + \max\left\{0, \underline{T}_{sp} - \hat{T}_i^{t+k|t}(\hat{u})\right\} \cdot \Delta t/60 \tag{4.8}$$

$$E_i^{t+k|t}(\hat{u}) = p_i^{t+k|t}(\hat{u}) \cdot \Delta t/60 \tag{4.9}$$

$$p_i^{t+k|t}(\hat{u}) = \hat{u}_{c1i}^{t+k|t} \cdot P_{c,s1} + \hat{u}_{c2i}^{t+k|t} \cdot P_{c,s2} + \hat{u}_{fi}^{t+k|t} \cdot P_f + \hat{u}_{h1i}^{t+k|t} \cdot P_{h,s1} + \hat{u}_{h2i}^{t+k|t} \cdot P_{h,s2}, \forall i, \forall k \tag{4.10}$$

$$\hat{T}_i^{t+k|t}(\hat{u}) = f_{CAM-LSTM(z_i)}(T_{i,t-l:t}, u_{i,t-l:t}, \hat{u}_{i,t+1:t+k}, v_{i,t-l:t}, \hat{v}_{i,t+1:t+k}) \forall i \tag{4.11}$$

$$0 \leq E_i^{t+k|t}(\hat{u}) \leq E_{max} \tag{4.12}$$

$$\underline{T}_{sp} \leq \hat{T}_i^{t+k|t}(\hat{u}) \leq \overline{T}_{sp} \tag{4.13}$$

$$\overline{T}_{sp}^{t+1} = \overline{T}_{sp} + \frac{\sum_i^{N_z}\left(\hat{T}_i^t - T^t\right)}{N_z} \tag{4.14}$$

$$\frac{\sum_{t=\tau_\eta}^{l+p-\tau_\eta}\left|T_i^{t+\tau_\eta}(\hat{u})-T_i^{t}(\hat{u})\right|}{\left(l+p-\tau_\eta\right)} \leq TR_\eta, \forall\eta\in[0,4], \forall i\in N_z \tag{4.15}$$

$$\sum_{i}^{N_z}\left(\left|\sum_{\iota=1}^{l}u_i^{t-l+\iota}-u_i^{t-l+\iota-1}\right|+\left|\sum_{\rho=1}^{p}u_i^{t+p-\rho+1}-u_i^{t+p-\rho}\right|\right)/(l+p-1)\cdot N_z\leq\lambda \tag{4.16}$$

$$\alpha+\beta+\gamma=1 \tag{4.17}$$

$$\hat{u}=\left\{\hat{u}_{c1}^{t+k|t},\hat{u}_{c2}^{t+k|t},\hat{u}_{f}^{t+k|t},\hat{u}_{h1}^{t+k|t},\hat{u}_{h2}^{t+k|t}\right\} \tag{4.18}$$

$$\hat{u}\in[0,5] \tag{4.19}$$

Table 4.2 Limits on Temperature Drifts and Ramps Standard (2010)

Time Period, h	0.25	0.5	1	2	4
Time Steps τ_η	3	6	12	24	48
Maximum Operative Temperature Change Allowed TR_η, °C (°F)	1.1 (2.0)	1.7 (3.0)	2.2 (4.0)	2.8 (5.0)	3.3 (6.0)

N_p represents the prediction horizon, $t+k|t$ indicates the predicted value of a certain variable at time step $t+k$ starting from time step t. $p_{power}^{t+k|t}$ and $p_{energy}^{t+k|t}$ are the time varying power and electricity price in dollars per kWh. The total energy consumption, the power peak and the discomfort are calculated using (4.6), (4.7) and (4.8) respectively. The discomfort is calculated according to the positive deviation ($\$/°C$) between temperature setpoint in occupancy and unoccupancy time and the predicted temperature as defined in (4.8). The $\underline{T}_{sp}^{t+k|t}$ and $\bar{T}_{sp}^{t+k|t}$ are the lower and upper temperature setpoint respectively, and they are depending on the occupancy and unoccupancy time. The energy consumption $E_i^{t+k|t}(\hat{u})$ is calculated according to (4.9). The operation system power $p_i^{t+k|t}(\hat{u})$ of each zone i is calculated by multiplying the control signals $\hat{u}_i$ by the power of the cooling stage 1 ($P_{c,s1}$ = 18.5 kW), the cooling stage 2 ($P_{c,s2}$ = 37 kW), the heating stage 1 ($P_{h,s1}$ = 39.8 kW), heating stage 2 ($P_{h,s2}$ = 59.8 kW) and the supply fan (P_f = 1.5 kW) as defined in (4.10). An optimal controller should be aware of the maximum peak power demand since the beginning of the month to not cause a new peak. $\hat{T}_i^{t+k|t}$ is the predicted temperature for the whole prediction horizon (4.11). The constraint in (4.12) indicates that the

energy generated by the cooling/heating should not exceed the maximum energy supplied per month E_{max}. The constraint in (4.13) indicates that the predicted temperature should be between the upper and lower temperature setpoint.

The upper occupancy setpoint in each future step $\overline{T}_{sp}^{t+1}$ is self-tuned according to the prediction value at each time t as described in (4.14). This tuned upper setpoint is computed by adding the mean error between the prediction values of temperature at time t and the feedback/current temperature values for all the zones N_z to the setpoint at time t.

Moreover, the indoor temperature ramp (TR) is considered in the proposed MPC model as described in (4.15). TR expresses the change over a different time interval as explained in Table 4.2 based on ASHRAE standard Standard (2010). The minimization of energy consumption leads to significant fluctuations of the temperature. In this paper, we compute the average TR for past and predicted temperature data from $t - l$ to $t + p$ for each time step τ_η. The consideration of TR results in a smoother control signal and energy savings.

In the proposed MPC model, the cyclic variation is considered as defined in (4.16) which represents the repeatedly rises and falls of control parameters. This constraint represents the variation mean of controls from $t - l$ to $t + p$ period that should be less than λ, a predefined maximum cyclic factor.

Each zone i is controlled by a vector $\hat{u}$ including five control parameters as described in 4.3.1. The optimization problem is solved using a genetic algorithm, which generates an optimized control vector $\hat{u}_{t+1:t+p}$ for each zone. Only the first control signal $\hat{u}_{t+1}$ is applied to the building. As the time step t progress, the optimization problem MPC-GA is solved again as closed-loop with the updated initial condition and shifted the constraints.

4.5.2 Proposed genetic algorithm

In this paper, GA is developed to solve the online optimization problem defined in section 4.5.1 to search the optimal values of control parameters $\hat{u}_{t+1:t+p}$ for all the zones, that minimize the overall cost within the prediction horizon N_p. Since the MPC-GA is deployed in real time,

the computation time to solve the optimization problem is very crucial and should not exceed the control horizon period (5-minute). GA is used because it uses a low computation time to solve our problem. GA starts with a random population including N_s initial individuals and this number is left constant for every generation. Each individual has M chromosomes, and includes the control parameters $\hat{u}_{t+1:t+p}$ for the whole prediction horizon. For the sake of simplicity, each individual represents one solution for N_p time ahead and N_z zones. At the computation of each generation, each individual is given to the prediction model to predict the temperature $\hat{T}_{i,t+1:t+p}$, which is used by the optimizer MPC-GA to compute the combined cost. Figure 4.6 depicts the proposed GA, which includes the following steps:

Algorithm 4.1 Multi-point crossover

Input: parents $p1$ and $p2$
Output: parents $p3$ and $p4$
Data: Selected parents

1 $\rho = \text{random}(2, (M/N_z))$ `//` ρ `is the random number of crossover points`
2 $\text{cut}_{\text{index}} = \text{random}(i_1, i_2, .., i_\rho)$ `//` cut_{index} `are the random index in each parent`
3 $p3$ and $p4 = \text{recombination}(\text{cut}_{\text{index}}, p1, p2)$

- Tournament selection: The selection of individuals for the next generation is evaluated by their fitness, which is computed by MPC-GA optimization function. We use a tournament selection as a selection strategy. Tournament selection selects a number of individuals from the current generation and hold a tournament amongst them. As explained in sub-section 4.5.5, according to our sensitivity analysis, 20% of the population size is selected. We compare each pair of individuals. If both are feasible, the individual with the better fitness will be chosen. If an individual is infeasible and the other is feasible, the feasible one will be chosen. If both individuals are infeasible, the individual with the lowest cost will be selected.
- Multi-point crossover: We created an offspring from the list of selected parents resulting from the tournament selection. In this list, two parents are selected randomly ($p1$ and $p2$) to be recombined and returns two new parents ($p3$ and $p4$). A random number of points

ρ are selected where $\rho \in \left[2, \frac{M}{N_z}\right]$. ρ starts from 2 because it is a multi-point crossover and we assume that the minimum can be two points. Then, a set of ρ random cut indexes $cut_{index} = \{i_1, i_2, .., i_\rho\}$ are selected where $cut_{index} \% N_z = 0$ which means that all cut indexes should be divisible by zones N_z to exchange the chromosomes between the same zones. The recombination of chromosomes is performed as follow: the chromosomes of the first parent are passed to the child until the first cut index, then the chromosomes of the second parent are passed to the second part of the child until the second cut index and so on until the end of n_{index}. Algorithm 3 summarizes our implementation of the multi-point crossover method.

- Offspring mutation: Our mutation strategy consists in randomly changing the genes of each offspring by a random control value $u \in [0, 5]$ with a certain probability (i.e., a mutation rate equal to 0.002). Only the gene of heating or cooling controls will be replaced in the offspring in the winter or summer season, respectively, in order to avoid heating during summer season and cooling during winter season.

This whole process is executed in a loop until we reach the terminal condition which corresponds to the number of generations (i.e., 60 generations), according to our sensitivity analysis in sub-section 4.5.5.

4.5.3 Results-I: Time series prediction

CAM-LSTM is compared against five baseline methods. Among them, there are two classic methods to address time series prediction e.g., NNARX Delcroix *et al.* (2020) and LSTM-MISO Mtibaa *et al.* (2020). The additional methods, DSTP-RNN Liu *et al.* (2020) and SA-LSTM Zheng *et al.* (2018), which use attention-based encode-decoder network, are also used as baselines.

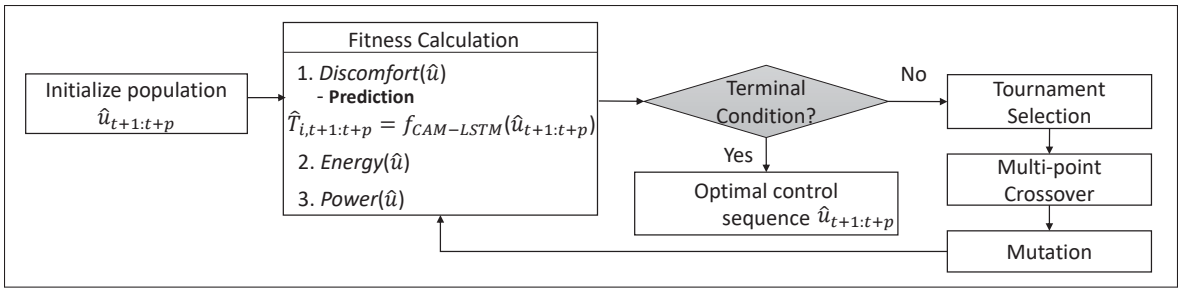


Figure 4.6 Genetic algorithm chart

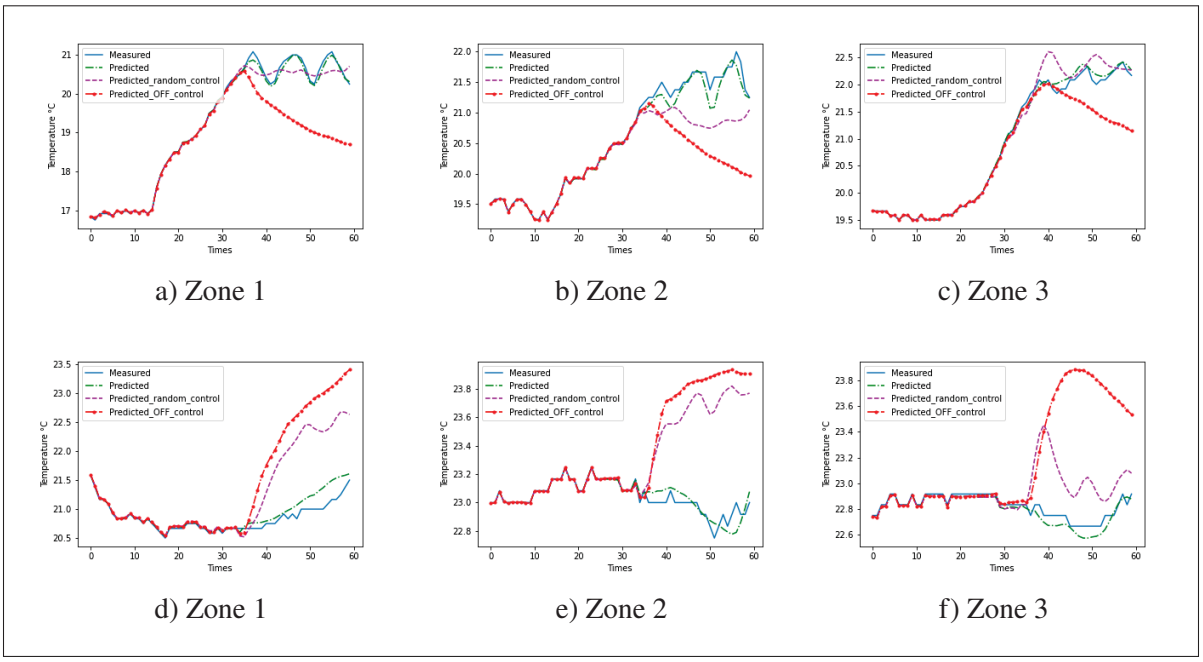


Figure 4.7 CAM-LSTM Model temperature prediction for the three zones with three case studies: (a) (b) (c) represent 3 case studies for the 3 zones in the winter season, and (d) (e) (f) represent 3 case studies for the 3 zones in the summer season

Finally, the context-aware neural network model (CANN) is based on the model proposed in Liang *et al.* (2019), named UrbanFM which uses a fusion network with a feature extraction module. All baselines are tested on the real data as described in the section 4.4.1. CAM-LSTM is evaluated on the test dataset and three metrics are used: the mean absolute percentage error (MAPE) in 4.20, the root mean square error (RMSE) in 4.21 and the mean absolute error (MAE) in 4.22. The MAPE measures the size of the error in percentage terms, a lower result indicates better performance. The RMSE penalizes more larger error values. The MAE corresponds to

the mean value of the sum of absolute differences between actual and forecast values, and it evaluates forecast accuracy.

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{4.20}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (y_k - \hat{y_k})^2} \tag{4.21}$$

$$MAE = \frac{1}{n} \sum_{k=1}^{n} |y_k - \hat{y_k}| \tag{4.22}$$

Where y and $\hat{y}$ define the real and predicted outputs respectively, and n is the total observation number.

In Table 4.3, we observe that the RMSE of the NNARX model is higher than all other methods. This is due to the error propagation over time caused by the recursive prediction strategy used to predict the two hours, since the RMSE penalizes large error values. In addition, we observe that LSTM-MISO outperform CANN and DSTP-RNN even with its simple architecture. The CANN model captures the sequential relationship between inputs using the external factor fusion component. However, it is less powerful than the gate mechanism used in the LSTM-MISO. Models using attention mechanism are generally more efficient than other models because they are able to select the relevant hidden states across all time steps. DSTP-RNN, SA-LSTM and CAM-LSTM use an attention mechanism, but in a different way. For each of them, the performance of SA-LSTM and CAM-LSTM are the closest. In addition to the attention mechanism, CAM-LSTM uses two-level feature extraction modules to model the complex mixtures of temporal patterns resulting the best MAPE, RMSE and MAE compared to baselines. CAM-LSTM is used with MPC-GA in a real deployment use case with never before seen data as it will be described in the section 4.5.6. The prediction behavior is very close to the real values as described in Figures 4.8 (a) and 4.9 (a) which leads to a better control decision, as will be further described in the following sections.

Table 4.3 Performance comparison of different prediction method with past time steps equal to 3 hours and future time steps equal to 2 hours

Models	MAPE (%)	RMSE (° C)	MAE (° C)
NNARX	0.4699	1.9431	1.449
LSTM-MISO	0.6487	0.1937	0.1373
CANN	1.0139	0.3103	0.2139
DSTP-RNN	0.7105	0.353	0.1682
SA-LSTM	0.2269	0.0039	0.048
CAM-LSTM	**0.0872**	**0.0005**	**0.0181**

4.5.4 Results-II: The impact of control signals on the prediction

Table 4.4 GA sensitivity analysis

(A) Best fitness, Fix: Pop size 400

	Elite			
Generation	20	40	**80**	100
25	90.96	71.55	88.97	88.64
40	70.25	61.55	59.56	53.85
60	48.38	47.88	**37.44**	43.48

(B) Fix: Generation 60, Elite 80

Population size	**Best fitness**
100	108.96
200	38.66
300	45.52
400	**37.44**
500	47.16

(C) Fix: Pop 400, Generation 60, Elite 80

Nb_Mutation	**Best fitness**
1	**37.44**
3	47.33
10	84.77

(D) Fix: Pop 400, Generation 60, Elite 80, Nb_mutation=1

Nb_crossover	**Best fitness**
3	40.44
6	47.35
12	**37.44**
18	51.11
24	51.58

In the control concept, CAM-LSTM is designed to capture the sensitivities of the temperature prediction with respect to the control commands. Failing to get these sensitivities with sufficient precision may result in a model that responds poorly to control commands. To evaluate the effectiveness of the input attention mechanism in CAM-LSTM, and since attention is only used on control signals, we studied the impact of these exogenous inputs on the prediction results. Three case studies were performed to study the influence of observed (l=3 hours) and known (p=2 hours) control signals on the temperature prediction output. For the first case study, the real control signals are used to predict the temperature. The second case study is performed

using random and noisy control signals instead of real ones. The third case study sets all real control signals (heating or cooling) to be off when are supposed to be on. Figure 4.7 shows an example of the effect of control with the three case studies described before. Figures 4.7 (a), (b) and (c) show that the temperature prediction decreases very fast when the heating controls are OFF when it is supposed to be ON in winter season. Figures 4.7 (d), (e) and (f) show that the temperature prediction increases very fast when the cooling controls are OFF when it is supposed to be ON in summer season. We notice also that the prediction of the temperature is generally off with a random control setting. In addition, the prediction values variability follows the real values using the test data without any modification. This indicates that CAM-LSTM can capture long and short dependencies by selecting relevant hidden states across all controls time steps. Consequently, CAM-LSTM is sensitive to control signals, therefore it is eligible to be used in a control closed-loop system.

4.5.5 Results-III: GA Sensitivity Analysis

We perform a sensitivity analysis to determine the best values of the population size, the generation number, the elite, and the number of mutation and crossover points as depicted in Table 4.4. This analysis is important in order to interpret the results of the GA as well as to avoid choosing obsolete solutions as optimal solutions. As the generations pass, the fitness value decreases in all five population size test cases. However, the test case with minimum fitness is used for the MPC-GA deployment. From the sensitivity analysis, the adopted parameters are marked in Table 4.4. We start by examining the elite and generation numbers as described in Table 4.4 (A). The elite and generation number of 80 and 60 respectively gives the best fitness value (i.e., 37.44). Then, we fixed these two parameters to obtain the best population size (i.e., 400 Table 4.4 (B)). Similarly, we tuned the number of mutations and the number of crossover points to 1 and 12 respectively (see Table 4.4 (C) and Table 4.4 (D)).

Table 4.5 Control results

	Deploy test day 1 (T1)			Deploy test day 2 (T2)		
Control method	MPC-GA simulation	MPC-GA real-time	RBC baseline	MPC-GA simulation	MPC-GA real-time	RBC baseline
Datetime Test	9/8/2020 12:25 to 17:15	9/8/2020 12:25 to 17:15	8/15/2019 12:25 to 17:15	9/18/2020 11:05 to 17:00	9/18/2020 11:05 to 17:00	10/30/2019 11:05 to 17:00
Day of week	Tuesday	Tuesday	Thursday	Friday	Friday	Wednesday
Min(OAT) ° C	20.13	20.13	19.52	11.97	11.97	12.12
Max(OAT) ° C	23.58	23.58	23.43	14.08	14.08	14.2
Mean(OAT) ° C	21.855	21.855	21.475	13.025	13.025	13.16
Energy zone 1 (kWh)	98.98	111.7	280.25	63.5	37.08	9
Energy zone 2 (kWh)	108.75	105.66	280.25	57.95	49.91	119.99
Energy zone 3 (kWh)	116.2	105.66	141.5	63.24	34.37	72.54
Total Energy (kWh)	**323.93**	**323.02**	702	**184.69**	**121.36**	201.53
Max Power (kW)	**11.16**	**14.25**	**14.25**	8.08	8.08	**3.4**
Discomfort (° C/h)	**0.008**	**0**	11.19	**0**	**0.04**	0.22

4.5.6 Results-IV: MPC-GA results

To demonstrate the potential for discomfort, power minimization and energy savings, MPC-GA has been tested under a simulation mode before applied it in a real on-line experiments. The simulation tests are used to examine the closed-loop performance of the MPC and test its stability by setting its parameters offline. For instance, the execution time of the MPC-GA process must not exceed the control horizon period, which is in our case 5-minute. Therefore, the related parameters in GA was tuned to not exceed the 5-minute control horizon as described in Table 4.4. The population size is set to 400, and the maximum number of iteration is set to 60 to find the near optimal solution. The proposed algorithm accommodates the preferences of the building administrator when assigning energy/temperature for a comfort level by changing the weight of each cost in the objective function. For example, if the administrator wants a higher energy efficiency, he can increase the weights of energy cost in (4.5). The weighting coefficients of the cost function were tuned experimentally to $\alpha = 0.2$, $\beta = 0.3$ and $\gamma = 0.4$. We transformed the constrained problem into unconstrained problem by using a penalty method. We converted all the constraints into penalty functions, then add them to the objective function. To control the violation severity of the penalty, we multiply the penalty function of each constraint by a positive constant which has been tuned experimentally. The tournament selection step of the GA will select the candidates with the lowest cost as explained in section 4.5.2. For simulation

purposes, the feedback resulting from the optimal controls are predicted using CAM-LSTM model. The advantage of this method is that the model output is very similar to the real output, so the optimal control decision will not be too much affected. However, this method can still lead to errors in the simulation test and this depends on the prediction accuracy errors. In the case of the real-time deployment mode, the controls resulting from the optimization model are executed and the system receives the feedback to improve the trajectory in the next steps. Table 4.5 presents the results of the two deployment tests which were conducted on two different days. All MPC-GA tests were executed with an occupancy setpoint between 19°C and 22.5°C. The first and second day tests were executed on Tuesday 08/09/2020 from 12:25pm to 5:15pm and Friday 18/09/2020 from 11:05am to 5pm, respectively.

We compared also the efficiency of MPC-GA with an advanced RBC model which was in operation in the building from August 2019 to September 2020. So all past controls data in the database are resulting from RBC model. The basic idea of the advanced RBC baseline control is that cooling is activated when the measured temperature exceeds a higher cooling setpoint. The cooling control is disabled when the measured temperature falls below a lower cooling setpoint. The control baseline check the outside air temperature's condition and the building status. It uses a recurrent neural network and a convolutional neural network model to predict the temperature which helps to decide when is the good moment to start or stop the systems.

To compare the two control approaches, we had to find days where the outdoor temperature profile was similar to the days when the MPC-GA was deployed. Thus, MAE and RMSE were used to compare the outdoor temperature measurements of the MPC-GA days with all other days available in the database. The day with the minimum error was used for the comparison. Figure 4.11 shows the outdoor air temperature for the two reference days compared to the real deployment test days and it can be seen that the outdoor trajectories are very similar. It is important to mention that the comparison days selected for test 1 and test 2 are also close in terms of month and day of the week. The results shown in the Table 4.5 clearly indicate that there is a significant reduction in energy and discomfort for MPC-GA simulation and real-time mode compared to RBC baseline controller. The results of the MPC-GA simulation and real-time

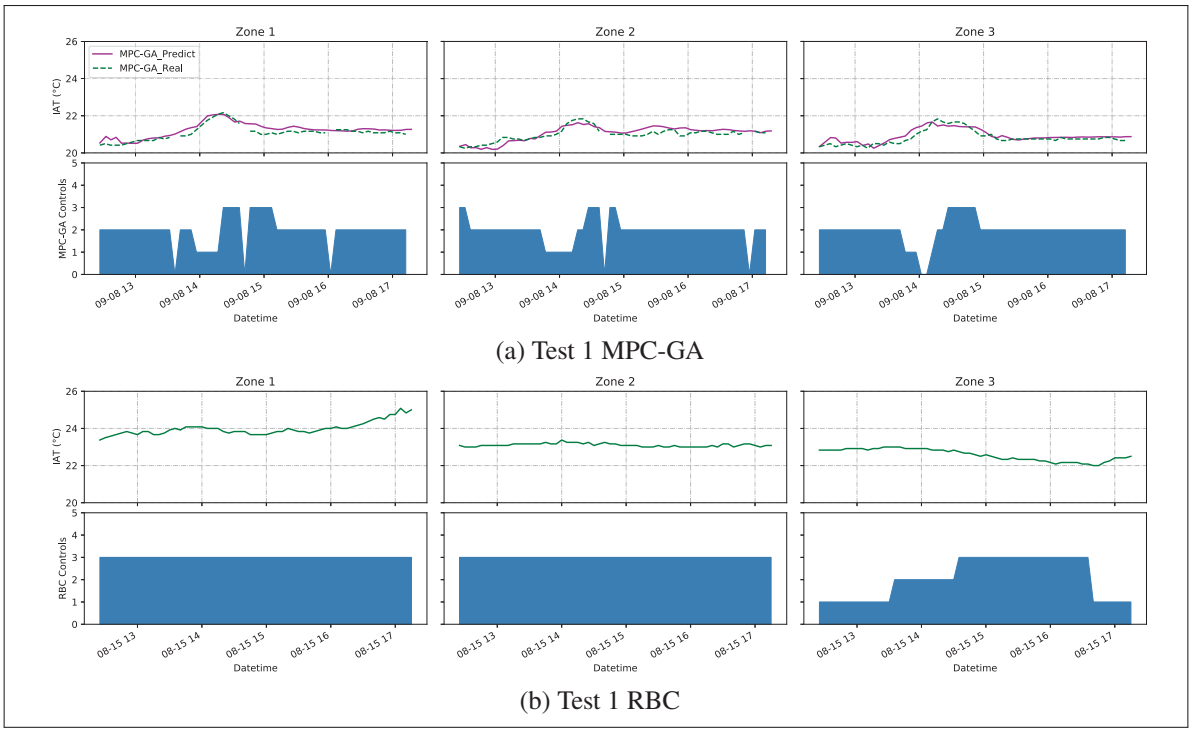


Figure 4.8 Comparison between MPC-GA in real time mode and RBC for the deployment test 1

modes are very close. Which shows that even without the real feedback and with only the accurate prediction of the state of the system, the model was able to give near-real results. A more predictive aware building controller leads to improvements over the traditional RBC controller. However, RBC slightly outperforms the MPC-GA for the maximum power consumption of test 2. To understand these savings and the behavior of the maximum power consumption, Figures 4.8 and 4.9 show the indoor temperature and the corresponding control resulting from the real-time deployment of the MPC-GA and RBC for tests 1 and 2 respectively. The upper graphs of the figures 4.8 and 4.9 (a) represent the real and the prediction of temperature using CAM-LSTM with the optimization model. The temperature prediction is stable and very close to the real (observed) values, which indicates an efficient accuracy of CAM-LSTM. This leads the system to know the future trajectory and to make the right control decision that minimizes the total costs. In addition, it can be observed that the MPC-GA more strictly maintains the indoor temperature within the setpoint range than RBC. The lower graphs of Figures 4.8 (b), 4.9 (b) and 4.8 (a), 4.9 (a) indicate the state of controls for each zone before and after optimization respectively. All

control status are described in detail in section 4.3.1. It is noticeable that after the optimization, the three control systems are not switched on at the same time for the three zones, in order to minimize the the maximum power consumption. However, before the optimization, RBC keeps

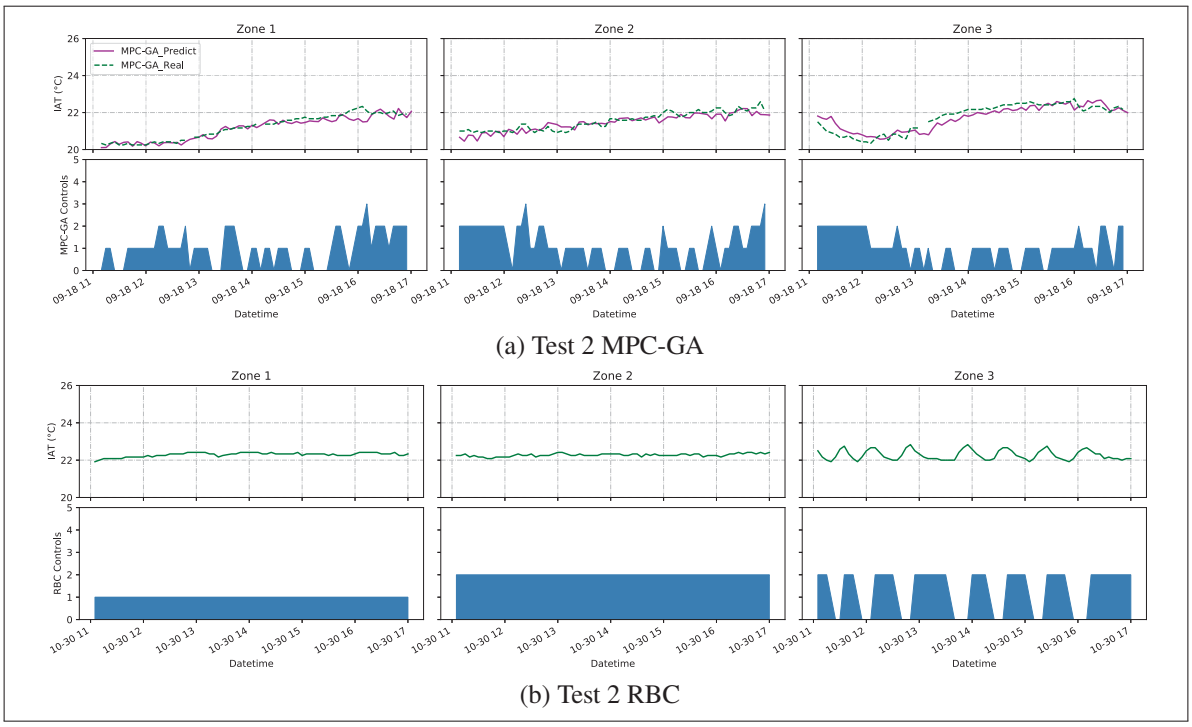


Figure 4.9 Comparison between MPC-GA in real time mode and RBC for the deployment test 2

on the controls for a long period of time. For example, in test 1, RBC keeps on the fan, cooling stage 1 and 2 for both zones 1 and 2 for the entire test period. This results in higher total energy consumption (702 kWh), as shown in Table 4.5. This high energy consumption did not allow the system to ensure comfort in the building. Figure 4.12 shows the percentage of time when the indoor temperature is outside of the setpoint range. The percentage of discomfort is 100% for zone 1 and 2 using RBC for test 1. Similarly for zone 3, the percentage of discomfort using RBC exceeds the percentage of discomfort using MPC-GA for both tests. This is due to the non-operation of the cooling stages for a long period of time, which also explains the lower maximum power consumption of the RBC compared to the MPC-GA. To investigate further the reason of the total of energy consumption of each zone described in Table 4.5, Figure 4.10

presents the fan, cooling stage 1 and 2 run time for deployment test 1 and 2 before and after optimization. Only cooling stages were activated since the two-day experiment was conducted in the cooling season. More importantly, MPC-GA was able to reduce the operation of the cooling stage 2 over the long term. The run time of cooling stage 1 with MPC-GA for both tests is much lower than RBC. The main source of the energy savings comes from the minimization of the operation of the cooling stage 2 for all zones, since it is the one with the highest capacity P_{c,s_2}. In addition, it can be noted that the run time of the fan, cooling stage 1 and cooling stage 2 is balanced between three zones for MPC-GA to avoid giving a lot of load to a single control system and preventing maintenance.

Table 4.6 shows the savings in energy, peak power and discomfort for both tests. The results conclude that the MPC-GA reduces energy by more than 50% and discomfort by more than 80 % for both tests. However, there was no reduction in power peak for either test. The lack of peak savings with MPC-GA is not necessarily an optimization failure. Since the power peak rate is applied on the maximum power demand during the month. The MPC-GA should be aware of the maximum power peak demand since the beginning of the month to not cause a new peak. The model keeps the power below the power consumed since the beginning of the month. The maximum of power consumption indicated in Table 4.5, still less than the maximum power consumed from the beginning of the month for the two tests. So there are no additional cost related to power peak.

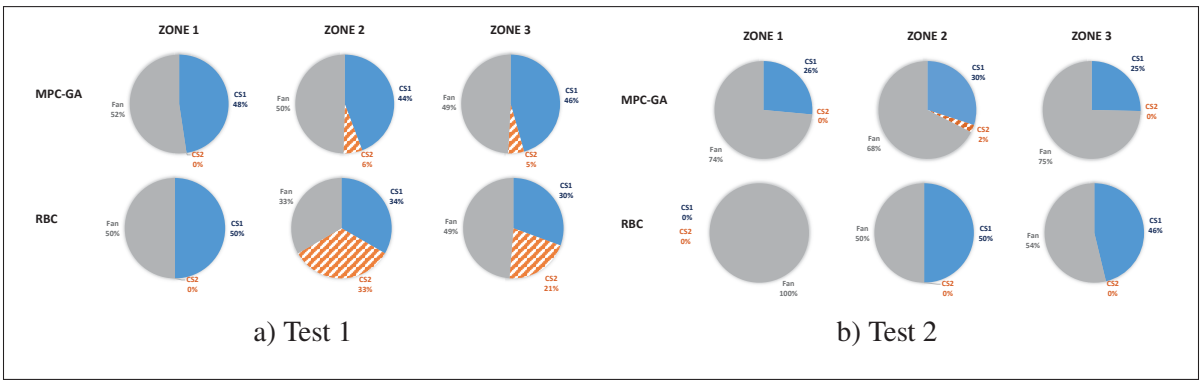
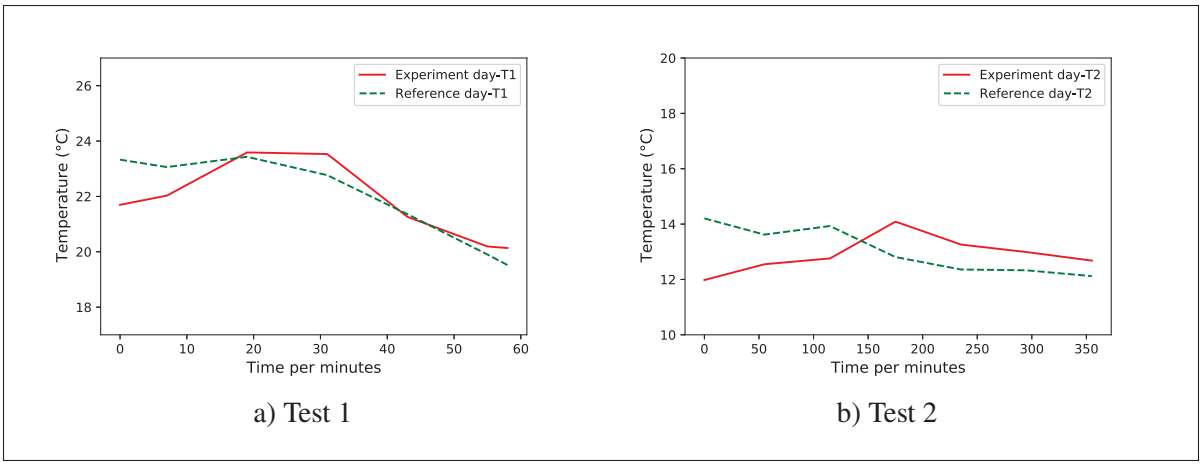


Figure 4.10 The runtime for each stage for deployment test 1 and 2 using MPC-GA and RBC



a) Test 1 b) Test 2

Figure 4.11 Outdoor air temperature for test 1 and 2

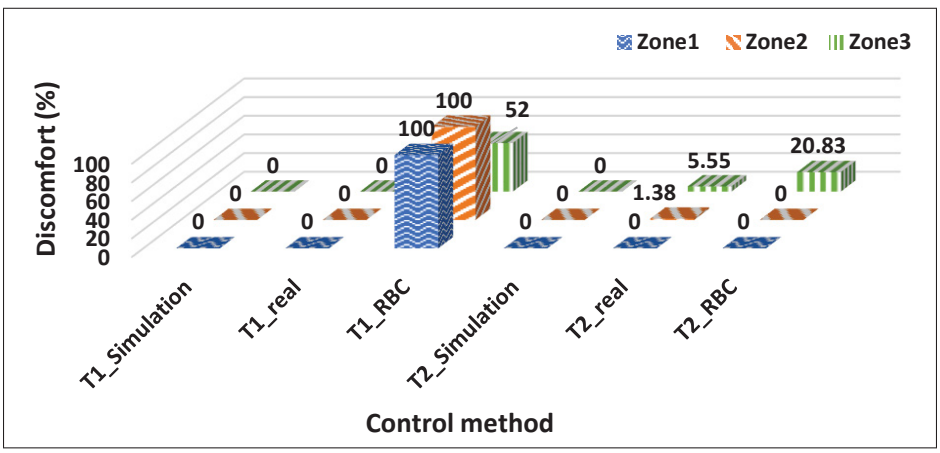


Figure 4.12 The percentage of time the temperature is outside of the dead band of the setpoint

Table 4.6 Savings for test 1 and test 2

Tests	Saving of energy consumption (%)	Saving of power peak (%)	Saving of discomfort (%)
Test 1	62.29	0	100
Test 2	58.40	0	81.81

4.6 Conclusion

In this paper a data-driven MPC model controller was described, implemented and evaluated in a real commercial building. A neural network attention based model named CAM-LSTM is proposed to predict the IAT. This model is used in the MPC process control and its accuracy has been proven. An online optimization with low computation time is developed to minimize the energy, power peak and discomfort that considers a self-tuned setpoint, cycling and temperature ramp as constraints. A genetic algorithm was used to solve the control optimization problem and to find the optimal combination of control parameters during two hours for all the zones. The MPC-GA controller ran an optimization in a receding horizon window with updated information. Results of the real deployment of the MPC-GA controller were very promising: the energy consumption and the discomfort was minimized by more than 50% and 80% respectively. Further work will include more tests on other type of HVAC system and building with more zones.

CHAPTER 5

HIERARCHICAL MULTI-AGENT CONTROL FRAMEWORK FOR ENERGY EFFICIENCY AND CARBON EMISSION REDUCTION IN MULTI-ZONE BUILDINGS

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Article accepted for publication in *Journal of Building Engineering*, December 2022

Abstract

Centralized optimization approaches to trade-off between comfort, energy and carbon emissions are widely adopted in the control of building heating, ventilation, and air-conditioning (HVAC) systems. However, the high computational complexity in each control horizon, single point of failure risks, and the limited number of zones to control make the centralized approach unattractive. Unlike centralized controls, multi-agent control (MAC) systems are flexible and modular. This paper proposes a scalable multi-agent based distributed approach for optimized control of a multi-zone smart building based on a set of local agents which represent individual zones in the building, coordinated by a central agent. For each control horizon, the coordinator minimizes the overall carbon emissions and assigns an individual energy budget to each local agent. Each local agent minimizes the discomfort in its zone while respecting the energy budget assigned by the coordinator. We propose a heuristic search based on a genetic algorithm to find the optimized control sequences in each zone, and formulate an integer linear programming (ILP) model for the coordinator problem which can be solved using an ILP solver. For a representative

winter test day, the proposed methodology gave an energy savings of 8.8% and reduced the carbon footprint by 23.4%.

keywords: HVAC, smart building, multi-agent, MPC, optimal controls, energy efficiency, carbon footprint reduction.

5.1 Introduction

The building sector in the United States consumes about 41% of the primary energy and contributes 39% of the carbon emissions Agency (2009). From which, the heating, cooling, ventilation and air conditioning (HVAC) systems are responsible for more than 50% of the energy consumed in commercial buildings DoE *et al.* (2011) and is an important producer of CO_2 emissions Péan *et al.* (2019). Improving the HVAC operation contributes to a sustainable future while reducing the carbon footprint of the building and is a strategy requiring very little capital expenditure. In general, centralized control methods achieve the best performance when control decisions are made using all available information Masero, Francisco, Maestre, Revollar & Vega (2021). However, many limitations make a centralized control no longer practical. First, the optimization strategies in the centralized control system can take very long time to find the optimal control decisions, which is a challenge for systems with a short period of operation (Thieblemont *et al.*, 2017). A centralized control framework can be computationally expensive for large scale optimization when applied to buildings with a large number of zones, equipped by complex distribution system and influenced by various factors. Compared to a centralized method, a multi-agent control (MAC) approach can potentially be more flexible and scalable (Wang *et al.*, 2021). However, implementing real-time optimal control strategies for multi-zone HVAC systems using multi-agent based distributed optimization methods can be challenging Wang, Nguyen, Xu, Tran & Caire (2020); Wang, Hong, Wang, Xu, Tang, Han & Kurths (2022). Distributed optimal controls require distributed optimization methods for which convergence is not always guaranteed Shaikh *et al.* (2014). Moreover, the optimization models proposed in previous work are limited to energy efficiency and discomfort minimization Mansy & Kwon (2020). More essential costs must be considered in the MAC optimization problem, such as

reducing the carbon footprint. In this paper, we propose a model predictive control (MPC) based multi-agent control framework allowing the optimal operation of HVAC system. The MAC framework is composed of a number of agents and one coordinator. Each agent is responsible for a specific zone which may have a different size and different power requirement. Each agent is formulated as MPC-based optimization problems and solves a local optimal control problem that minimizes discomfort during the control horizon N_p. The coordinator's role is to entrust an individual power budget to each agent while minimizing carbon emissions.

This paper extends our prior work in Mtibaa, Nguyen, Dermardiros & Cheriet (2021a) where a centralized-based control approach has been proposed to optimally control the HVAC system in smart buildings with subject to minimal energy consumption. Unlike our prior work, in this paper, we propose a distributed control approach that considers carbon emission reduction in addition to energy and discomfort. Additionally, in this paper, we present more scalable case studies implemented using the Modelica simulator Wetter, Zuo, Nouidui & Pang (2014). A comparison between the centralized approach proposed in Mtibaa *et al.* (2021a) and the proposed distributed approaches is also provided in this paper.

The contributions of this paper are: (1) modeling a scalable multi-agent control system formulated as MPC-based optimization problems for multi-zone buildings; (2) modeling carbon emission cost by considering the marginal emissions factor (MEF) rate that categorizes the footprint of the power grid and minimizing it in the coordinator optimization model; and, (3) carrying out extensive simulations using Modelica to validate the proposed MAC approach.

This paper is structured as follows: Section 2 summarizes the prior work related to our research. Section 3 describes the use case and the description of the multi-agent framework. Section 4 details the proposed multi-agent model and describes the control algorithm. Section 5 presents the validation methodology and baselines. Section 6 discusses the experimental results and compares the performance of the proposed models. Finally, we conclude key findings and present future research directions.

5.2 Related work

To optimize HVAC control, centralized MPC-based approaches which are solved using different optimization algorithms, for instance, mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP), nonlinear programming algorithm (NLP) and evolutionary algorithms like genetic algorithms (GA), have obtained more attention in recent years Reynolds *et al.* (2018); Song *et al.* (2020). Dullinger et al. Dullinger *et al.* (2018) developed a centralized predictive HVAC controller based on a MILP approach. The proposed control system is based on two levels of operation. On the upper level, the global thermal system performance and the HVAC modes are controlled using a long prediction horizon to take care of the slow dynamics of the plant. Then, on the lower level, the system operation is optimized with a shorter horizon that corrected possible prediction deviations without increasing the computation time. Similarly, Tarragona et al. Tarragona *et al.* (2020) presented a two level centralized MPC control strategy to improve the operation of a space-heating system coupled with renewable resources. The proposed control approach is formulated as an MINLP. These double levels of control helped the system to find the optimal solution with less computation time. Raman et al. Raman *et al.* (2021) designed an NLP-based centralized control approach incorporating humidity and latent heat in the MPC optimization problem for energy-efficient HVAC control. Song et al. Song *et al.* (2020) proposed a GA-based centralized control method to optimize the configuration of a combined cooling, heating and power (CCHP) plant. Mtibaa et al. Mtibaa *et al.* (2021a) proposed an online centralized data-driven control framework based on a GA allowing the optimal operation of the HVAC system and has been experimentally validated in a multi-zone retail building. A centralized MPC is developed in Seal *et al.* (2020) aimed at occupant comfort and energy efficiency with variable cost rates. The authors obtained a reduction of 13% in the energy cost with the proposed control strategy compared to a rule-based approach. Different centralized control frameworks have been proposed in the literature Mtibaa *et al.* (2021a); Tarragona *et al.* (2020). However, for large-scale buildings, it is not practical to calculate control actions in this manner due to time limitations, a single point of failure risks, and the limited number of zones to control. Compared with centralized control-based methods, MAC systems are more

flexible and scalable Wang *et al.* (2021). MAC system, has lately caught significant attention for HVAC control systems. Su and Wang Su & Wang (2020) designed an agent-based distributed optimal control approach for multi-zone building. The authors studied different implementation challenges including convergence rate, computation complexities and computation loads. Results showed that the proposed control had a low computation load and a high convergence rate. Li et al. Li *et al.* (2020) developed a three-layered multi-agent system based optimal control method using the chaotic search particle swarm optimization. The results demonstrated that the proposed control solution could reduce the operating cost by 1.84%. MPC has become a common choice for distributed implementation Masero *et al.* (2021). Pertzborn Pertzborn (2019) adopted an MPC and distributed optimization by using the distributed agents for optimal operation of a central chilling system combined with an ice-storage system. The distributed models divided the computational load between multiple local models and optimizations, providing an effective global control policy for the entire operating system. Joe et al. Joe *et al.* (2018) studied a distributed MPC scheme and has demonstrated a high potential of reducing energy consumption by up to 27% within the cooling season. A real-time optimal control method is developed in Li *et al.* (2021) to solve the optimization problem in a distributed manner and find the proper trade-off between maintaining thermal comfort and indoor air quality as well as minimizing energy use. Li and Wang Li & Wang (2020) designed a multi-agent based hierarchical distributed approach for the optimal control of multi-zone ventilation systems to improve indoor air quality by regulating the operation of the primary air-handling units. A centralized multi-objective optimization scheme was formulated and decomposed into different simpler distributed sub-schemes. In this way, complex control optimization problems can be solved collectively by multiple agents. Such studies Pertzborn (2019); Li & Wang (2020) demonstrate the effectiveness of using distributed optimal control approaches to improve the energy efficiency of HVAC systems. However, operational issues when these control approaches are implemented on physical environments, for instance the convergence rate and computation load distribution have not been addressed. In addition, the scalability of the proposed distributed control systems can be improved. Furthermore, the implementation of optimal control strategies for multi-zone HVAC systems using multi-agent based distributed optimization approaches

is a challenging research direction. Moreover, the optimization models proposed in previous work are limited to energy efficiency and discomfort minimization. The carbon footprint is an essential factor to consider in the optimization problem. Vogler-Finck et al. used MPC to control and optimize multi-zone operation Vogler-Finck *et al.* (2018). The results show that carbon footprint and energy optimization are relevant objectives for predictive control, while price optimization is secondary. Carbon emission reduction is also considered in Pedersen *et al.* (2017), in which the authors proposed an economic model predictive control (E-MPC) scheme for space heating operation. Simulation results showed that E-MPC increases cost savings by up to 6% and CO_2 emissions by up to 3%. In Siler-Evans *et al.* (2012), MEF is used instead of the average emissions of the electrical grid. The MEF is also used in Péan *et al.* (2019), in which an MPC controller has been developed and tested within a co-simulation framework which combines an optimization approach with a dynamic building simulation tool. Their proposed solution achieves a marginal emissions saving in the range of 19%-29%. The aforementioned approaches have successfully reduced carbon emissions, however they do not use a multi-agent data-driven MPC approach. In this paper, a multi-agent control framework named MAC is proposed to optimize operations of HVAC system. Our approach relies on data-driven MPC control.

5.3 System description

5.3.1 Building description

Table 5.1 Control stages

$\hat{u}_i$	$\hat{u}_{c1i}$	$\hat{u}_{c2i}$	$\hat{u}_{h1i}$	$\hat{u}_{h2i}$	$\hat{u}_{fi}$	P_{u_i} **(kW)**
0	0	0	0	0	0	0
1	0	0	0	0	1	0.7
2	1	0	0	0	1	2.95
3	1	1	0	0	1	5.2
4	0	0	1	0	1	2.95
5	0	0	1	1	1	5.2

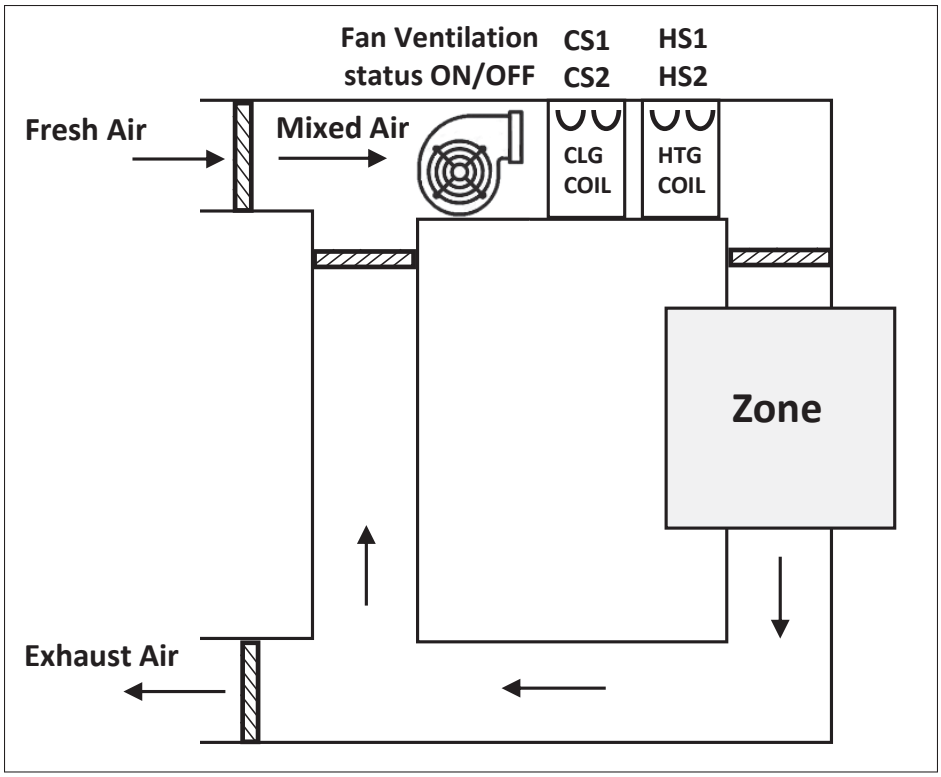

Figure 5.1 Schematic diagram of RTU for one zone

In this paper, we consider a multi-zone retail building equipped with a rooftop unit (RTU). The building has five zones equipped each with a RTU and controlled by a separate thermostat. Each RTU contains a fan with two heating and two cooling stages as described in Fig. 5.1. We assume a constant fan flow-rate and it is actuated either ON or OFF. There is significant thermal coupling between all zones since there are no walls between them. Given a zone i, it is controlled by a vector $\hat{u}_i$ including five control parameters $\hat{u}_{c1i}$, $\hat{u}_{c2i}$, $\hat{u}_{fi}$, $\hat{u}_{h1i}$ and $\hat{u}_{h2i}$ which represent cooling stage 1, cooling stage 2, fan ventilation stage, heating stage 1 and heating stage 2. The control signal is binary: 0 signifying OFF and 1, ON. The set of valid operation combinations contain six possibilities as shown in Table 5.1. The first stage of either heating or cooling modes can be activated alone, however the second stage requires the first to be ON. The fan can run independently but needs to be ON whenever the heating or cooling system is ON. The energy efficiency of a building can be achieved by orchestrating the sequence of control signals across the different units over a time horizon while respecting system and comfort constraints. The building operates following a tiered utility rate. In this case study, the energy is charged at

0.05303 \$/kWh if the energy consumption is less than the maximum energy supplied per month $E_{max} = 210'000kWh$ and 0.0373 \$/kWh otherwise. The power demand rate is 14.58 \$/kW and charged on the maximum demand during the month. This rate structure can be updated given another building's local utility rates.

5.3.2 Multi-agent control system description

The multi-agent control system is described in Fig. 5.2, and is a distributed control decision process based on two main entities:

- Local agent: each local agent is an independent control decision maker who represents each RTU or separated zone in the building. There are as many agents as RTUs. An agent is in charge of its own local control parameters decision and responsible for generating a local optimal decision regarding some constraints. Moreover, the agents compete for global optimality at each time cycle and then modify their local control decision dynamically according to the coordination message received from the coordinator. The prediction model proposed in Mtibaa *et al.* (2021a) is used to predict the temperature over a control horizon for each agent. Each agent entity uses the temperature prediction data in its optimization model (section 5.4) to compute the optimal control sequence. An agent is ignorant to other agent's control decisions.
- Coordinator: the coordinator minimizes the carbon emission in order to assign a power budget for each agent while respecting a maximum power budget during each control horizon.

The local agent operates on a receding horizon by solving for a fixed prediction horizon (2 hours in our case) from the current time step t. The first control signal $u^*_{zi}(t+1)$ is applied to the building. All this process is executed as a closed-loop behavior.

5.4 Multi-agent control model

We consider N zones operating with local agents each controlling a rooftop unit (RTU), and one coordinator. The zones have different sizes with different power requirements. We minimize the

discomfort level in each zone within an interval of time N_p. The power consumed in each zone should be bound to a power budget determined by the coordinator. The coordinator minimizes the carbon emissions and assign an optimal power budget for each zone with a condition that the sum does not exceed a maximum power budget during N_p.

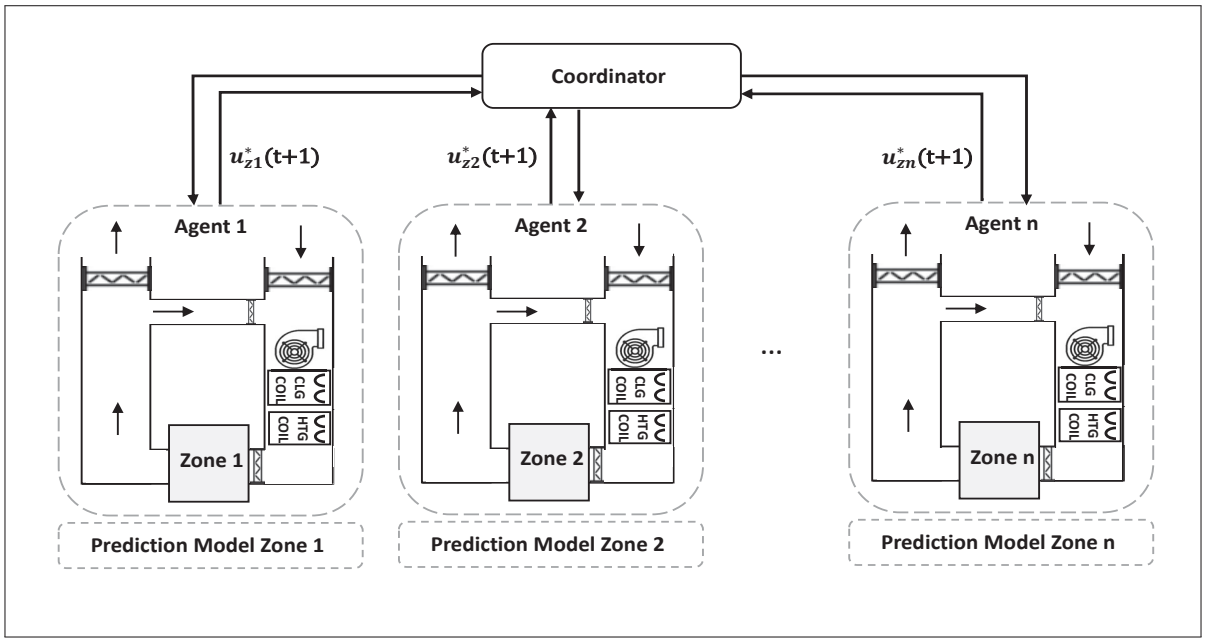

Figure 5.2 The overall structure of Multi-agent framework

5.4.1 Local agent model

Each agent solves a local optimal control problem to minimize discomfort during a prediction horizon N_p. The discomfort is calculated according to the positive deviation ($\$/°C$) between temperature setpoint in occupied and unoccupied times and the predicted temperature as formulated in (5.2). $t+k|t$ indicates the predicted value of a certain variable at time step $t+k$ starting from time step t. $\hat{T}_i^{t+k|t}$ is the predicted temperature for the whole prediction horizon (5.3). The $\underline{T}_{sp}$ and $\overline{T}_{sp}$ are the lower and upper temperature setpoint respectively, and they vary based on occupied and unoccupied times. The T_{sp} is between 15° C and 26° C in unoccupied period and between 21° C and 23° C in occupied period. The power consumption $P_i^{t+k|t}$ $(\hat{u})$ of each zone i is calculated by multiplying the control signals $\hat{u}_i$ by the power of the

cooling stage 1 ($P_{c,s1}$), the cooling stage 2 ($P_{c,s2}$), the heating stage 1 ($P_{h,s1}$), heating stage 2 ($P_{h,s2}$) and the supply fan (P_f) as defined in (5.4). The constraint in (5.5) indicates that the power consumed by each agent at each time step t must not exceed a power budget pre-computed by the coordinator in section 5.4.2. Table 5.2 summarizes the various symbols and related meanings.

Table 5.2 Table of notations for agent model

Symbol	Explanation
Input parameters	
v_i	the uncontrolled variables includes outdoor temperature, hour of day and day of week
T_i	Indoor air temperature of agent i
$\overline{T}_{sp}$	upper temperature setpoint
$\underline{T}_{sp}$	lower temperature setpoint
$P_{c,s1}$	power of the cooling stage 1
$P_{c,s2}$	power of the cooling stage 2
P_f	power of the fan
$P_{h,s1}$	power of the heating stage 1
$P_{h,s2}$	power of the heating stage 2
P_{budget_i}	power budget for agent i
$P^t_{budget-max}$	power consumption limit of the HVAC system
Δt	sampling rate of 5 minutes
N_z	number of agents
N_p	prediction horizon
Auxiliary variables	
Discomfort($\hat{u}_i$)	discomfort cost of agent i
P_i	operation system power of agent i
Decision Variables	
$\hat{u}_i$	control parameter of agent i,

The optimization problem of each local agent, name P1_i is defined as follows.

$$\text{P1}_i = \min_{\hat{u}_i} \text{Discomfort}(\hat{u}_i) \tag{5.1}$$

$s.t.$

$$\text{Discomfort}(\hat{u}_i) = \sum_{k=0}^{N_p} \max\left\{0, \hat{T}_i^{t+k|t}(\hat{u}_i) - \overline{T}_{sp}\right\} + \max\left\{0, \underline{T}_{sp} - \hat{T}_i^{t+k|t}(\hat{u}_i)\right\} \cdot \Delta t/60 \quad (5.2)$$

$$\hat{T}_i^{t+k|t}(\hat{u}_i) = f_{\text{CAM-LSTM}(z_i)}(T_{i,t-l:t}, u_{i,t-l:t}, \hat{u}_{i,t+1:t+k}, v_{i,t-l:t}, \hat{v}_{i,t+1:t+k})\ \forall i, k \quad (5.3)$$

$$P_i^{t+k|t}(\hat{u}_i) = \hat{u}_{c1i}^{t+k|t} \cdot P_{c,s1} + \hat{u}_{c2i}^{t+k|t} \cdot P_{c,s2} + \hat{u}_{fi}^{t+k|t} \cdot P_f + \hat{u}_{h1i}^{t+k|t} \cdot P_{h,s1} + \hat{u}_{h2i}^{t+k|t} \cdot P_{h,s2}\ \forall i, k \quad (5.4)$$

$$P_i^{t+k/t}(\hat{u}_i) \leq P_{\text{budget}_i}^{t+k/t}\ \forall k \quad (5.5)$$

$$A_{u_i^t, u_i^{t+1}} = 1 \quad (5.6)$$

$$\hat{u}_i \in [0, 5] \quad (5.7)$$

The state transition constraint is presented in (5.6), which reduces the wear-and-tear of HVAC equipment. All the possible state transitions from a control state u_i^t to a possible state u_i^{t+1} are defined in matrix $A_{u_i^t, u_i^{t+1}}$. For instance, state 0 can only change to state 1 or remain at state 0, as follows.

$$\mathbf{A}_{\mathbf{u_i^t},\mathbf{u_i^{t+1}}} = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{Vmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{Vmatrix} \end{array}$$

5.4.2 Coordinator model

In the coordinator model the MEF is considered and it indicates how the emission factor changes if an additional unit of energy is produced or consumed Huber, Lohmann, Schmidt & Weinhardt (2021). MEF is calculated using the linear regression approach described in Siler-Evans *et al.* (2012) and originally demonstrated by Hawkes Hawkes (2010) and used to calculate marginal CO_2 rates for the United Kingdom. As described in (5.8), (5.9) and (5.10), the regression expresses the change in fossil generation $\Delta G^t[kWh/h]$ and the change in emissions $\Delta\Gamma^t[gCO_2/h]$, across a set of intervals ($t \in T$) Huber *et al.* (2021). The regression coefficient β represents the MEF, typically expressed in $[gCO_2/kWh]$.

$$\Delta\Gamma^t = \beta.\Delta G^t \tag{5.8}$$

$$\Delta\Gamma^t = \Gamma^t - \Gamma^{t-1} \tag{5.9}$$

$$\Delta G^t = G^t - G^{t-1} \tag{5.10}$$

In this paper the coordinator solves a global optimal control problem to minimize the carbon emission price ($c^t_{carbon}(u_i)$) which is computed by multiplying the MEF by a fixed carbon related cost π_{carbon} which presents the market price of the gram of CO_2 and by the power budget of each agent i at each time step $t \in N_p$. The constraint in (5.12) indicates that the parallel operation of several agents at each time step must meet the power consumption limit $P^t_{budget-max}$ of the HVAC system. For a scenario with 5 zones, we assume that:

- During the unoccupied period, only the fan can be turned ON, so the control $\hat{u}_i$ takes the state 0 or 1. We assume that only two zones will be set to state 0 and a maximum of three zones will be set to state 1 at the same time on each control horizon. In this case $P_{\text{budget}-max}$ will be equal to 2.1 kW.
- During the occupied period, we assume that from 7 AM to 9 AM, heating stage 2 cannot be activated. The control $\hat{u}_i$ takes state 4 as the maximum for all 5 zones. In this case $P_{\text{budget}-max}$ will be equal to 14.75 kW at each control horizon from 7 AM to 9 AM. The rest of the occupancy period, we assume that $\hat{u}_i$ takes state 5 for up to 3 zones at the same time on each control horizon and state 4 for the other 2 zones. In this case, $P_{\text{budget}-max}$ will be equal to 21.5 kW at each control horizon from 9 AM to 6 PM.

The constraint in (5.14) describes the state transition constraint.

$$\text{P2} = \min_{u_i} \sum_{k=0}^{N_p} \sum_{i=1}^{N_z} \beta.\pi_{carbon}.P^{t+k|t}_{\text{budget}_i}(u_i) \tag{5.11}$$

$s.t.$

$$\sum_{k=0}^{N_p} \sum_{i=1}^{N_z} P^{t+k|t}_{\text{budget}_i}(u_i) \leq P^{t+k|t}_{\text{budget}-max} \; \forall k \tag{5.12}$$

$$P^{t+k|t}_{\text{budget}_i}(u_i) = u^{t+k|t}_{c1i} \cdot P_{c,s1} + u^{t+k|t}_{c2i} \cdot P_{c,s2} + u^{t+k|t}_{fi} \cdot P_f + u^{t+k|t}_{h1i} \cdot P_{h,s1} + u^{t+k|t}_{h2i} \cdot P_{h,s2} \; \forall i, k \tag{5.13}$$

$$A_{u_i^t, u_i^{t+1}} = 1 \tag{5.14}$$

$$u_i \in [0, 5] \tag{5.15}$$

Table 5.3 Table of notations for coordinator model

Symbol	Explanation
Input parameters	
$P_{c,s1}$	power of the cooling stage 1
$P_{c,s2}$	power of the cooling stage 2
P_f	power of the fan
$P_{h,s2}$	power of the heating stage 1
$P_{h,s2}$	power of the heating stage 1
$P^t_{budget-max}$	power consumption limit of the HVAC system
β	marginal emission factor
π_{carbon}	fixed carbon related cost
α	the weight vector associated to power budget during prediction horizon N_p
N_z	number of agents
N_p	prediction horizon
Auxiliary variables	
c^t_{carbon}	carbon emission price
P_{budget_i}	power budget for agent i
P_i	operation system power
Decision Variables	
u_i	control parameter of agent i

5.4.3 Multi-agent control algorithm

The details of the proposed multi-agent control framework in a multi-zone building are shown in Algorithm 5.1. The applied multi-agent control algorithm is further explained as follows:

At first, the CAM-LSTM model Mtibaa *et al.* (2021a) is trained for each zone, as shown in lines 1–4. Starting from line 5, the power budget is initialized as follows: if the experiment starts at the unoccupied time, we assume that the control of each zone is set to state 1, which means that only the fan is turned ON. In this case, the power budget of each zone is equal to 0.7 kW. On the other hand, if the experiment starts at occupancy time, we assume that the control

of each zone goes to state 5, which means that the fan and heating stages 1 and 2 are on. In this case, the power budget of each zone is equal to 5.2 kW. For each simulation step, data is acquired from simulation environment. The data includes past and future steps of uncontrolled variables (e.g. outdoor air temperature, day of the week and hour of the day), past controlled data, and past indoor temperature data for each zone i. As shown by line 8, the coordinator solve (P2) using ILP to compute $P^{t}_{budget_i}(\hat{u}_i)$ for all agents. Next, in lines 9–10, the algorithm 5.2 is executed in parallel for all local agents. Each agent computes its optimal control sequence $\hat{u}_i{}^{t+k|t}$. A heuristic search algorithm based on genetic algorithm defined in Mtibaa *et al.* (2021a), is used to find the possible optimal solutions of agent problem described in (5.1), as shown in the algorithm 5.2. Each agent optimal control sequence $\hat{u}_i{}^{t+k|t}$ is then passed to the simulator environment.

Algorithm 5.1 Multi-agent Control Framework

```
   Input: dataframe
   Output: optimal agent controls
1  for agent in zonesNz do
2      Collect data
3      Preprocess data
4      Train zone model using CAM-LSTM Mtibaa et al. (2021a)
5  end for
                                          // Retrain the model monthly
6  P^{t+k|t}_{budget_i} initialization
7  for simulation step do
8      Get data with past and future data
                                          // including previous feedback
9      Solve (P2) to compute P^{t+k|t}_{budget_i} for all zones using ILP
                                          // execute coordinator model
10     do in parallel for each agent
11         Execute Agent Algorithm 5.2
                                          // execute agent model
12     end
13     Get output from agents
14 end for
```

5.5 Validation and baselines

To validate the proposed MAC approach, a Modelica-Python co-simulation testbed has been established, as shown in Fig. 5.3. The testbed is built on the foundation of two tools: the Modelica Buildings Library Wetter *et al.* (2014) used to create the RTU-based building model, and ModelicaGym Lukianykhin & Bogodorova (2019) used to integrate the control algorithms described in section 5.4.3, written in Python, with the time evolution of the Modelica model. A five-zone RTU building model is developed using base models inspired from Wetter *et al.* (2014) using the commercial Modelica software, Dymola.

Details of the model and its control points are provided in section 5.3.1. The model has been exported out of Dymola as a Functional Mockup Unit (FMU), a model that follows the Functional Mockup Interface (FMI) standard for exporting and exchanging models amongst a variety of simulation software. Once the FMU is outside of the modeling software, there is a communication layer between the control algorithm and simulation, implemented via ModelicaGym Lukianykhin & Bogodorova (2019). The ModelicaGym software is an open-source project designed to allow OpenAI Gym style simulation of FMUs in a Python environment. Specifically, this tool simulates the FMU by successively passing controls to the FMU, taking a single user-defined time step, and retrieving updated data from the FMU regarding the state of the simulation. This process is iterated for the duration of the simulation. ModelicaGym was adapted and utilized as a communication layer between the control algorithm and the FMU model.

In Modelica, five zones are simulated and equipped with a RTU as discussed in section 5.3.1. In the other hand, in Python, a real-time optimal multi-agent controller model is programmed, as shown in Fig. 5.3. The outputs of the controller $u^*_{zi}(t+1)$ are sent to Modelica which applies these controllers and returns the temperature feedback. Both the simulation time step and optimal control horizon are 5 minutes.

Algorithm 5.2 Local Agent Algorithm

Input: dataframe, $P^{t+k|t}_{budget_i}(\hat{u}_i)$
Output: optimal agent control

```
Load CAM-LSTM Mtibaa et al. (2021a) prediction models for each agent
for generation do
    Predict temperature
    Compute fitness using model defined in (5.1)
    Select individual by tournament
    Crossover
    Mutation
    Get argmin of scores
end for
Get optimal control û
Save outputs in csv file
Create new population
Add best chromosomes to new population
```

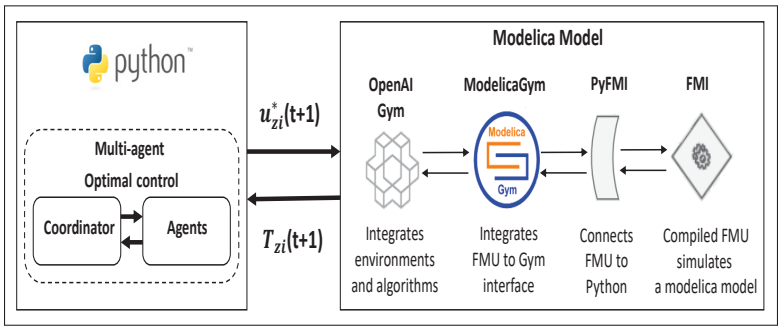

Figure 5.3 Co-simulation testbed

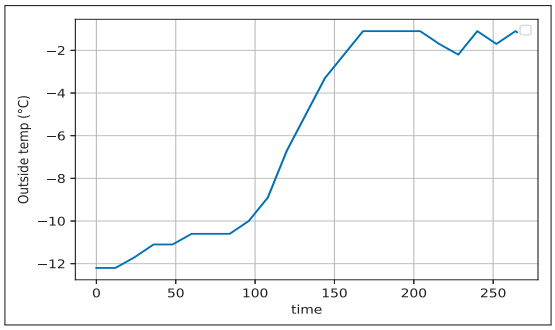

Figure 5.4 Outside temperature profile

Outdoor weather, hour of the day, day of the week and controllers parameters are exogenous inputs to the prediction models used in each agent. Fig. 5.4 shows the outdoor temperature for the conducted simulation day. In this study, the proposed multi-agent method which minimizes carbon-emissions for optimal control is compared with MAC approach which only minimizes power budget, centralized control method defined in a previous study Mtibaa *et al.* (2021a) and the bang-bang controller Chen & Li (2021).

- **Baseline control approach**: The bang-bang controller (ON-OFF controller) is a commonly used control approach for HVAC systems Chen & Li (2021). It is a feedback controller that switches ON or OFF when a desired setpoint has been reached. There is typically a small deadband to reduce excessive cycling. No optimization model is implemented in this baseline. The control operation follow a fixed schedule, and the occupancy time is from 7 AM to 6 PM.
- **Optimal centralized control approach**: The controller collects all required information from all the zones. An online optimization model using GA is used to find the possible optimal solutions of the control optimization problem in centralized manner, as defined in Mtibaa *et al.* (2021a). The output of the centralized controller is considered as the "near-optimal", and is be used as benchmark to evaluate the performance of the proposed approach in this paper.
- **Optimal MAC approach**: We implement MAC approach and in this case the coordinator minimizes only power budget without considering carbon emissions as follows:

$$\text{P2a} = \min_{\hat{u}} \sum_{k=0}^{N_p} \sum_{i=1}^{N_z} P_{\text{budget}_i}^{t+k|t}(\hat{u}_i) \tag{5.16}$$

with the constraints (5.13)-(5.15). The agents are optimized and controlled in a distributed manner. Each agent minimizes discomfort according the power budget computed by the coordinator as described in P1_i.

- **Optimal MAC_CO2 approach**: We implement MAC approach and in this case the coordinator minimizes the carbon emissions, as described in P2, and assign an optimal power budget for each agent with a condition that the sum does not exceed a maximum power budget. In the other hand, agents minimize discomfort according the power budgets computed by the coordinator.

5.6 Results and discussion

5.6.1 Results-I: MAC without considering carbon emission cost

In the first experiment, we implement the MAC approach with P2a for the coordinator and P1 for the agent. Fig. 5.5 represents the three simulation results for bang-bang, centralized approach and MAC approach. In the first row, the orange line identifies the temperature feedback of bang-bang control. The green line represents the temperature results from centralized control approach. The blue line and the pink line represent the true temperature value and predicted temperature value of MAC approach respectively. We notice that the prediction is accurate compared to the real value. The temperature remains between the set points most of the time (21° C in occupied period and 15° C in unoccupied period). The temperature for the MAC approach remains consistent during occupied periods due to discomfort constraints. However, with a bang-bang controller, there are no discomfort restrictions and temperature fluctuations may be greater. The three bottom graphs of Fig. 5.5 indicate the state of controls for each zone for MAC, centralized and bang-bang control approaches respectively. All control states are described in detail in Table 5.1.

The centralized control method, as indicated in Mtibaa *et al.* (2021a), calculates the optimal control by considering all zones' control parameters. One of its objectives is to prevent simultaneous activation of all zones, particularly at the starting time, to avoid power peak. Due

to this, the rise in temperature in zones 1, 4, and 5 was delayed, as observed in Fig. 5.5. In the morning of this winter time, as shown in Fig. 4.11, the outside temperature is very low, i.e., between -12° C and -10° C. The control in the bang-bang method fluctuates between all controls OFF and heating stages 1 and 2. Therefore, the temperature in some zones fails to reach the setpoint because the control is not stable. On the other hand, the centralized method does not activate the heating stage 2 to minimize energy and respect power peak constraints.

As a result, the temperature responses in the bang-bang and centralized method are different in the morning. It is noticeable that multi-agent control keeps the heating stage 1 (u_{h1}) ON and avoids turning ON the heating stage 2 (u_{h2}), thus reducing energy consumption. Overall the control is stable and there are not many fluctuations. However, bang-bang turns ON heating stage 2 more frequently, and the control values fluctuate a lot between the fan and the heating stage 2. MAC shifts the morning ramp on zone 1, 2 and 5 to be earlier and delays zone 3 and 4 in order to avoid a power peak caused by ramping all zones at once.

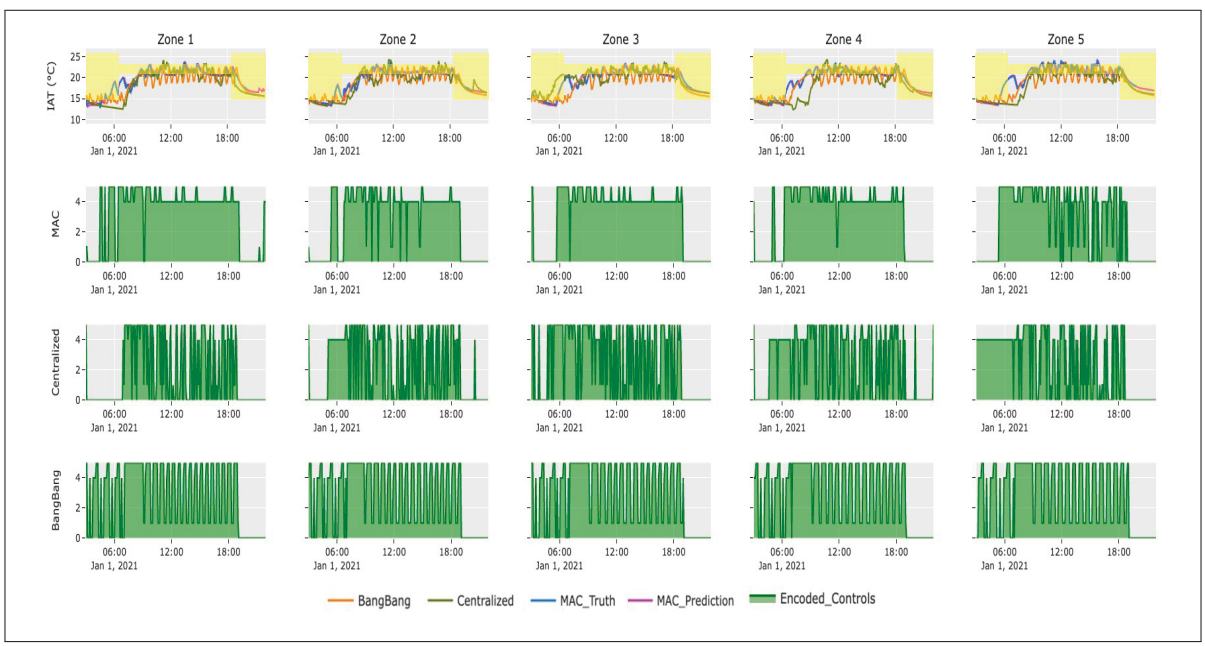

Figure 5.5 Comparison between MAC, centralized and bang-bang control results

5.6.2 Results-II: MAC with considering carbon emission cost

In the second experiment, we minimizes carbon emissions cost as described in P2. Fig. 5.6 presents the results of MAC without and with considering CO_2.

The temperature prediction is close to the ground truth values. However it is around 20° C in most of the time, which makes discomfort cost higher than the discomfort cost in the MAC approach as described in Table 5.4. The aim of MAC_CO2 is to minimize carbon emissions while also limiting energy consumption. To achieve this, the coordinator will allocate a lower power budget to each agent. This can prevent turning ON heating stage 2 (u_{h2}) more frequently, however it may result in an increase in discomfort. Fig. 5.7 shows the difference in terms of the cumulative carbon emission between two experiments. The blue line represents MAC without considering the cost of CO_2 and the orange line represents MAC considering the cost of CO_2. We notice that the emission of MAC_CO2 is less than for MAC. At the beginning of the day, both operate almost the same way, then MAC_CO2 consumes less at the end of the day. In general, there is a reduction of 23.4%. Table 5.5 provides more details on these results. We have calculated the electrical emission and the gas emission separately. We can see that there is a reduction of 0.02 tons of CO_2 equivalent for electrical emissions and 1.42 tons of CO_2 equivalent for gas emissions for one experiment day.

Table 5.4 Cost results

	MAC	Centralized	bang-bang	MAC_CO2
Energy (kWh)	351.2	278.13	415.18	320.09
Discomfort(°C/day)	47.95	122.94	82.17	93.16

Table 5.5 CO2 electric and gas consumption

	CO2 electrical [ton CO2eq]	CO2 gas [ton CO2eq]	CO2 global [ton CO2eq]
MAC	0.14	5.99	6.13
MAC_CO2	0.12	4.57	4.69

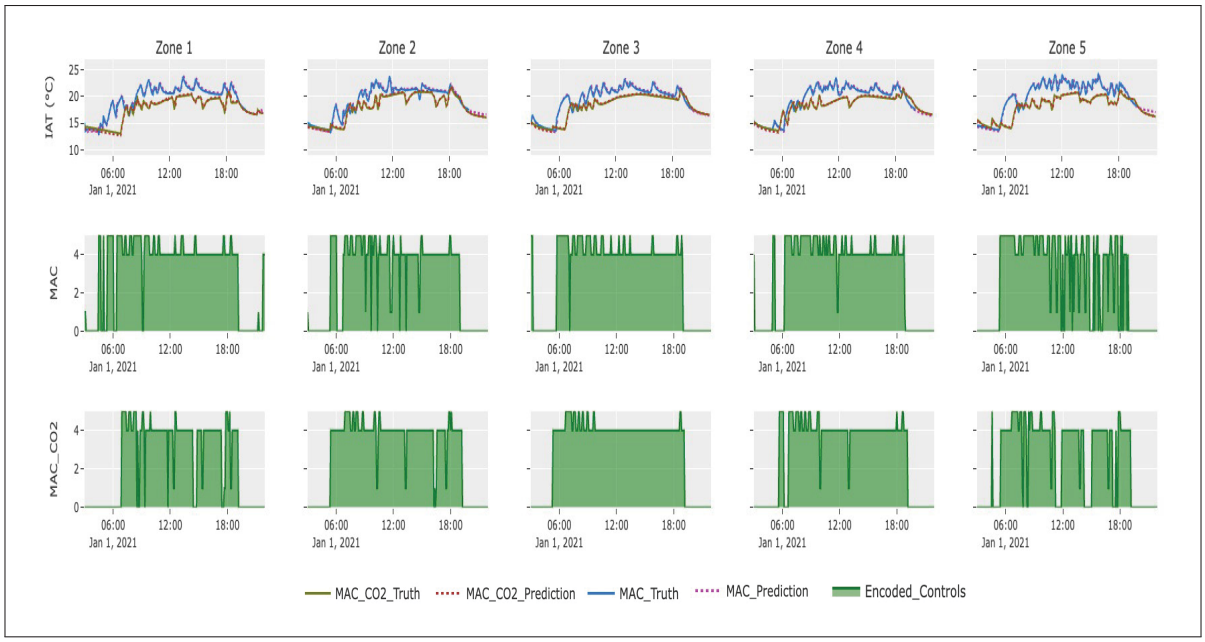

Figure 5.6 MAC with CO_2 cost results

5.6.3 Algorithm performance

5.6.3.1 Algorithm convergence

In the MAC approach, the local agents run in parallel to resolve the control optimization problem. Each zone is controlled by its own local agent, so the search space is relatively small for their GA algorithm. The centralized approach requires more time than MAC as described in Table 5.6. Moreover, in the centralized approach, we are limited with the number of zones. When the number of zones increases, the convergence time also increases. Whereas in the MAC approach, the number of zones has no impact on the execution time as shown in Table 5.6. We observe that the execution time of a cycle does not exceed the control horizon which is 5 minutes. Thus, the centralized approach supports no more than 10 zones, otherwise it will exceed the control horizon. However, in the MAC approach, since the agents run in parallel with a multiprocessor approach, the number of zones may be scalable according to the number of CPU cores contained in the computing machine.

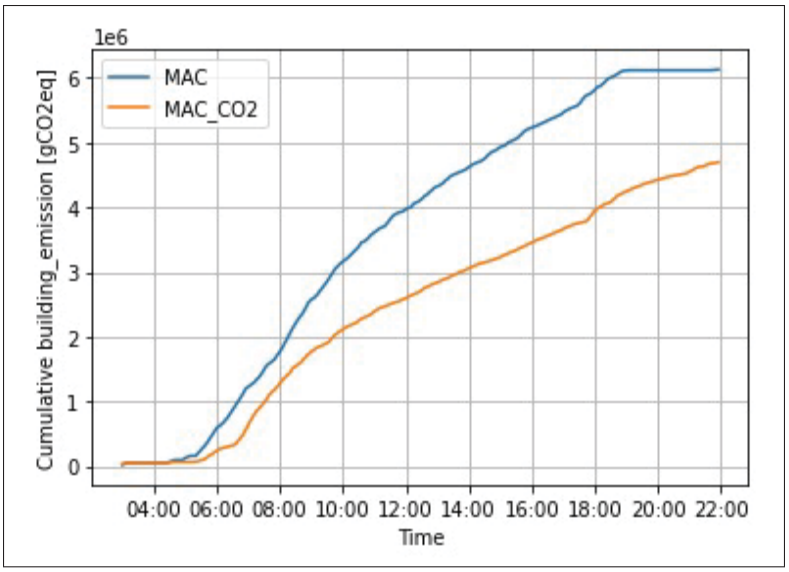

Figure 5.7 Comparison of cumulative building emissions

5.6.3.2 Algorithm scalability

The centralized algorithm has a linear time complexity. In other words, its execution time increases linearly with the size of zones. However, the proposed MAC approach is more scalable. If more zones are involved in the system, more local agents can be added without increasing the computation complexity. Therefore, one or more local agents can be easily updated or added/removed without significantly increasing the computation time since the agents are executing in parallel as described in Table 5.6. On the other hand, the centralized approach requires the entire formulation of the optimization problem to be updated when a zones changes.

Table 5.6 Scalability test

	5 zones	10 zones	20 zones	30 zones
Computation time (s/5min) **MAC**	9.31	9.58	12.04	14.57
Computation time (s/5min) **Centralized**	50.66	252.09	475.63	898.5

5.6.3.3 MAC algorithm reconfigurability

The enhanced reconfigurability of the MAC approach is an additional significant advantage for the optimal control of multi-zone HVAC system. It allows to manage flexibility by scaling up/down the control system and adding/removing terms in the optimization problem regarding user concerns in a specific agent. It also improves the robustness of the control decision under constantly changing indoor and outdoor conditions. When the outside climate changes or if a client wants to customize the control goals, the objective function of an optimization problem must be adapted. The MAC approach adopts different methods than the centralized approach. For the centralized optimal control approach, the optimization function is deployed in the central station. Reconfiguring this function must be done in the central station. Therefore, there is a risk of interrupting the overall control system. On the other hand, in the MAC approach, only a control agent needs to be reconfigured with no need to modify the entire control system when the dynamics of an agent component change. Moreover, any local failures do not interrupt the operation of the whole control system. For instance, if zones are offline in real buildings, the MAC approach may still be functional. This improves the resilience and robustness of the control system.

5.7 Conclusion

In this paper, a multi-agent based on MPC model controller has been described, implemented and evaluated in a simulation environment using Python and Modelica. A multi-agent and coordinator optimization framework with low computation time is developed to minimize the discomfort, energy consumption and carbon emissions in the same time. A MAC approach based on genetic algorithm is proposed to solve the local agents optimization problems in parallel and its convergence, scalability and reconfigurability have been discussed. MAC is compared with centralized and bang-bang control baselines. MAC performs better than bang-bang in

terms of energy consumption and discomfort. From the optimal controls, the centralized control approach performs the best in terms of energy consumption, but its computation time is the least suitable for real-time implementation. The efficiency of MAC is very close to the centralized approach, while taking less execution time. A scalability study shows that the centralized control approach supports up to 10 zones while the MAC approach is much more scalable. Our proposed approach improves the energy savings of 8.8% and a carbon footprint reduction of 23.4%. In future work, we will focus on: (1) deploying and validating the MAC approach in real building case study and, (2) extending our MAC system to optimize simultaneously building-level and grid-level objectives.

CONCLUSION AND RECOMMENDATIONS

6.1 General conclusion

The general objective of this thesis was to design an efficient and scalable control solution for HVAC systems that minimizes energy consumption, carbon emissions, peak demand, and discomfort during occupancy hours. Our work is based on the hypothesis of accurate indoor air temperature modeling, consideration of control sensitivities over the prediction horizon, and optimization of the control decision, we minimize energy and carbon footprint while maintaining comfort and improving control efficiency and scalability for the HVAC system in smart buildings. The proposed research work consists of three themes. We first introduced an accurate model that uses LSTM and based on a direct S2S multivariate multi-step model to predict the indoor air temperature with multi-step in a multi-zone smart building and with different types of HVAC control systems. We then presented an MPC based online data-driven control framework, called MPC-GA, which combines a context-aware multivariate LSTM (CAM-LSTM) model to predict a multi-step IAT with an MPC framework. The CAM-LSTM is an improvement of the previous methodology. It considers the impact of controls on temperature prediction in the control decision loop, leading to a robust optimization decision for the control outputs. Finally, we proposed a scalable multi-agent based distributed approach for optimized control of a multi-zone smart building based on a set of local agents which represent individual zones in the building, coordinated by a central agent. The scalability and reconfigurability of the proposed solution are demonstrated. Each theme is the subject of a separate published journal article to disseminate as widely as possible. Below, we highlight the strengths and weaknesses of the proposed methods as reflected in each theme.

6.1.1 LSTM-based framework for accurately IAT prediction

The first theme covers the issue of accurate modeling of IAT in multi-zone HVAC systems. In chapter 3, we defined an accurate prediction model LSTM-based to predict IAT for multi-zone building based on direct multi-step prediction with sequence-to-sequence approach. In addition, we designed and implemented two architecture types, LSTM-MISO and LSTM-MIMO. While most of prior work only investigate a specific type of HVAC system, the modeling framework proposed in this study covers both VAV and CAV HVAC systems. The consideration of control variables as the input increases the prediction accuracy of the LSTM models. This study showed that LSTM-MISO model is efficient for VAV buildings. However, since there is an effect of thermal coupling between adjacent zones in CAV building because of its open space area, it is found that the overall prediction accuracy increases using the MIMO model. We can conclude that LSTM-MIMO is a valuable method for modeling IAT in a light-weight building with CAV type of HVAC system. This method has been described in an article published by Neural computing and applications journal. The performance of the proposed models has been evaluated and tested in two different types of buildings: the first floor of a hotel in Montreal with five VAVs systems and a small retail store with three zones supplied by three CAVs systems. For both buildings, experimental results showed that the LSTM models outperform Multilayer Perceptrons models by reducing the prediction error by 50%.

6.2 Context-aware MPC framework for efficiently multi-zone HVAC control

The second theme covers two issues; the accurate modeling of IAT in multi-zone HVAC systems with considering the impact of controlled parameters on the prediction results, and the real-time control efficiency of HVAC system in multi-zone building. In Chapter 4, we modeled a CAM-LSTM model to predict a multi-step IAT composed by dual-stream neural network with an attention mechanism that selects not only past but also future multivariate time series,

including controlled and uncontrolled inputs to predict a multi-steps temperature output. This model is integrated in the online data-driven MPC framework. This control optimization model minimizes energy, peak power and discomfort costs with considering of self-tuned setpoint, cycling and temperature ramp. In addition, we defined a new heuristic based on genetic algorithm to find the possible optimal solutions of the online data-driven control model over a prediction horizon. This study has been published in building engineering journal. The benchmark results showed that the MPC-GA outperforms baseline control systems with more than 50% and 80% reduction in energy consumption and discomfort, respectively.

6.3 Hierarchical multi-agent control framework for energy efficiency and carbon reduction

The third theme covers the issue of designing a more scalable data-driven control system for the HVAC system while reducing energy consumption and carbon footprint. In Chapter 5, we presented a new scalable multi-agent based distributed approach for optimized control of a multi-zone smart building based on a set of local agents that represent individual zones in the building, coordinated by a central agent. For each control horizon, the coordinator minimizes the overall carbon emissions and assigns an individual energy budget to each local agent. Each local agent minimizes the discomfort in its zone while respecting the energy budget assigned by the coordinator. We proposed a heuristic search based on a genetic algorithm to find the optimized control sequences in each zone, and formulated an ILP model for the coordinator problem which can be solved using an ILP solver. This paper has been submitted to journal of building engineering. For a representative winter test day, the proposed methodology gave an energy savings of 8.8% and reduced the carbon footprint by 23.4%.

In future work, we will focus on: i) improving the CAM-LSTM model by making it a hybrid modeling scheme by combining physics with machine learning. ii) including more tests for MPC-GA control framework on other type of HVAC system and building with more zones.

iii) considering of more inputs into the control model, especially due to the growth in energy demand associated with the electrification of transportation. iv) improving MAC approach by considering information sharing between different agent or set of agent. v) deploying the MAC approach in real building use case. vi) extending our MAC system to optimize simultaneously building-level and grid-level objectives.

6.4 Major contributions

The major contributions of this thesis are:

1. **Data-driven IAT modeling:** We propose a data-driven framework for modeling IAT with LSTM-MISO and LSTM-MIMO models based on the S2S approach.
2. **CAM-LSTM prediction model:** We propose a CAM-LSTM models based on dual-stream neural network including attention mechanism which include past and future controlled and uncontrolled inputs.
3. **Model an efficient MPC-GA control framework:** We model an optimization model to minimize energy, power peak and discomfort that considers a self-tuned setpoint, cycling and temperature ramp as constraints.
4. **GA control algorithm:** We develop an heuristic search algorithm using a genetic algorithm to solve the online data-driven MPC-GA models and obtain the future optimal combination settings of all controls for all the zones over a prediction horizon.
5. **Deployment in a real multi-zone building use case:** We conduct a real deployment in order to validate the closed-loop MPC-GA control framework in a real multi-zone retail building.
6. **Model a scalable multi-agent control approach:** We model a scalable multi-agent control system formulated as MPC-based optimization problems for multi-zone buildings

7. **Model carbon cost for MAC system:** We model carbon cost by considering the MEF rate that categorizes the dirtiness of the footprint of the power grid. We include this carbon cost in the coordinator optimization model.
8. **Create a MAC simulation environment:** We validate the proposed MAC approach in simulation environment using Modelica.

6.5 Articles in peer-reviewed journals and conferences

1. F. Mtibaa, K.-K. Nguyen, M. Azam, A. Papachristou, J.-S. Venne and M. Cheriet, "LSTM-based indoor air temperature prediction framework for HVAC systems in smart buildings", Neural Computing and Applications, 1–17, 2020.
2. F. Mtibaa, K.-K. Nguyen, V. Dermardiros, and M.Cheriet, "Context-aware model predictive control framework for multi-zone buildings", Journal of Building Engineering, 42, 102340, 2021a.
3. F. Mtibaa, K.-K. Nguyen, V. Dermardiros, S. McDonald, J.-S. Venne and M. Cheriet, "Hierarchical Multi-Agent Control Framework for Energy Efficiency and Carbon Emission Reduction in Multi-Zone Buildings", Journal of Building Engineering, submitted to Journal of Building Engineering (9 September 2022).
4. F. Mtibaa, K.-K. Nguyen, V. Dermardiros, and M.Cheriet, "Online Genetic-Algorithm-based Model Predictive Control Framework for Multi-Zone Buildings", European Control Conference (ECC), pp. 1011–1017, 2021b.

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