An Empirical Investigation of the Demographics of Top Management Team (TMT) and its Influence in Forecasting Organizational Outcome in International Architecture, Engineering and Construction (AEC) Firms: A Fuzzy Set Approach

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Yousif ALHOSANI

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BOARD OF EXAMINERS (THESIS PH.D.)

THIS THESIS HAS BEEN EVALUATED

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Department of Construction Engineering at École de technologie supérieure

Mr. Sabah Alkass, Thesis Co-supervisor
College of Engineering at United Arab Emirates University

Mr. Maarouf Saad, President of the Board of Examiners
Department of Electrical Engineering at École de technologie supérieure

Mr. Gabriel Assaf, Member of the jury
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Mr. Mohamed Al-Hussein, External Evaluator
Department of Civil and Environmental Engineering at University of Alberta

THIS THESIS WAS PRENSENTED AND DEFENDED

IN THE PRESENCE OF A BOARD OF EXAMINERS AND PUBLIC

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UNE ENQUÊTE EMPIRIQUE SUR LA DÉMOGRAPHIE DE L'ÉQUIPE DE HAUTE DIRECTION (TMT) ET SON INFLUENCE SUR LA PRÉVISION DES RÉSULTATS ORGANISATIONNELS DANS LES ENTREPRISES INTERNATIONALES D'ARCHITECTURE, D'INGÉNIERIE ET DE CONSTRUCTION (AEC) : LA MÉTHODE D'ENSEMBLES FLOUS

Yousif ALHOSANI

RÉSUMÉ

Tandis que les Equipes Dirigeantes sont sélectionnées afin d'être intégrées à la stratégie d'une entreprise, des études antérieures ont mis en évidence l'impact significatif des TMT (Top Management Teams - Equipe de Haute Direction) sur sa performance.

Les résultats précédents ont montré que le défi de la double causalité était ambigu, incohérent et parfois conflictuel. Poursuivre sur la même ligne de recherche peut conduire à une conclusion incomplète voire même truffée d'erreurs. En revanche, cette recherche laisse entendre que l'incohérence des résultats parmi les données démographiques d'Equipe de Haute Direction présentées dans des travaux antérieurs peut indiquer une possibilité d'étudier la nature cachée de ces relations, et constituer un outil pour les prévisions futures. Plus précisément, dans cette recherche nous utilisons une structure multi-entrées (Equipe de Haute Direction démographiques) multi-sorties (performance organisationnelle) afin d'explorer le futur pouvoir de prédictibilités démographiques d'Equipe de Haute Direction pour les entrepreneurs en architecture, en génie et en génie civil internationales.

Afin de construire un modèle de prévision fiable, ces contradictions ont été évitées par l'utilisation de l'intelligence artificielle en formant, testant et produisant des résultats sans hypothèses antérieures ou structures connues. Nous avons notamment utilisé le système adaptatif d'inférence floue neurale (ANFIS) comme base de construction d'un ensemble de règles « Si-Ensuite » floues avec des paires entrée-sortie pré-testées.

Nous avons construit trois stratégies de prévision différentes, où nos résultats démontrent la connaissance et le potentiel du modèle ANFIS (série chronologique) dans les prévisions de performances organisationnelles, mais qui dans le même temps, suggèrent que la distinction devrait être établie entre les différentes constructions de données démographiques d'Equipe de Haute Direction et les constructions de performances.

Les résultats démontrant les données démographiques liées à l'emploi (Equipe de Haute Direction, diversité de l'éducation, diversité fonctionnelle et tenure) pourraient fournir une précision de prévision satisfaisante pour les constructions à court terme (Liquidité) et à moyen terme (Stabilité Trésorière et Structure du Capital). Le futur pouvoir de prédictibilité des données démographiques non liées à l'emploi n'a pas pu être mis en évidence dans cette recherche. En outre, les constructions de performances à nature dynamique ne peuvent pas être prédites. Enfin, des opportunités de futures recherches ont été suggérées pour les chercheurs. Plus important encore, il comprend la nécessité de redéfinir la diversité dans le contexte de la composition Equipe de Haute Direction (avoir différentes significations telles que : Variété, Séparation et Disparité). D'autres recherches méthodologiques futures sont également proposées à la fin de cette étude.

Mots-clés: Architecture, Ingénierie, construction, performance, ensembles flous

AN EMPIRICAL INVESTIGATION OF THE DEMOGRAPHICS OF TOP MANAGEMENT TEAM (TMT) AND ITS INFLUENCE IN FORECASTING ORGANIZATIONAL OUTCOME IN INTERNATIONAL ARCHITECTURE, ENGINEERING AND CONSTRUCTION (AEC) FIRMS: A FUZZY SET APPROACH

Yousif ALHOSANI

ABSTRACT

Whereas Top Management Teams (TMTs) are selected to fit a firm's strategy, prior studies have evidenced that TMTs have significant impact on firm performance. The challenge of the two-way causality has been reflected in previous findings being ambiguous, inconsistent and sometimes conflicted. Pursing the same line of research may lead to incomplete and even error-prone conclusion. In contrast, this research suggests that inconsistency of findings among TMT demographics shown in prior work may point the possibility of studying the black-box nature of such relationships, and provide a tool to future forecast the organization outcome. More specifically, a multi-input (TMT demographics) multi-output (organization outcome) structure was used in this research to explore the future predictability power of TMT demographics for international Architects, Engineers and Construction firms (AEC firms). In order to build a reliable forecasting model, those contradictions were avoided by the utilization of artificial intelligence methods by training, testing and producing results without any prior assumptions or known structures. In particular, the Adaptive Neural Fuzzy Inference System (ANFIS) have been employed as a basis for constructing a set of fuzzy "if–then" rules with pre-tested input–output pairs. Three different forecasting strategies were constructed, the findings have demonstrated the learning and potential of the ANFIS model (time series based) in forecasting organization outcome, but at the same time, suggest that distinction should be established among different constructs of TMT demographics and outcome constructs. The results demonstrated that job-related demographics (i.e., TMT Educational Diversity, TMT Functional Diversity and TMT Tenure) could provide a satisfactory forecasting accuracy for the short-span (Liquidity) and medium-span (Cash Flow Stability and Capital Structure) outcome constructs. The future predictability power of other non-job demographics could not be evidenced in this research. Additionally, outcome constructs with dynamic nature could not be forecasted. Lastly, future research opportunities have been suggested for researchers. Most importantly, it includes the need to re-define diversity in the context of TMT composition (having different meaning as in: Variety, Separation and Disparity). Other methodological future opportunities are also suggested at the end of this study.

Keywords: Architecture, Engineering, Construction, Performance, Fuzzy Set

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LIST OF ABREVIATIONS

A	Architects
AI	Artificial Intelligence
AEC	Architecture, Engineering and Construction Firms
ANNs	Artificial Neural Networks
C	Contractor
CEO	Chief Executive Officer
CFA	Confirmatory Factor Analysis
CFO	Chief Financial Officer
COO	Chief Operation Officer
C.V	Coefficient of Variation
E	Engineers
ECOC	The Error Correcting Output Coding Classifier
FIS	Fuzzy Inference Systems
ENF	Environment Specialist
ENR	Engineering News and Records
GC	General Contractors
GE	Geo-Technical
IQR	Interquartile Range
L	Landscaping
MAPD	Mean Absolute Percentage Deviation
MAPE	Mean Absolute Percentage Error

MaVLs	Classical Majority Vote Learns
MF	Membership Functions
MNC	Multi-National Corporation
MIMO	Multi-Input, Multi-Output
P	Planner
PICTs	Plug in Classification Techniques
RBV	Resource-Based View
R&D	Research and Development
SIC	The Standard Industrial Classification of Economic Activities
TMT	Top Management Team
TSK	Tagaki– Sugeno–Kang
V.P	Vice President

LIST OF SYMBOLS

B	Blau's Diversity Index
C_v	Coefficient of Variation
σ	Standard Deviation
μ	Mean
|μ|	Absolute Mean
R_k	Fuzzy Rule
A_i^k	Input label attached to rule R_k,
y	Output of the fuzzy system
f_k	Function of the input variables based on fuzzy rule
O_i^1	Layer 1 of ANFIS structure
O_i^2	Layer 2 of ANFIS structure
O_i^3	Layer 3 of ANFIS structure
O_i^4	Layer 4 of ANFIS structure
O_i^5	Layer 5 of ANFIS structure
A_i	Linguistic variable
μ A_i	Membership function of linguistic variable A_i
Wi	Firing strength of ANFIS node
$\overline{Wi}$	Normalized firing strength
f	ANFIS structure output
M	Mean Absolute Percentage Error (MAPE)
Y	Dependent variable of multiple linear regression

X	Independent variable of multiple linear regression
$P_C(n)$	Probability of the majority opinion
$C(X)$	Majority Vote Classifier
$h_1(X)$	ANFIS classifier
$h_2(X)$	Decision Tree classifier
$h_3(X)$	K-Nearest Neighbours classifier

INTRODUCTION

Construction industry has been argued in many studies for being a reflection of the economic status, a healthy construction market is a reflection of healthy overall economy and vise versa. However, construction industry is known as discrete commodity, along different dimensions. From one perspective, it has two levels of organizational objectives: temporary objectives of the project and the organization that is set up to build it, and permanent objectives of the involved firms, whereas it includes the desire for firms to enhance their position in the marketplace. From another perspective, construction is a "multi-industry", or a form of “network organization” which compromised from professional and commercial enterprises, ranging in their size, scope, objectives and specialities. That kind of fragmentation intrinsic in the construction process promotes the challenges faced by managers in construction organizations.

At the same time, forecasting and deciding the mixture of businesses are among the primary roles of any organization, whereas one of the core responsibilities of its upper echelons is to create a business content that will deliver sustainable value to the shareholders. Todays’ international market has been mutable in different aspects, which in turn, shifted how firms’ senior executives are leading their organizations. The quest to sustain, perform and compete has never been stronger compared to today’s turbulent business environment. Top Management Team (TMT) that leads an organization in such environment should develop and adjust the strategies to align with markets volatility and avoid complacency. In a quest to avoid adverse impact on the organizations performance, a substantial body of research has already examined the importance of exploring different TMT related topics including its formation, governance and understanding of their internal processing known as a “black-box”. In fact, it is more of a “jewel-box” that could positively drive organizational performance and enable them to respond to business challenges. Despite the invaluable contributions of prior studies on Top Management Teams’ (TMTs) impact on organization performance, there are significant gaps in the field. This research focusses on exploring the predictability power of TMT to forecast an organization's future performance, which was not evident in prior studies.

Given the continuously increasing diversity and turbulence in the business environment, and associated market competitiveness, the importance of business forecasting requires further scholarly attention. Based on a hidden structure, the principle of forecasting is to extrapolate the behaviour of a system (whether identified or unknown) to the future. The explanatory system will provide a fundamental approach to process the uncertainty of the future, or in general, on the trend analysis of quantitative data. However, the sole use of quantitative data is challenging in the study of Top Management Team. This research tackles both challenges:

1. The lack of measurement of managerial sides of organizations' upper echelons and its ability to uncover fundamental perspectives caused by team diversity;
2. The organization's performance needs to be operationalized in order to obtain a construct for competence measurement that can be used to empirically assess the TMT's predictability power;

The following subsections discuss the motivation behind this research and its objectives.

0.1 Motivation of the Study

Ever since the early days of research into the strategic management, there has been a vibrant academic debate on the role of Top Management Team in an organization's performance. This debate is rooted in the Upper Echelon Theory (Hambrick & Mason, 1984) in their watershed article, "Upper Echelons: The Organization as a Reflection of its Top Managers". As argued by their theory, the observable characteristics of the Top Management Team are in part, a reflection of the situation that the organization faces. Since the original articulation of the theory in 1984, a sizable stream of empirical investigations and several enhancements of theory have been introduced to explore the relations between different organizations behaviour and the Top Management Team demographics.

As explained by Hambrick and Mason in their theory, the argument is traced back to March and Simon's (1958) in their "Behavioral Theory" of the organization as well as Cyert and March (1963) with their theory of the "Dominant Coalition". Additionally, a significant amount of research proposes that Top Management Teams (TMTs) play an influential role on firm's performance, and those are largely based on (Hambrick & Mason, 1984) theory of upper echelons, whereas, the argument examines the individuals responsible for the organization. The theory suggests the existence of relationships between a variety of TMT demographic indicators and firms' outcomes (Certo, Lester, Dalton, & Dalton, 2006). Top Management Team attributes have been related to a variety of outcomes, such as firms' action and performance, corporate strategic orientation and change, innovation and creativity, firm diversification and functioning. Firm capabilities embody those collective insights, knowledge and activities that directly translate firm's vision and mission into concrete actions that produce financial results (Joyce & Slocum, 2012). Those capabilities are mainly influenced by individuals or groups within the firm who are responsible for such critical decisions; namely, the top managers (i.e., executives, board of directors). Those people are often chosen precisely because they have the "right" background or temperament to carry out actions anticipated by the controlling parties (Hambrick & Mason, 1984). They make decisions based on their attitudes, therefore, it is important to understand the impact of top managers' collective attitudes on a variety of organizational outcomes (Caligiuri, Lazarova, & Zehetbauer, 2004).

The central premise of the Upper Echelon Theory is that executives' experiences, values and personalities greatly influence their interpretations of the situations they face and, in turn, affect their choices (Hambrick, 2007). The view taken by this study is that demographic characteristics (emphasis is on the observable characteristics) of executives can be used as valid, albeit incomplete and imprecise, proxies of executives' cognitive frames. Moreover, the characteristics of the TMT may well provide useful indicators of corporate competitive performance (Norburn & Birley, 1988). Hence, this research supports the view that organizations' outcomes could be partially forecasted by the managerial background and characteristics of the TMT.

On the other hand, (Pereira, 2014) reported that "little research in forecasting has been done to aid in understanding the managerial side of forecasting". Sanders (1995) also concluded that the use of forecasting in business has greatly lagged the development in other fields. Therefore, this research is aimed at extending the Upper Echelon Theory by developing a forecasting model that will enable predicting future status of the organization outcome by utilizing its TMT observable characteristics. Various approaches and models have been applied to describe and explain the relationship between different TMT characteristics and the firm performance. Among that, statistical approaches were more extensively applied, while artificial intelligence and soft-computing approaches (which refers to the combination between fuzzy logic, neuron-computing, probabilistic reasoning, and genetic algorithms, in an attempt to study, model, and analyse complex phenomena) were scarce in this field. Due to the changeable nature of measuring TMT variables and operationalization of organization performance, using conventional methods may not give accurate results. Thus, employing soft-computing models can be utilized to alleviate this problem (Azadeh et al., 2011).
Previous researchers have indicated many major limitations in conventional methods:

1. Statistical models have the limitations that the number of rules in prediction is limited by the inherent characteristics of the model (Cheng, Quek, & Mah, 2007);
2. Large number of historical data are required to satisfy the results;
3. Most of the conventional methods are assuming linearity (Mombeini & Yazdani-Chamzini, 2014), while real-world are rarely pure linear combinations (Marlin, Lamont, & Geiger, 2004).

By contrast, Artificial Intelligence (AI) models (sometimes referred to as Soft Computing Models) can generate as many rules as they can capture and predict future trends (Cheng et al., 2007). Also such models are powerful tools for modelling the non-linear structures (Mombeini & Yazdani-Chamzini, 2014). Intelligence analysis gives researchers the ability to model both experimental design and data in a number of different forms than the statistical approaches (Abbasi & Mahlooji, 2012 ; Sedighi, Keyvanloo, & Towfighi, 2011). The objective of soft computing approaches is to synthesize the human ability to tolerate and process uncertain, imprecise, and incomplete information during the decision-making process

(Cheng et al., 2007). Given the complexity and the dynamics of real-world problems, such systems should be able to successfully perform incremental learning and online learning, deal with rules and handle large amounts of data quickly (M. Y. Chen, 2013).

The widely known Adaptive Neuro-Fuzzy Inference System (ANFIS) is a form of artificial intelligence models. It is a fuzzy inference system applied in the form of a neuro-fuzzy system with crisp functions (which are used to describe mathematical operations for variables with non-fuzzy values) in consequents as in the Takagi-Sugeno type fuzzy system (Mombeini & Yazdani-Chamzini, 2014). ANFIS can serve as a basis for constructing a set of fuzzy “if-then” rules with appropriate membership function to generate the stipulated input–output pairs. The membership functions are tuned to the input–output data (Petković, AbHamid, Ćojbašić, & Pavlović, 2014). ANFIS is able to incorporate intuitiveness in the process of training and testing of the data. It is able to “train” systems to generate rules within a “black box”, where those rules would be able to “test” the system if live data are fed into the model to test the rate of accuracy of the model (Cheng et al., 2007). Such a feature is of great value for the purpose of this study (Multi Input – Multi Output nature: MIMO). It assists in predicting and understanding behaviours, as there can be many rules, and the rules may be unknown to researchers due to the “black-boxing” variables of TMT (Carpenter & Fredrickson, 2001 ; Levy, 2005).

The combination of business forecasting, Top Management Team (TMT) and Fuzzy Inference System is a unique approach to explore Top Management Team observable characteristics. Thus, drawing on the upper echelon perspective, this research was motivated to investigate the power of Top Management Team (TMT) demographics to forecast organization performance. A Multi Input – Multi Output Adaptive Neuro-Fuzzy Inference System (MIMO–ANFIS) approach was used in two dimensions, cross-section (time dependent) and time series forecasting (company dependent).

0.2 Main Theoretical Perspectives

The research draws upon three main streams of management and performance research – Upper Echelons Theory, operationalization of performance and Fuzzy Set Theory.

0.2.1 Upper Echelon Theory

The theory suggests that the composition of the top management team creates the basis for managerial decisions and ultimately firm behaviour (S. Nielsen, 2010) and focuses upon the pinnacle of the organization's structural hierarchy (Norburn & Birley, 1988). However, given the great difficulty of obtaining conventional psychometric data on TMTs (especially those who head major firms), researchers can only reliably use information on executives' functional backgrounds, industry and firm tenures, educational credentials, and affiliations to develop predictions of strategic actions (Hambrick, 2007). Due to the "mixed blessing" nature (whereas in the group effectiveness literature, TMT diversity has positive as well as negative impact), the inconsistency among the different propositions of various studies has led to confusion and multiple possible conclusions, consequently, the previous research of Top Management Teams was mainly focused towards exploring the type and strength of the relationship between their diversity parameters and the firm's performance. There was less focus on how to employ those knowable parameters and utilize them to forecast the future performance of organizations. As suggested by (Cannella, Park, & Lee, 2008), this research claim that the relationship of TMT diversity to organizational performance is not positive or negative, yet team diversity in terms of age, tenure, education background, functional background and work experiences are enablers to that relationship.

0.2.2 Operationalization of Performance

Organization performance is one of the most important constructs in management research, whereas determination of organization performance is essential for gaining robust results. Measurement of performance is a way to review organization's financial and nonfinancial goals. The operationalization of firm performance provides rich implications for both researchers and practitioners. Given that it is multifaceted and dynamic, selection of performance measures may affect the research results and interpretations (Deng & Smyth, 2013). Many organizations are investing considerable amount of resource implementing measures that reflect all dimensions of their performance. Consideration is being given to what should be measured today, but little attention is being paid to the question of what should be measured tomorrow (Kennerley & Neely, 2002). Despite numerous topics and examples that have been demonstrated in the literature on performance measurement, limited attention is paid to its measurement in empirical studies (Richard, Devinney, Yip, & Johnson, 2009). Furthermore, approaches of operationalizing firm performance are also limited (Deng & Smyth, 2013).

This research proposes a multidimensional performance construct for the construction industry, categorized in different dimensions, as well as indicators. The proposed construct captures and measures the construction organization performance, combining financial wealth of the organization (of different time spans) complemented with the intangible strategic assets. Therefore, an overall construct rather than narrow, strictly economic criteria is proposed.

0.2.3 Fuzzy Set Theory

Artificial Intelligence (AI) models, in particular the hybrid fuzzy neural networks, can be used to train and test market and event-related data. Sometimes referred to as Soft Computing (collection of methodologies like fuzzy system, neural networks and genetic algorithm, designed to tackle imprecision and uncertainty involved in a complex nonlinear system) (Buragohain & Mahanta, 2008). In the modelling process, such models discover the rules or the relationships between the variables and the outcome that may even be unknown to researchers. Since these methods automatically learn from historical data, they can easily learn the non-linear relationships or hidden structures among independent and dependent variables. They can make decisions like humans by adapting themselves to situations and taking correct decisions automatically for similar future situations (Kharb, Ansari, & Shimi, 2014). They have a better performance in comparison to traditional methods and most importantly, having the ability to conform to the new knowledge (Asgari, Abbasi, & Alimohamadlou, 2016 ; Boer, Labro, & Morlacchi, 2001 ; Kuo, Hong, & Huang, 2010 ; Saghaei & Didehkhani, 2011). Recent reviews on artificial intelligence or soft computing indicate that the number of soft computing based engineering applications is increasing (Dote & Ovaska, 2001). The evolution of soft computing techniques has helped in understanding the various aspects of nonlinear systems and thereby making it possible to model them, enable easier analysis and control as well as predict their future response (Zadeh, 1994).

Among the fuzzy neural models, the ANFIS model is chosen for its strong modelling capability and computational flexibility, and hence its suitability for system modelling of complex, dynamic, and nonlinear relationships, which is common in real case scenarios that include financial market behaviour (Azadeh et al., 2011). The unique forecasting features of ANFIS make this technique more popular in comparison with the traditional forecasting techniques (Mombeini & Yazdani-Chamzini, 2014). The method has been applied in this research as it offers the ability to model both experimental design and data in a number of different forms (Abbasi & Mahlooji, 2012 ; Sedighi et al., 2011).

0.3 Research Objectives and Guiding Questions

As a result of above review, this research addresses gaps within organization performance research. Specifically, it focusses on the role of the strategic seniors, or those who are known as the “Supra TMTs” (Finkelstein, Hambrick, & Cannella, 2009) in forecasting the future outcome of organizations. Despite the invaluable contributions of prior studies on top management team studies, the conflicting findings raise the question of whether the collective upper echelons composition explains organizations performance, and which construct is most beneficial for performance in the long term. While there are evidences that Top Management Team matters for organization performance, existing literature lacks consistency on possible conclusion. Therefore, this research is extending the current literature by introducing an empirical approach to examine the demographics of Top

Management Team and forecast the outcome of organizations. Although forecasting is always difficult due to the uncertainty arising from the different contextual factors, this research is motivated to utilize the "knowable" characteristics to some "interpretable" future situations.

The main research objective is to explore whether organization outcome can be forecasted in the context of Top Management Team composition. In order to systematically explore and achieve the understanding of the main objective, the research has been divided into several questions (or sub-objectives). Those were used as guiding questions that will ensure consistency and manageability of the empirical analysis. Those questions are:

Question 1: What are the Top Management Team observable characteristics that affect organization performance?

A major concern regarding the existing literature is that it encompasses a wide variety of contextual measures related to a series of performance outputs. The literature also includes an on-going debate about the nature and kind of influence that TMT has on the performance representing conflicted conclusions. Different authors studied the influence of different TMT variables on organizational performance. While it is impossible to include all TMT characteristics, the first sub-objective is to include those variables that have been identified repeatedly as major boundary conditions in prior TMT studies. Those will be used as the input data for the model, and are identified in Chapter 2 of this research.

Question 2: What factors drive performance?

As indicated earlier, organization performance is one of the most important constructs in management research, and it is a function of the performance of a particular industry. It is a function of the industry’s structure whereas each industry has its specific variables and performance meaning. It is essential when developing a forecasting model, an outcome measure for the specifics of the industry is to be counted. In this research, the construction industry is selected (Architecture, Engineering and Construction – AEC). Therefore, the second sub-objective is to analyse and provide an operationalization approach of AEC organizations performance that will be included in the research model as the output variables.

Question 3: How to model a process of hidden structure and unknown "black-box" rules?

The third research sub-objective relates to the application of the appropriate forecasting model. The "black-box" nature of TMT processes and the multiple conclusions from previous studies have provided challenges in which approach to be used to structure the forecasting model. The non-linear nature of research variables has led to the preference of using alternative models in-lieu of conventional statistical approaches. Therefore, the final sub-objective is to apply different structures of models in order to gain a comprehensive view of the forecasting capabilities of TMT in the realm of AEC industry.

Answering above questions guides us to the main objective of the research, within Top Management Team research (related to question 1), the operationalization of performance (related to question 2), and the modelling of forecasting (related to question 3). Consequently, the order in which the research is presented in subsequent chapters reflects the order of the guiding questions and a progression toward the research main objective.

0.4 Structure of the Research

This work consists of theoretical and empirical parts. Starting with (Introduction) a general introduction that provides easy access to the research in addition to the articulation of research motivation, objectives and guiding questions. The remainder of the report is organized in four main chapters. The main theoretical headings represent the core of this research (Top Management Team, performance operationalization and forecasting by Fuzzy Set Theory) which are integrated in three different Chapters. Those Chapter are: Chapter 1: representing literature reviews in different subjects related to Top Management Team, such as expanding on the Upper Echelon Theory and other related theories, defining the Top Management Team and concluding by the inconsistency within the current literature. Chapter

2: expanding on the selected variables and more importantly the selection and development of an operationalization concept for organizational outcomes. Then, in Chapter 3: the research methodology is detailed in terms of Fuzzy Set Theory, its structure, application and more specifically the implementing of ANFIS structure to achieve the research objectives.

Afterwards, Chapter 4 represents the empirical findings of the research and proceeds with two analysis steps, whereas three different forecasting models were used. The chapter concludes with a discussion that synthesizes the chapter's main results and research's major limitations, which also links them to empirical results from other studies. The final section (Conclusions and Recommendations) presents many suggested theoretical and methodological future extension, and lastly the report provides a final general conclusion. Figure 0.1 provides a graphical illustration of the research approach.

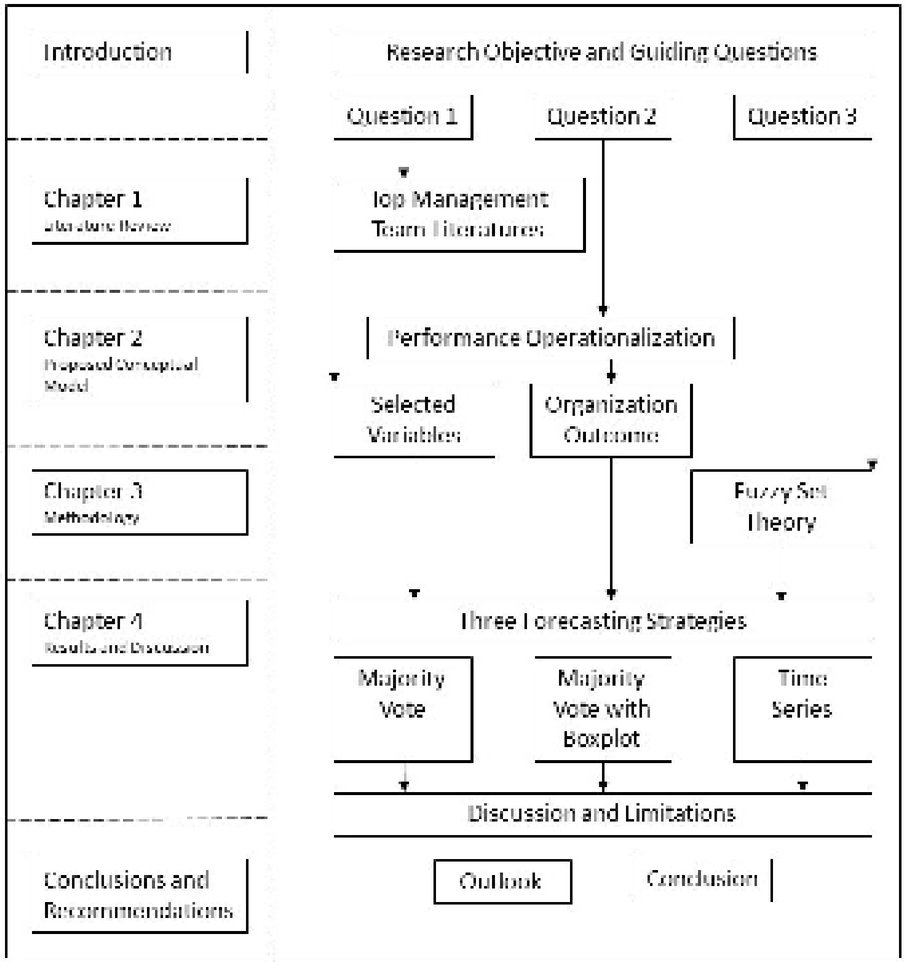

Figure 0.1 Structure of the disseration

CHAPTER 1

LITERATURE REVIEW – TOP MANAGEMENT TEAM

1.1 Upper Echelons and Other TMT Theories

The study of Top Management Teams (widely referred to in scholars as “TMTs”) in the strategic leadership literature, has blossomed since the 1980s (Glunk, Heijltjes, & Olie, 2001). In their review, (Finkelstein & Hambrick, 1996) examined almost forty empirical studies that focus primarily on the Top Management Team, its composition, and its impact on strategic actions or organization outcomes. While previous research has almost mainly considered the Chief Executive Officer (CEO) or a single individual leader, a new line of research emerged in the mid-1980s under the name of "Upper Echelon" perspective. (Hambrick & Mason, 1984) article, "Upper Echelons: The Organization as a Reflection of Its Top Managers" has generated a vital and productive stream of research on top management teams (Pitcher & Smith, 2001). They provided in their Theory a lift to the observational research by arguing that top management teams’ demographic characteristics (e.g., age, education, tenure, diversity) are good proxies for the underlying traits and cognitive processes of the top executives (Srivastava & Lee, 2008).

Furthermore, (Hambrick & Mason, 1984) manifested that the organization's performance is a consequence of these constructs (Díaz-Fernández, González-Rodríguez, & Pawlak, 2014). The theory centres upon the apex of the organization's structural hierarchy (Norburn & Birley, 1988) and proposes that the composition of the top management team makes the basis for managerial decisions and ultimately firm behaviour (S. Nielsen, 2010). (Hambrick & Mason, 1984) propositions were grouped into seven categories; age related, functional experiences, corporate influences, education, socioeconomic background, stockholding, and group heterogeneity (Norburn & Birley, 1988). They propose that executives’ characteristics serve to filter and distort information in a three-step process: executives’ experiences, values, and personalities which has effect on: their field of vision (the directions they look and listen), their selective perception (what they actually see and hear), and their interpretation (how they attach meaning to what they see and hear) (Hambrick, 2007).

Reviewing the theory briefly (illustrated in Figure 1.1), the left-hand side of the original model shows the organization's internal and external situation. Upper echelon observable characteristics (e.g., age, functional background, and educational experiences) are next taken as observable proxies for the psychological constructs that shape the team's interpretation of the internal and external situation. It also facilitates formulation of appropriate strategic alternatives. Since these psychological constructs are unobservable, the theory posits that observable managerial characteristics are efficient proxies that provide reliable indicators of the unobservable psychological constructs. The last right-hand box reports a range of strategic variables/choices, from innovation to response time, which is expected to reflect executive team characteristics. As indicated by (Hambrick & Mason, 1984), those observable characteristics and strategic variables are not comprehensive, but will alter from one situation to another, and from one construct to another (Carpenter, Geletkanycz, & Sanders, 2004). The core idea of Upper Echelon Theory is that these executives personalized interpretations of the strategic situations are a function of the executives' experiences, values, and personalities.

In a latter refinement of the theory, authors suggested the introduction of new moderating variables, such as managerial discretion (Hambrick & Finkelstein, 1987) and executive job demands (Hambrick, Finkelstein, & Mooney, 2005). While evidence has been studied for the introduction of the managerial discretion, the empirical work on executive job demands has not yet commenced, and it is anticipated that measurement will be difficult (Hambrick, 2007). Similarly, the Organizational Demographic Theory (Pfeffer, 1983) infers that measures of heterogeneous TMT demographic characteristics hold great promise for organizational research. The Organizational Demography Theory fills in as a valuable instrument in understanding corporate strategy, competitive behaviour, and organizational performance (Auden, Shackman, & Onken, 2006).

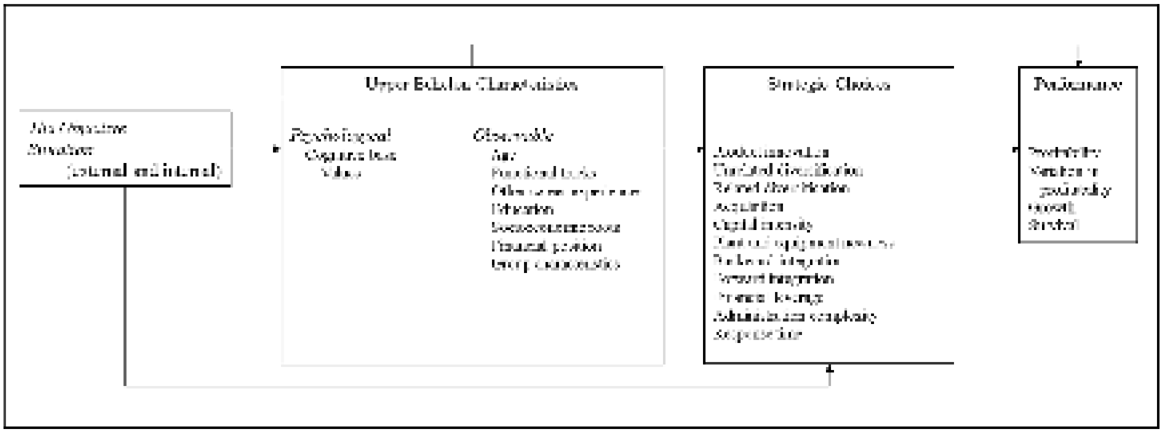

Figure 1.1 Upper Echelon Theory framework
Taken from Hambrick & Mason (1984)

Other researches viewed the TMT from a resourced based view perspective, where the Resource Based View (RBV) conceptualizes the firm as a bundle of resources (Athanassiou & Nigh, 2000 ; Hutzschenreuter & Horstkotte, 2013 ; Pegels & Yang, 2000). The (RBV) offers that physical, human, and organizational resources are a source of sustained competitive advantage for firms. Those resources are valuable, rare, non-substitutable and inimitable. Additionally, these resources may be adjusted as a firm's knowledge of markets, technologies, consumer needs and attitudes is affected by external inputs (Athanassiou & Nigh, 2000). The TMT, as formed over time, can be viewed as a rare, non-substitutable, and inimitable resource.

Researchers have extended (Hambrick & Mason, 1984) upper echelons perspective arguing that, since demographic characteristics serve as valid proxies for deep-level characteristics, then the relative heterogeneity or diversity of those former characteristics among team members may be associated with firm performance (Finkelstein & Hambrick, 1996). Thus, if demographic diversity has implications for top team behaviours and, most importantly, those behaviours being integral to effective management, then heterogeneity is likely to be reflected in firm performance (Carpenter, 2002).

Other theories were also developed to explain how TMT is related to the firms' different behaviour and activities. Two famous examples are the Behavioural Theory and the Signalling Theory. The Behavioural Theory proposes that the more comprehensive the information available and evaluated during the decision-making process is, the more innovative a group’s decision will be. Signalling Theory, on the other hand, sets that firms use visible signals to gain reputation and status among the public. In previous literature, both the demographics of board members and the composition of such board itself have been shown to signal the quality of the firm to the public, influencing its reputation (Miller & Triana, 2009). Additionally, (Norburn, 1986) have tested the characteristics of top managers who formed the prevailing coalition inside U.K.'s largest organizations against the financial performance of those industries in which they were strategically competing.

However, (Díaz-Fernández et al., 2014) stated that despite the fact that researchers have appeared after (Hambrick & Mason, 1984) attempting to test if the backgrounds or behaviours of managers have any effect on entrepreneurial outcomes, their outcome both lack unique and reliable results because of the opposite findings achieved among the two principle dimensions, level and diversity. A latent debate around whether demographical managerial constructs have effects on firm performance has been incited. In order to clarify this argument (the nature of TMT team processes in interaction with TMT diversity), (Boone & Hendriks, 2009) proposed to study how team mechanisms (in terms of three dimensions: collaborative behaviour, accurate information exchange, and decision-making decentralization) moderate the impact of TMT diversity on financial performance.

As apparent, numerous theories have been introduced and even developed to clarify the role of TMT and their composition in firm performance. It agrees with (Cannella et al., 2008) claims that organizations experience difficulties in solely relying on their CEOs capabilities due to the increased complexity and inconsistent competitive environment. Furthermore, the consolidated capacity of the TMT members is considered influential to the organization success on the long term. In fact, many studies have demonstrated significant relationships between certain demographic features of Top Managers Teams and important strategic firms' actions. However, the inconsistency around the exact correlation between TMT composition, processes and the firm performance is still not resolved, and the argument has been growing widely over time especially that the findings achieved are contradictory, insufficient, imprecise and unreliable.

1.2 Definition of Top Management Team

The basic unit of analysis for this research is the Top Management Teams (TMTs), in doing so, there are different streams presented in the literature to define TMT. Per (Katzenbach, 1997), "a real team is a small number of people with complementary skills who are committed to a common purpose, performance goals, and an approach for which they hold themselves mutually accountable". Three main features of such teams are (Stovall, 2005):

1. Distinct abilities, skills and perspectives which add value to the collective output;
2. Sharing of leadership to completely utilize talents;
3. Mutual accountability.

Probably the most adopted definition of Top Management Team is the one as proposed by (Hambrick & Mason, 1984) in their Upper Echelons Theory. They proposed that researchers could distinguish members of a Top Management Team by equating executive titles with enrolment in the team. Recent studies of Top Management Teams have used this approach (Knight et al., 1999). In the same vein, alternative definition of TMT can be found in the literature, for example, (Carpenter, 2002) define TMT as the two tiers of the organization's management (e.g., CEO, Chairman, Chief Operation Officer "COO", Chief Financial Officer "CFO", and the next highest management tier). This definition generally resulted in examining all executives above the Vice President (V.P) level, and yielded teams of approximately six members.

Sometimes, TMT is defined as all those executives around and above the president level, as well as any other officers who served as directors of the company, i.e., vice president, senior vice president, vice chairman, CEO, and any other officers who are members of the board of directors (Díaz-Fernández et al., 2014). (Ruigrok, Georgakakis, & Greve, 2013) suggested to define the term TMT as the highest level of corporate management by relying on companies' self-reported definitions provided in the annual reports and corporate websites. They even added that in cases where two or more levels of senior management were reported, they define the TMT as the CEO and immediate subordinates. Similarly, TMT was defined by (S. Nielsen, 2010) as the officers who were members of the management board or executive committee as identified in the firm′s annual report. (Rivas, 2012) and (Finkelstein et al., 2009) define the TMT as ‘‘the constellation of the top three to ten executives reporting directly to the CEO’’.

Some of the general TMT features as recorded within the literature are:

1. TMT can be characterized by the title (Lee & Park, 2006);
2. The average number of TMT members is 5.9 (Rivas, 2012), although this averaged number varies in different regions as it will be shown in later sections of this report;
3. Top Management Teams of those corporations should make strategic decisions that deal with complex and uncertain environments (Angriawan, 2009).

However, in most definitions presented in the literature, the members of the extended executive committee were generally not included in the top management team. It is clear that the Top Management Teams have been defined by various scholars depending on the research objectives, hypothesis and approach of each specific study.

1.3 TMT and Firm Performance

Looking at organizations' performance on a long-term span, some of those organizations could prevail to sustain competitiveness, others are nearly still performing, while some other organizations no longer exist. Researchers in different fields have studied organizations from different perspectives. Economics have long considered how industries emerge, evolve, and decline. Similarly, sociology has long studied the entry and exit dynamics of populations of firms. While reasons for long-term success vary, researchers have suggested that top managers play a crucial role in strategic change and strategic decision. Research on the TMT addresses these questions by linking the TMT's characteristics to outcome variables such as strategic change, innovation, and firm performance (Camelo, Fernández-Alles, & Hernández, 2010).

In order to understand firm behaviour and its longevity, researchers have presented different approaches. For example, many of the studies have looked at the value the Top Management Team can bring to the organization performance (Díaz-Fernández et al., 2014 ; Eisenhardt, 2013 ; Khan, Lederer, & Mirchandani, 2013 ; Ruigrok et al., 2013). Other researchers studied how the Top Management Team can adopt different approaches to providing on-going support for managing the organizational challenges (Camelo et al., 2010 ; Dahya, McConnell, & Travlos, 2002 ; Norburn & Birley, 1988). Additionally, many of the theories (like the Upper Echelons Theory) have long recognized the influence of managerial characteristics and experiences on organizations strategic choices and behaviour, which ultimately will affect organizations' long-term performance. As the top management takes important corporate decisions and sets strategic directions, it is recognized as a key component affecting a firm's performance (Auden et al., 2006).

Characteristics of the Top Management Team could well provide useful indicators of corporate competitive performance (Norburn & Birley, 1988). As an example, (Eisenhardt, 2013) discussed that top management teams emergence is the drive of entrepreneurial organizations success or failure. His research recommended that teams with high diversity and size who share an experience of previous cooperation have higher chances of success. Moreover, teams' effectiveness in strategic decision-making can be accomplished when members get along rapidly. Another example is the Code of Practice issued in 1992 (Dahya et al., 2002) where the Cadbury Committee through its report (titled "Financial Aspects of Corporate Governance") recommending the structure and responsibilities of corporate boards of directors for better governance and performance, appreciating the reality that Top Management Team is crucial to the success and sustainability of the organizations. The capacity of an organization to respond to its various internal and external conditions partially varies with the composition of its Top Management Team.

Extant upper echelons literature implies that TMT configuration has an important impact on international strategy and performance (Ruigrok et al., 2013). Research results found strong relation between organizations performance and TMT demographic characteristics, such as age, functional background, and team tenure influence firm performance (Auden et al., 2006). (Hutzschenreuter & Horstkotte, 2013) argued that top management's demographics influence the decisions that they make and consequently the actions adopted by organizations that they lead. It occurs because demographic characteristics are associated with many cognitive bases, values and perceptions that influence the decision making of top management.

Literature in particular investigates the operationalization of TMT cognitive diversity by the proxies of age, team tenure, industry experience, and functional background heterogeneity most often used in statistical work, and compares those operationalization with cognitive diversity itself (Hutzschenreuter & Horstkotte, 2013). Considerable amount of research has investigated the linkage between Top Management Team characteristics and firm performance. Much of this research relies on demographic data. While these data are reliable and accessible, findings across studies are not consistent (Khan et al., 2013). More insight is provided in the next section and its inherited topics.

1.4 TMT Diversity Influence

Business organizations today have employees that are increasingly diverse in terms of their age, ethnic background, and gender (Darmadi, 2013). As (B. B. Nielsen & Nielsen, 2013) currently manifest: "Top Management Teams have become increasingly diverse over the past several decades, yet the performance implications of TMT diversity are not clearly established in the literature".

While Upper Echelons Theory expects both positive and negative impacts of diversity, in the group effectiveness literature, diversity is often characterized as a “double-edged sword” which is beneficial only if managed successfully (Milliken & Martins, 1996 ; Naranjo-Gil, Hartmann, & Maas, 2008 ; S. Nielsen, 2010). The same has been referred to as “mixed blessing” by (Williams & O’Reilly, 1998). From a positive perspective, higher diversity provides more choices, accurate calculation of environmental changes and better assessment of alternatives. The negative aspects include slower decision-making, communication breakdowns, and interpersonal conflict. From another point of view, (Cannella et al., 2008) proposed the “dual aspect” of TMT diversity, which claims that its relationship to organizational performance is not positive or negative, yet team functions works as a moderated effect to that relationship.

The inconsistency among the different propositions of various studies has led to confusion and multiple possible conclusions. For example, (Díaz-Fernández et al., 2014) argue that TMT’s education-level diversity has a negative and significant impact on corporate performance and no significant effects for functionality and education background diversity have been found. (Hutzschenreuter & Horstkotte, 2013) study concludes that differences in educational background and in length of organizational tenure have a positive effect on information processing, task conflict, and learning, and thus may help the team to successfully handle adding new products in a given time period resulting in improved firm performance. The same study concludes that differences in age and nationality between TMT members can lead to friction within the team that disrupts information processing and coordination and thus may have a negative moderating effect, which contradicts with the findings of (B. B. Nielsen & Nielsen, 2013) where nationality diversity was found to be positively related to performance, and this effect is stronger in: longer tenured teams, highly internationalized firms, and munificent environments. Furthermore, the findings of (S. Nielsen, 2010) is supporting the same positive correlation. (Glunk et al., 2001) suggest that nationality of TMT and more specifically top management across countries differ in background characteristics as well as in-group dynamics. Moreover, (Hutzschenreuter & Horstkotte, 2013) findings related to age diversity (negatively moderating effect) is also in conflict with (Clark & Soulsby, 2007) who believe that young, less tenured and heterogeneous TMTs have the composition most likely to produce strategic and structural changes in turbulent contexts.

Although (Miller & Triana, 2009) argue that no research has investigated the effect of gender and racial diversity of the board on firm performance through the mediators, innovation and reputation, there is a growing number of studies that link gender diversity and firm profitability or financial performance, suggesting that female representation is not associated with an improved level of performance (Darmadi, 2013). The results of (Miller & Triana, 2009) study also contradicts with the earlier research. It found a positive relation between board gender diversity and innovation. In addition, a positive relation between board racial diversity and firm reputation and innovation is also discovered.

On the other hand, (Camelo et al., 2010) results show that a higher educational level in the TMT has a positive and direct effect on innovation performance, while functional and tenure diversity in TMT have a direct and negative effect. However, in a situation of strategic consensus in the TMT, the relation between functional diversity and innovation is positive. Their findings are very close to the developed notion "dominant logic" by (Prahalad & Bettis, 1986), defined as “a shared cognitive map (or set of schemas) among the dominant coalition”. The authors theorized that top managers’ cognitive backgrounds and experiences play a key role in managing a firm’s diversified product portfolio.

Moreover, (Naranjo-Gil et al., 2008) argue that heterogeneous management teams are better able to handle the simultaneous and conflicting demands of refocusing the organization strategically and keeping up operational performance, those teams are also better able to keep up operational performance when engaging in strategic change than homogeneous TMTs, as their larger combined set of skills, experiences and competences enables them to successfully address the organizational dynamism and environmental complexity that accompany strategic reorientation. (Dahlin, Weingart, & Hinds, 2005) add that the proportion of outside board membership on the relation between Top Management Team heterogeneities and firm performance can work as a moderating effect. Additionally, (Knight et al., 1999) results showed that demographic diversity alone did have effects on strategic consensus the overall fit of the model was not strong, suggesting to add two intervening group process variables, interpersonal conflict and agreement-seeking, to the model greatly improved the overall relationship with strategic consensus.

Internationalization was also the subject of many studies exploring how TMT can influence the organization approach for expanding in overseas opportunities. (Daily, Certo, & Dalton, 2000) explored the effect of the internationalization of the Multi-National Corporation (MNC) on the behaviour of its Top Management Team. Tacit knowledge perspective was used to explain the link between the MNC's internationalization and both the extent of its TMT members' personal presence overseas and the extent of its TMT members' face-to-face interaction on international business matters of strategic importance. Results indicate a significant interactive effect between Chief Executive Officer (CEO) tenure and outside succession on CEO international experience. The results of (Levy, 2005) study indicated the firms were more likely to develop an expansive global strategic posture when their Top Management paid attention to the external environment and considered adverse set of elements in this environment. On the other hand, firms led by top management that paid more attention to the internal environment were less likely to be global.

However, empirical support of these studies has been inconclusive suggesting that other factors, including the management, may play a crucial role in the performance of the firm (Auden et al., 2006 ; Camelo et al., 2010 ; Daellenbach, McCarthy, & Schoenecker, 1999). This has led, within the Upper Echelon Theory, to a new line of inquiry proposing that organizational decisions and results cannot be explained by the composition of the TMT alone, the analysis also requires consideration of the processes and situations deriving from the relationships between TMT members (Camelo et al., 2010).

1.5 TMT Processes

Over the past decade, researchers have begun increasingly focus on the processes underlying TMT decision making such as comprehensiveness, consensus, social integration, conflict, and decision speed (Certo et al., 2006). The previous section has provided more explanation on the demographic attributes of TMT (the demographic attributes that have been studied most often are age, executive tenure, functional expertise and formal education), which were heavily based on Upper Echelons Theory. In recent years, scholars have criticized the theory approach and its reliance solely on demographic characteristics to predict organizational outcomes (Lee & Park, 2006). Other TMT attributes (other than demographic) were also the main theme of many scholars. For example (Daily et al., 2000) considered the Top Management Teams' behaviour rather than the demographic attributes. (Glunk et al., 2001) even stated that process variables, such as communication, conflict and social cohesion have received some attention from scholars, however, power and influence has received distinctively less attention. (Simsek, Veiga, Lubatkin, & Dino, 2005) distinguish between two stream of research: one links TMT characteristics to such firm-level outcomes as global strategic posture, expansive global strategies, strategic change, commitment to innovation, and competitive moves. The second stream focuses more narrowly on fine-grained aspects of team process, including communication quality and frequency, social integration, inter dependence, and consensus. Whereas researchers in the first stream assumed that TMT characteristics adequately captured or were congruent with, a team's various processes, those in the second stream attempted to specify intervening process mechanisms. They have tried to shed light into the “black box” or "causal gap" left by the first stream of research (Simsek et al., 2005). Rather, the majority of research in this area has used demographic variables as proxies for underlying cognitive capabilities and processes, thereby "black-boxing" cognitive variables of interest (Carpenter & Fredrickson, 2001 ; Levy, 2005). Some of the study outcomes are; innovation, strategy, strategic change, executive turnover and organizational performance (Glunk et al., 2001).

Researchers interested in the upper echelons of firms have long acknowledged the impact of Top Management Team characteristics and functions on organizational behaviour and outcomes (Hambrick & Mason, 1984). However, beyond gaining a greater understanding of the relatively distal role of a TMTs demographic characteristics in shaping limited aspects of team process, researchers have not gained a good understanding of the nature of TMT process (Simsek et al., 2005).

1.6 Inconsistency and Limitations

(Jackson, 1992) argued that top management theory is an oversimplified and rigid definition of strategic decision-making units. One problem is that the composition of this unit changes per the issues at hand. There is a significant body of research analysing the direct impact of Top Management Teams characteristics on decisions and results pertaining to their activities. However, demographic studies have been widely criticized for producing inconsistent findings and theoretical construction (Clark & Soulsby, 2007). Despite the large number of TMT diversity studies, research has yielded inconsistent results. Thus, the question of whether diversity in managerial backgrounds is advantageous for firms still remains open (Rivas, 2012). Inconsistent, non-significant, or weak results may arise for several reasons both theoretical and methodological, those may include:

1. The hypothesized relationships are in fact insignificant;
2. A slight misspecification of both independent and dependent variables may attenuate otherwise significant results (Pitcher & Smith, 2001);
3. Simplifying assumptions underlying the research designs used (Marlin et al., 2004);

4. Contextual factors like strategy, environmental stability, and team member interactions must be considered in relation to the TMT diversity–firm performance relationship (Cannella et al., 2008);
5. Prior research has neglected important mediating variables that can influence the association between TMT diversity and organizational outcomes (Lee & Park, 2006).

The Upper Echelons Theory is no exception. One of the major limitations is the indirect or causal black box approach of the theory (Lawrence, 1997). The underlying processes (such as direct assessments of the intervening cognitive or group processes) could mediate the relationship between Top Management Team demographics and firm performance, which is currently not measured in the Upper Echelons Theory.

As indicated in (Angriawan, 2009) research, many authors argue that demographics data (which are used by Upper Echelons Theory as proxies) can represent many cognitive processes. They have raised the question of which cognitive processes are represented by which demographic diversity. Additionally, the demographics data also do not tell their causal relationships with the predicted variables. Similarly, (Lawrence, 1997) observed that demographic variables might represent more than one cognitive processes. The results have confirmed the need jointly with the demographic variables, a careful methodology to capture other unknown situations or processes that affect the TMT's decision making processes (Camelo-Ordaz, Hernández-Lara, & Valle-Cabrera, 2005 ; Camelo et al., 2010).

However, (Hambrick, 2007) believed that direct assessments are extremely difficult. He preferred demographic data which are more accessible, reliable, and valid (Angriawan, 2009). Similarly, (Pfeffer, 1983) preferred the parsimoniousness of a theory and argued that direct assessment of cognitive process constructs also have measurement errors, conceptual definition flaws, and validity problems.

In their comparative analysis, (Pitcher & Smith, 2001) that inconsistent findings in upper echelons studies were due to methodological problems including sample selection, measurement of heterogeneity, measurement of outcomes, and lack of requisite moderators and mediators rather than weaknesses in the Upper Echelons Theory. They argued that the indirect approach to linking team composition with outcomes needs to continue (Angriawan, 2009).

CHAPTER 2

PROPOSED CONCEPTUAL MODEL

2.1 Introduction

Although researchers in management studies typically focus on the selection and measurement of their explanatory (input) variables, firm performance was widely used as a response (output) variable, whereas limited attention is paid to its measurement in empirical studies (Richard et al., 2009). Additionally, in construction industry the project-oriented management tendency may be partly due to project demands such as budgets, schedules, and quality issues and thus the long-term objectives, with the result that corporate issues receive far less attention (Choi & Russell, 2005). Despite the growing recognition of strategic planning in the field of construction as evidenced by the works of (Kale & Arditi, 1999 ; Kangari, 1988 ; Katsanis, 1998 ; D. Langford, Iyagba, & Komba, 1993), however, approaches of operationalizing organization performance are still limited and understudied (Deng & Smyth, 2013). As (Kale & Arditi, 2002) have noted, many of the published works in construction industry are largely descriptive in nature and rely on anecdotal evidence. Moreover, existing performance measurement models do not assist in understanding where the organization is positioned compared to the other firms, or how the organization will perform in the future, nor if the firm is improving over time. It is clear that more empirical findings are required to refine existing conceptual models and furnish a better picture of performance issues encountered by construction firms. The importance of performance as a measure of organizational effectiveness in construction industry has been identified as a critical research issue (Katsanis, 1998) and could provide rich implications for both researchers and practitioners.

In this research, the predictability power of TMT observable characteristics is explored. It was noticed that previous studies define both the TMT and firm performance associated variables differently. While some researchers have selected their TMT variables based on previous literature, others used their own unique measures, an example is (Auden et al., 2006).

2.2 Variables Selection

The Upper Echelon Theory concept was meant to serve as an anchor for continued theory building (Carpenter et al., 2004). Thus, the TMT demographics, strategic choices, performance outcomes, and later propositions articulated were not meant to be exhaustive. Rather, as the authors stated “they are illustrative and appear to be some of the most supportable and interesting” (Hambrick & Mason, 1984). In that vein, new directions and extensions were expected to emerge.

Additionally, TMT in most studies was a function of diversity measure among the group (heterogeneities versus homogeneities). Each of the studies was unique in defining its "independent or input" variables. Although TMT Compositions (TMT tenure, TMT age, TMT experience, etc.) are the most widely independent variables, there were differences between the studies. For example, when a study is looking at firm internationalization, its variables are selected to capture that concept (Angriawan, 2009 ; H. L. Chen, 2011 ; Díaz-Fernández et al., 2014 ; B. B. Nielsen & Nielsen, 2013 ; S. Nielsen, 2010). Another example is the study conducted by (Auden et al., 2006) where a specific risk oriented measure was used. Furthermore, (Simsek et al., 2005 ; Tihanyi, Ellstrand, Daily, & Dalton, 2000) added more variables related to behaviours of the CEO, while (Lee & Park, 2006) had in their study more focused variables to study Research and Development (R&D) within firms.

This research is introducing three types of variables, namely:

1. Input/independent/predictor/explanatory variables: or identified as the TMT demographic attributes that would affect the organization outcome. This research selects six demographic attributes identified by most previous studies as being particularly important in influencing a firm’s performance. Those are: TMT age, TMT organizational tenure, TMT tenure, TMT educational diversity, TMT functional diversity and a more specific

indicator for construction, the TMT industry experience. The selected dimensions of TMT demographics are recommended to be studied as a bundle of attributes of the executive characteristics;

2. Controlled variables: to correctly control for contextual conditions that logically supersede any TMT effects. In this research five contextual elements and those are: TMT size, Economy Dynamism, Degree of Internationalization, Degree of Diversification and Organization Past Performance;

3. Output/dependent/predicted/response variable; based on a specific construction industry measure of performance, this research is introducing a multidimensional construct for organization outcome that consists of four performance dimensions; Profitability, Growth, Reputation and Continuity. The research is also introducing measuring indicators for the construct as detailed later in this chapter.

2.3 Input Variables: TMT Observable Demographics

Business organizations today have employees that are ever more diverse (Darmadi, 2013). As (B. B. Nielsen & Nielsen, 2013) currently manifest: "Top Management Teams have become increasingly diverse over the past several decades, yet the performance implications of TMT diversity are not clearly established in the literature". The basis of the Upper Echelon Theory is that Executives' experiences, values, and personalities greatly influence their interpretations of the situations they face and, in turn, affect their choices, which affect the organization outcome (Hambrick & Mason, 1984). Given the great difficulty obtaining conventional psychometric data on TMTs (especially those who head major firms), researchers can only reliably use information on executives' functional backgrounds, industry and firm tenures, educational credentials, and affiliations to develop predictions of strategic actions (Hambrick, 2007). In that vein, this research selects six demographic attributes identified by most previous studies as being particularly important in influencing a firm's performance.

First of all, and consistent with previous studies, this research is defining the TMT as those executives who also served on the board of directors (Finkelstein, Hambrick, & C., 1990 ; Haleblian & Finkelstein, 1993 ; Norburn, 1989). More specifically, the study will consider the TMT as all officers above the Vice President level (Carpenter & Fredrickson, 2001 ; Hambrick, Cho, & Chen, 1996), and those who are inside board members (Haleblian & Finkelstein, 1993). Such a definition allows this study to include the most important organizational decision makers in the sample (Tihanyi et al., 2000).

There is almost a consensus between different studies on the way to measure the diversity. Two methods have been widely used for that purpose: Blau's Diversity Index (Blau, 1977) with categorical variables and Coefficient of Variation with quantitative variables. Blau's Diversity Index expressed as:

$$B = 1 - \sum_{i=1}^{k} P_i^2 \tag{2.1}$$

"P" is the proportion of executives that belongs to the i^{th} regional category. This formula has been applied by a range of past upper echelons studies to measure TMT diversity in categorical variables (Carpenter & Fredrickson, 2001 ; Joyce & Slocum, 2012 ; S. Nielsen, 2009 ; Tihanyi et al., 2000). High values imply more diversified team, while low values indicate more homogeneous team members. This index measures the degree to which there are a number of categories in a distribution and the dispersion of the group members within these categories (Rivas, 2012).

On the other hand, Coefficient of Variation (C.V) calculated as the standard deviation (σ) divided by the mean (μ), or its absolute mean|μ| and can be expressed as:

$$C_v = \frac{\sigma}{\mu} \tag{2.2}$$

Coefficient of Variation was suggested by (Allison, 1978) as a tool to measure diversity. Different studies used this methodology to measure quantitative values of different TMT attributes; examples are age and organization tenure diversity. Higher scores indicated greater diversity and scores approaching zero indicated greater homogeneity teams.

In this research, the following definition and measurement methods are proposed (refer to Table 2.1):

1. TMT Age Diversity: the diversity between the team members in terms of their age and measured by Coefficient of Variation;
2. TMT Organization Tenure: the diversity between the team members in terms of their total length of stays in the organization and measured by Coefficient of Variation;
3. TMT Tenure: the diversity between the team members in terms of their total length of stays as members in the Top Management Team and measured by the Coefficient of Variation;
4. TMT Educational Diversity: the diversity between the team members in terms of their educational background and measured by the Blau's Diversity Index. The variable background education was categorized into eight categories; sciences, engineering, math, business, economics, law, arts, and others, as traditionally approached within the literature (Cannella et al., 2008 ; Carpenter & Fredrickson, 2001 ; Díaz-Fernández et al., 2014);
5. TMT Functional Diversity: the diversity between the team members in terms of their organizational functions and similarly will be measured by the Blau's Diversity Index;
6. TMT Industry Experience: the degree of diversity among Top Management Teams in terms of their previous experience; measured as the proportion of TMT members with previous work experience in an industry different from construction.

Table 2.1 Input variables - definition and method of measurement

Input Variables	Definition (and method of measurement)
TMT Age Diversity	The diversity between the team members in terms of their age (measured by: Coefficient of Variation)
TMT Organizational Tenure	The diversity between the team members in terms of their total length of duration in the organization (measured by: Coefficient of Variation)
TMT Tenure	The diversity between the team members in terms of their total length of duration as a member in the Top Management Team (measured by: Coefficient of Variation)
TMT Educational Diversity	The diversity between the team members in terms of their educational background (measured by: Blau's Diversity Index *)
TMT Functional Diversity	The diversity between the team members in terms of their organizational functions (measured by: Blau's Diversity Index **)
TMT Industry Experience	The degree of diversity among Top Management Teams in terms of their previous experience (measured by proportion of TMT member with previous work experience in construction)

* Eight Categories; sciences, engineering, math, business, economics, law, arts, and others (Cannella et al., 2008 ; Carpenter & Fredrickson, 2001 ; Naranjo-Gil et al., 2008);
** Categories were defined at individual level for each firm, depending on its internal governance system.

2.4 Controlled Variables

Controlled Variables were used extensively in studies to avoid the potential impact on measured outcomes. In the realm of this study, the most widely used control variables are firm age, firm size, TMT size, industry effect and firm location (H. L. Chen, 2011 ; Marlin et al., 2004 ; S. Nielsen, 2010). Some other studies added specific control variables that are unique to their hypothesis. (H. L. Chen, 2011) for example added Institutional Stock Ownership and Management Stock Ownership as two additional control variables. (S. Nielsen, 2010) added Firm Leverage and Product Diversification, while (Camelo et al., 2010) suggested to control Firms Past Performance. The method of calculations was also subject to variations between the studies. For example, Firm Size was widely calculated by the total number of firm's employee, however, it was also measured by the natural log of total asset

(Levy, 2005), by natural logarithm of sales (Rivas, 2012), and by natural log of firm assets for each year (Lee & Park, 2006). Another example is the Firm Age, while it has been widely calculated by the number of years since incorporation, (Lee & Park, 2006 ; Marlin et al., 2004) suggested to calculate Firm Size by subtracting the year of incorporation from the current year.

This research is controlling five variables, and those are:

1. **TMT Size:** The extent by which the TMT size (i.e., board size) may impact the financial performance of construction firms is an important matter that has yet to be fully investigated (Rebeiz & Salameh, 2006). Supporters of a large board size argue that there will be diversity in the board in terms of experience, knowledge, ethnic background, and gender providing an increased pool of expertise and resources for the organization, which would eventually translate into value-added decision-making. However, having large board numbers faces the difficulty of reaching a timely consensus on important matters (O'Reilly, Caldwell, & Barnett, 1989). They are also more difficult to coordinate due to the increased frequencies of potential interactions among group members (Gladstein, 1984).

   The cohesiveness of the board is also likely to decrease when the size increases, which may weaken its ability to monitor the actions of managers. Conversely, a smaller board is perceived to react faster to avert unwarranted risks to the shareholders than larger boards. Therefore, measuring TMT diversity is known to be size-dependent (Carpenter, 2002) where (larger teams can be more diverse by definition. Additionally, the size of the board varies across geographical borders. The average board size in Australia, the United States, and the United Kingdom is around 10 members. In comparison, a board size of 40 members is not uncommon for Japanese firms (Rebeiz & Salameh, 2006). Consequently, failing to control for team size makes one unable to infer whether significant statistical associations should be attributed to heterogeneity or to the unobserved effects of TMT size (Carpenter et al., 2004).

In this research, the TMT size (board size) is controlled as the total number of executives on the board (Angriawan, 2009 ; Athanassiou & Douglas, 1999 ; Athanassiou & Nigh, 2000 ; Auden et al., 2006 ; Cannella et al., 2008 ; Carpenter, 2002 ; H. L. Chen, 2011 ; Darmadi, 2013 ; Marlin et al., 2004 ; B. B. Nielsen & Nielsen, 2013 ; S. Nielsen, 2010 ; Simsek et al., 2005);

2. **Economy Dynamism:** studies have shown that factors affecting competitiveness of construction firms differ from country to another, due to both capability of local firms as well as environmental factors including industry demand, political factors, and international competitors (Vorasubin & Chareonngam, 2007). Economy dynamism refers to the environmental stability/instability (or volatility) and the extent to which the organization is affected by changes in the industry (Dess & Beard, 1984). Since this research is based on data primarily driven from different regions, it is suggested that the country level differences should be controlled to avoid any unknown factors. Dynamism was controlled as the volatility in sales growth of each firm. Specifically, dynamism firm's sales have been calculated as the standard error of the regression slope coefficient divided by the mean value of sales over a five-years period (Carpenter & Fredrickson, 2001 ; Dess & Beard, 1984 ; B. B. Nielsen & Nielsen, 2013 ; Rajagopalan & Rajagopalan, 2004);

3. **Degree of Internationalization:** The construction industry is usually regarded as a localized industry due to having such characteristics as onsite construction, one-off manufacturing, and an unmovable and unduplicated product. Therefore, it is more difficult for construction firms to become global and realize international goals than firms in other industries. Extending the organization boarder to serve (and compete) in international markets is seen as one of the major strategic decisions that the organization's top management is responsible for. The internationalization of construction companies has become of significant interest as the global construction market continues to be integrated into a more competitive and turbulent business environment. However, due to the complicated and multifaceted nature of international

business and performance, there is as yet no consensus on how to evaluate the performance of international construction firms (Jin, Deng, Li, & Skitmore, 2013). Internationalization was also the subject of many studies exploring how TMT can influence the organizational approach for expanding overseas opportunities. (Daily et al., 2000) explored the effect of the internationalization of the Multi-National Corporation (MNC) on the behaviour of its Top Management Team. Firms led by top management that paid more attention to the internal environment were less likely to be global. Since the internationalization is not the major interest of this research, it is suggested that the organization degree of internationalization should be controlled as the ratio of international revenue to total organization revenue (Angriawan, 2009 ; H. L. Chen, 2011 ; Daily et al., 2000 ; Lee & Park, 2006 ; Rivas, 2012);

4. **Degree of Diversification:** defined as “the process by which firms extend the range of their businesses outside those in which they are currently engaged”. A diversified firm can therefore be considered as one having operations in more than a single industry, whether for related or unrelated businesses (Ibrahim & Kaka, 2007). The consequence of diversifying can be examined for the individual firm with respect to its long-term growth or profit. Numerous studies both within and outside the construction management literature have sought to establish the impact of diversification on the performance of the firm. Even so, little agreement exists amongst researchers on the subject (Palich, Cardinal, & Miller, 2000). Construction researchers generally support specialization rather than diversification. Theoretically, both in construction and non-construction industries, it is generally recommended that firms focus rather than diversify (Choi & Russell, 2005). An investigation into the possible reasons for the differences in profitability between firms conducted by (Akintoye & Skitmore, 1991) showed that the degree and type of diversification is a major factor. The subject of diversification is hence an important area of a construction firm’s strategy (Ibrahim & Kaka, 2007). From the preceding arguments, it can be postulated that performance difference may exist between related and unrelated diversification strategies. Therefore, in this research, the Degree of Diversification was controlled by introducing the standard industry classification. The

Standard Industrial Classification of Economic Activities (SIC) was used by many studies (Angriawan, 2009 ; S. Nielsen, 2010 ; Rivas, 2012 ; Ruigrok et al., 2013). However, specifically for construction industry, the business segments (industry group) was determined by utilizing the industry classifications that are found in the Engineering News and Records (ENR) databases (i.e., A: for Architects, E: for Engineer, C: for Contractors, ENF: for Environment, GE: for Geo-Technology, L: for Landscaping, P: for Planner and O: that will include all other specialties and subspecialties). Blau's Diversity Index for each firm will be calculated to define the extent that each firm is active in more than one industry;

5. **Past Performance:** this variable is considered for many reasons: first, production cycles and cash conversion cycles in construction firms last more than an accounting year (Muscettola, 2014), therefore limiting the analysis to single annual financial statements may lead to misunderstanding of results. Secondly, resources in construction become abundant when a company performs well, and finally, Top Management Teams' decisions and actions (which reflect Top Management Teams' reflection on firms' output), is claimed to have an impact on firm performance after a period of time (Rivas, 2012). Hence, this research is controlling the past performance by lagged two-years average of the Returns on Assets (ROA) (Camelo et al., 2010). Other studies have used Return on Sales (ROS) instead of ROA as a measure of a firm's financial performance. However, (Muscettola, 2014) concluded that both measures will produce similar results (but slightly weaker in ROA). Therefore, it is recommended to measure ROS with samples that consist of firms operating in different regions.

Table 2.2 Selected controlled variables

Controlled Variables	Measurement Method
TMT Size	Number of Members at the Board
Economy Dynamism	Standard error of the regression slope coefficient divided by the mean value of sales over a three-year period
Degree of Internationalization	Ratio of International revenue to total organization revenue
Degree of Diversification	Blau's Diversity Index *
Past Performance	Two lagged years of RoA

* Eight Categories were used: Architects, Engineer, Contractors, Environment, Geo-Technology, Landscaping, Planner and Others.

2.5 Operationalization of Performance in Construction Industry

Organization performance is one of the most important constructs in management research, whereas determination of organization performance is essential for gaining robust results. Many organizations are investing considerable amount of resource implementing measures that reflect all dimensions of their performance. It is reported in the literature that consideration is being given to what should be measure today, but little attention is being paid to the question of what should be measured tomorrow. Despite numerous topics that have been demonstrated in the literature on performance, limited attention is paid to its measurement in empirical studies. The operationalization of firm performance provides rich implications for both researchers and practitioners. This issue is becoming more prominent in construction industry (AEC firms: Architect, Engineers and Construction), where the industry processes are typically prone to risks, which ultimately affects organizations' performance.

The main objective of this section is to introduce a concept that will explore various factors contributing to the performance of construction firms, making it more predictable, rather than measuring a single-item indicator. It captures the different operationalization aspects of performance in construction industry. This section presents an extension to the work done on Dominant Dimensions of Performance (Katsanis, 1998). Furthermore, it addresses two issues in the proposed performance operationalization: the dimension (establishing which measures are appropriate to the research context), and secondly, selection and combination of measures (establishing which measures can be usefully combined). Therefore, an overall concept rather than narrow, strictly economic criteria will be presented.

Firm Performance was widely used as a "dependent variable or output measure" (Angriawan, 2009 ; Auden et al., 2006 ; Boone & Hendriks, 2009 ; Cannella et al., 2008 ; Carpenter, 2002 ; Clark & Soulsby, 2007 ; Daily et al., 2000 ; Díaz-Fernández et al., 2014 ; Hutzschenreuter & Horstkotte, 2013 ; B. B. Nielsen & Nielsen, 2013 ; S. Nielsen, 2010 ; Ruigrok et al., 2013). However, the method of calculating firm performance was subject to slight differences between the studies. For example, Total Returns to Shareholders (TRS) was used by (Joyce & Slocum, 2012), Return Index (S. Nielsen, 2010) and Return on Assets (ROA) (Angriawan, 2009 ; Cannella et al., 2008 ; Carpenter, 2002 ; Díaz-Fernández et al., 2014 ; Hutzschenreuter & Horstkotte, 2013 ; B. B. Nielsen & Nielsen, 2013), while (Auden et al., 2006) suggested to use (ROA) but averaged over three years. Some other studies used combination between the Return on Assets (ROA) and Return on Sales (ROS) (Boone & Hendriks, 2009 ; Clark & Soulsby, 2007), however, (Ruigrok et al., 2013) is also accepting (ROA) and (ROS) but to be averaged over two years. Finally, (Daily et al., 2000) is suggesting combining three measure, those are Return on Assets (ROA), Return on Investment (ROI) and market-to-book ratio.

2.5.1 Performance in Construction Industry

Existing research on construction industry (also referred in different scholars as building industry or Architects, Engineers and Construction – AEC) is dominated by project level studies. It is a project-based industry where each product (project) represents a large proportion of a firm’s total sales (Kaka & Lewis, 2003), and known to be a contract-based industry in which each contract has considerable influence on the firm’s financial performance. Focus of research in the construction industry was dominated by issues and problems at the project level (Yee & Cheah, 2006). That has resulted in organizational issues gaining very limited interest (Deng & Smyth, 2013) and lacking of studies on long-term strategic issues at organization level (Yee & Cheah, 2006). (G. Lin & Shen, 2007) review shows that approximately 68% of reviewed Project Management studies in construction are focused on the project level. In this context, the success of projects is generally regarded as an antecedent to construction firm's success (Phua, 2007). Organization performance in the construction industry is typically measured at the project level (Choi, 2014), and each project stakeholder assesses project success on the basis of evaluation dimensions that fit within his/her own agenda or within the interests of the group he/she represents (K. R. Nielsen, 2006). It is probably fair to conclude that the bulk of the published work on construction management is on the management of construction projects, rather than on the firms (Choi & Russell, 2005).

However, successful projects are likely to be a function of the general "health" of the construction organizations undertaking the projects in terms of strategic functions/activities. Hence, as reported by (Seaden, Guolla, Doutriaux, & Nash, 2003) organization is the key factor that influences project tasks completion and project performance. Therefore, measuring project-level performance for only a few (even well chosen) metrics does not translate into robust evaluation of an entire firm (El-Mashaleh, Minchin, & O'Brien, 2007). Furthermore, the success of the firm depends in turn on strategic decisions, because these decisions determine the business mix of the firm (Choi & Russell, 2005). The need for such strategic decisions, especially amongst construction firms, is due to the volatility of the construction market (Ibrahim & Kaka, 2007). For sustainable competitiveness of construction organization, management must shift their focus from project level more towards the organization strategic direction (Vorasubin & Chareonngam, 2007).

According to (G. Lin & Shen, 2007), the number of papers focusing on measuring project-level performance is much greater than those focusing on organizational-level performance because of the project-based nature of the construction industry. However, the same study indicated that the number of papers during the last three years has increased significantly showing a growing interest in performance measurement in construction. It can be attributed to several reasons: first, the boom in research on performance measurement in construction is a continuation of the rapid development of performance measurement in other sectors during the 1990s. Secondly, the increasing complexity of construction projects that require appropriate measurement tools to improve performance. The development of construction project management as well as building technology is third reason for growing interest on performance measurement.

2.5.2 The Dominant Dimension of Performance

The importance of performance as a measure of organizational effectiveness in construction industry organizations has been identified as a critical research issue (Katsanis, 1998) and could provide rich implications for both researchers and practitioners. It is argued by (Kaplan & Norton, 1992) that economic performance of an industry is a function of the industry's structure, and dimensions of performance can be very diverse and even subjective and context-sensitive (Katsanis, 1998). Each industry has its specific variables and performance meaning and it is essential for the specifics of the industry to be counted when developing an organizational outcome measure.

In the context of the construction industry (or building industry), organizational outcome requires the identification, consideration and analysis of factors, tangibles as well as intangibles, that affect the outcome specifically applicable for this industry. In his research (Katsanis, 1998) studied how each enterprise within the building industry (Architects, Engineers, and Construction) organizes their business. Using a multiple case study method, he studied the relationships between strategy, structure and performance in those three enterprises that operate under the current construction business environment. His research has introduced the concept of Dominant Dimensions of Performance, which are grouped in three categories (business, practice and project performance). Those categories are linked to each enterprise of the building industry (refer to Figure 2.1).

Business Related	Apply to:
Financial Performance	E/A/GC
Business Volume Growth	GC
Client Base Growth	A
Staff Growth	GC
Continuity/Future/Stability	A/GC
Reputation/Image	GC
Practice Related	
Reputation	E/A
Project Quality / Prestige	E/A
Employee/Self Satisfaction	E/A
The Process of Architecture/Related	A
Inventiveness	A
Ageless Projects	A
Project Related	
Client Satisfaction	A/GC
Project Quality	A/E
• Time	A/E
• Cost	A/E
• Technical	A/E
• Aesthetic	A
Quality of Work	GC
• Zero Defects	GC
• On Time	GC
• On Budget	GC

Figure 2.1 The Dominant Dimensions
of Performance
Taken from Katsanis (1998)

In the realm of building industry, the Dominant Dimensions of Performance has provided several contributions towards the understanding of construction organization performance. More specifically, there were three main conclusions that provided significant insights towards this research, and can be summarized as follow:

1. Although performance indicators tended to be financial for engineers and general contractors, with architects are more commonly focusing on issues of professional reputation, the financial performance has become important for all enterprises. Those should make financial performance a priority to balance the other appreciations of success;

2. Construction is an industry that is based on two levels of organizational objectives, those are:
   a. The temporary objectives of the project and the organization that is set up to build it;
   b. The permanent objectives of the involved firms, whereas it includes the desire for firms to enhance their position in the marketplace.

   This unique structure of the industry where organizations are operating in a discrete domain (project by project basis), is presented in (Katsanis, 1998) research through its third proposition, where "performance – usually broadly defined – is translated into measures of short to medium term financial performance which have repercussions on firm strategy and structure";

3. Having identified the relevant elements of performance, the suggested next step by (Katsanis, 1998) is to empirically measure its dimensions and to assess how performance evaluation produces information about the environment.

Giving that construction firm performance is confirmed as being multidimensional in nature (Vorasubin & Chareonngam, 2007), and expanding on the above three core ideas, this research is proposing a multidimensional organization performance construct, or an operationalization approach for organization outcome.

2.5.3 Organization Outcome – Output Variables

Given that performance is multifaceted and dynamic, selection of performance measures may affect the research results and interpretations (Deng & Smyth, 2013). More importantly, conceptualizing and measuring firm performance depends on various issues, such as research questions, disciplinary focus, and data availability (Venkatraman & Ramanujam, 1987). Therefore, this study is suggesting a generic reform of the "Business Related" aspects of the Dominant Dimensions of Performance.

In Table 2.3 below, (Financial, Growth, Reputation and Continuity) are four different dimensions that found to be generic between all three enterprises of construction industry (Architects, Engineers and General Contractors).

Table 2.3 Generic Dominant Dimensions of Performance

Dimension	**Dominant Dimensions of Performance (Katsanis, 1998)**	**Enterprise***
Financial	Financial Performance	E / A / GC
Continuity	Continuity / Future / Stability (Business)	A / GC
Reputation	Reputation / Image	GC
	Reputation	E / A
Growth	Business Volume Growth	GC
	Client Base Growth	A

* A: Architect, E: Engineers, GC: General Contractors

Presenting organization outcome in dimensions, domains or categories is aligned with many previous studies. For example, (Venkatraman & Ramanujam, 1986) presented three domains of business performance: financial performance, business performance (financial performance and operational performance) and organizational effectiveness. Another example is the methodology proposed by, (Kim & Arditi, 2010) where they applied 13 performance indicators under seven dimensions (i.e., financial stability, customer satisfaction, business efficiency, learning and growth, job safety, technological innovativeness, and quality management) to measure firm performance. The suggested four dimensions in this research (and their indicators that will be presented later) are important in determining financial as well as non-financial dimensions of performance. It is, in reality, responding to the different other performance measurement frameworks which started to develop in full force by the late 1980s and into the early 1990s (Azzone, Masella, & Bertele, 1991 ; Brignall, Fitzgerald, Johnston, & Silvestro, 1991).

2.5.4 Operationalization of Performance: Suggested Measures

Two issues are argued by (Richard et al., 2009) that should be addressed in any firm performance-related study: the dimension (establishing which measures are appropriate to the research context) and selection and combination of measures (establishing which measures can be usefully combined) (Deng & Smyth, 2013). This approach is consistent with the widely-accepted idea that organization outcome (or performance) is multidimensional and should include broader dimensions rather than more narrow, strictly economic criteria (Kaplan & Norton, 1992 ; Richard et al., 2009 ; Venkatraman & Ramanujam, 1986). Furthermore, performance measures are the means for determining the status of a success factor. A single success factor can be assessed using multiple measures. Terms such as indicators, metric and measurements are often used as synonyms for the term measure. However, (Ho, Chan, Wong, & Chan, 2000) stated that there is an essential difference between these terms. According to them, the major difference between measurement and indicators is that the former is direct representation of the scale of the organization (internal) whereas the latter are figures that are comparable between organizations (external). Table 2.4 shows the suggested measures, based on a literature review, a total of six different measures that could capture the overall organization outcome.

Table 2.4 Proposed organization outcome

Dimension	Link to Dominant Dimensions	Measures
Financial	Short Term Performance	Profitability
		Liquidity
Continuity	Medium Term Performance	Cash Flow Stability
		Capital Structure
Reputation	Balance other appreciations of success – Long Term	External Customer Satisfaction (Reputation)
Growth		Internal Customer Satisfaction (Shareholder Value)

1. **Profitability:** sometimes referred to as positive financial performance, profit margin (Choi, 2014), growth in revenue (Kim & Arditi, 2010) and effective capital investment (Vorasubin & Chareonngam, 2007). Profitability has been measured differently in various studies. For example, it is measured as the sales volume (Choi & Russell, 2005), calculated as the growth in revenue (Kim & Arditi, 2010), or defined as the pre-tax operating margin (Seaden et al., 2003). In this research, profitability is calculated following the suggested measure by (El-Mashaleh et al., 2007) net profit after tax as a percentage of total sales;

2. **Liquidity:** also, known as access to capital or leverage. This measure is particularly necessary for construction firms because of financial cash flow fluctuations resulting from delay of payment by owners (Vorasubin & Chareonngam, 2007) and the requirement of financial support (H. L. Chen, 2011). (Cheah, Garvin, & Miller, 2004) concluded that some firms failed due to a lack of liquidity and/or high leverage. Liquidity is a relative measure of the "nearness to cash" of the assets and liabilities of a firm. The nearness to cash, in turn, refers to the length of time before assets can be converted into cash in order to cover short-term liabilities and obligations (Yee & Cheah, 2006). This measure is particularly important in the contracting business, since a sufficient level of working capital is often vital to soften the effects of a timing mismatch between cash inflows and outflows. Liquidity has been widely measured in literature by the ratio of the total debt of the organization (H. L. Chen, 2011 ; B. B. Nielsen & Nielsen, 2013 ; S. Nielsen, 2010 ; Vorasubin & Chareonngam, 2007 ; Yee & Cheah, 2006);

3. **Cash Flow Stability:** the financial stability of an organization is commonly used / quoted in different models proposed by different researchers (El-Mashaleh et al., 2007 ; Phua, 2007). Depending on profitability alone will only provide a great view of where the company has been but does not provide much guidance for the future (Kim & Arditi, 2010). It also represents how the organization was efficiently managing its cash flow (Vorasubin & Chareonngam, 2007). Cash flow stability was measured by the ratio of annual revenue to total asset;

4. **Capital Structure:** in corporate finance practices, the proportion between debt and equity has strategic implications on a firm's outlook, since it can both create opportunities and impose limitations (Hillier, Grinblatt, & Titman, 2011). Capital structure is believed to be closely related to risk management. This is because debt per se would impose additional financial risks, such as the risk of bankruptcy, if a firm were unable to meet its debt service obligations. In this research, capital structure is calculated as a ratio of total debt to the value of total assets (Yee & Cheah, 2006). Effectively, it measures the proportion of the assets of a firm that is financed by debt rather than equity.

   All of the above measures were related to the financial wealth of the organization (whether on the short or medium span). From the Resource Based Theory, the intangible strategic assets are also to be considered to complement the organization competency (Wethyavivorn, Charoenngam, & Teerajetgul, 2009). Intangible resources including human resources, reputations, customer loyalty, valuable relationships, and technological as well as managerial competencies are necessary complementary sources of advantage (Vorasubin & Chareonngam, 2007). Following the literature in construction industry, in this research the intangible resources are defined by two measures: External Customer Satisfaction and Internal Customer Satisfaction;

5. **External Satisfaction – Reputation:** is mostly known as a subjective indicator in practice, and frequently used by researchers in construction to quantify the performance of construction firms (Deng & Smyth, 2013). Excellent reputation development was ranked as the number one strategic asset in developing capabilities in construction industries (Wethyavivorn et al., 2009). 65% of the respondents of The Economist in a 2002 survey reported customers as their main focus (Kim & Arditi, 2010), reflecting its importance in a project-based and various stakeholders involved industry. Client satisfaction is closely related to the intangible organizational reputation (Y. H. Lin & Ho, 2013), which is found to be the one of most important elements in explaining organizational performance (Carmeli & Tishler, 2004). It affects the profitability of an organization. Reputation was measured by repeated business (Kim & Arditi, 2010), more

specifically in this research, the growth in sector specific revenue is calculated (i.e., growth in organizations' outcome in the largest sector revenue; education, healthcare, leisure, etc.). Similar methodology has been utilized by (Ibrahim & Kaka, 2007);

6. **Internal Satisfaction – Shareholder Value:** the objective of top management is to manage a sustained performance that leads to superior returns for shareholders in the short and long term (Deng & Smyth, 2014). According to Neoclassical Economic Theory, the true owners of a publicly traded firm are its shareholders. This means that the firm's management should focus on increasing the shareholders' economic wealth (Choi, 2014), whereas the primary objective of modern firms is to increase shareholder value (Akalu, 2001). In other words, sustained efforts to increase the firm's value are the core elements of managing construction firms. In this research, increasing shareholder value refers to the total market value of an organization, which is calculated as the Price / Earnings ratio.

2.6 Conclusion

The objective of introducing a new construct for Organization Outcome is to explore various factors that contribute to the performance of construction firms, making firm performance more predictable in practice, rather than measuring a single-item indicator. (Venkatraman & Ramanujam, 1986) argue that multiple-approach conceptualization of organization outcome can enhance the quality of business performance operationalization. Past research has strongly urged the reliance on multiple measures to adequately capture firm performance (Daily et al., 2000). The special conditions of the construction industry, where the accounting cycle (accounting is based on period more than a year due to the project's lifecycle), imposes certain approaches for data collection and analysis. Whether a researcher is looking for a statistical correlation, mathematical modelling or trend recognition, the accurate definition of those variables is critical to the success of any methodology and its validation. Table 2.5 shows the overall suggested operationalization of organization outcome in construction industry as proposed by various researchers. Table 2.6 shows a summary of the proposed measures and measurement methods as suggested in this research.

Table 2.5 Operationalization of organization outcome in construction industry

Dimension	Measure	Definition	Measurement Method	Example Reference
Financial	Profitability	positive financial performance, profit margin, growth in revenue, effective capital investment	Net Profit after Tax as a Percentage of Total Sales.	(Choi, 2014) (Kim & Arditi, 2010) (Vorasubin & Chareonngam, 2007) (El-Mashaleh et al., 2007)
	Liquidity	Access to Capital, leverage, relative measure of nearness to cash	Ratio of the Total Debt of the Organization	(Vorasubin & Chareonngam, 2007) (H. L. Chen, 2011) (Cheah et al., 2004) (Yee & Cheah, 2006) (S. Nielsen, 2010) (B. B. Nielsen & Nielsen, 2013)
Continuity	Cash Flow Stability	financial stability of an organization	Ratio of Annual Revenue to Total Asset	(Phua, 2007) (El-Mashaleh et al., 2007) (Kim & Arditi, 2010) (Vorasubin & Chareonngam, 2007)
	Capital Structure	proportion of the assets of a firm financed by debt rather than equity	Proportion between Debt and Equity	(Hillier et al., 2011) (Yee & Cheah, 2006)

Table 2.5 (continuation) Operationalization of organization outcome in construction industry

Dimension	Measure	Definition	Measurement Method	Example Reference
Reputation	External Customer Satisfaction	Client satisfaction, reflecting its importance in a project-based and various stakeholders involved industry	Organizations' Outcome in the largest sector revenue	(Deng & Smyth, 2013) (Wethyavivorn et al., 2009) (Kim & Arditi, 2010) (Carmeli & Tishler, 2004) (Ibrahim & Kaka, 2007)
Growth	Internal Customer Satisfaction	Shareholder Value, increasing the shareholders' economic wealth	Price / Earnings Ratio	(Deng & Smyth, 2014) (Choi, 2014) (Akalu, 2001)

Table 2.6 Proposed measurement methods

Measures	Measurement Methods
Profitability	Profit Margin = Net Profit After Tax / Total Revenue
Liquidity	Current Ratio = Current Asset / Current Liability
Cash Flow Stability	Asset Turnover Ratio = Ratio of Annual Revenue to Total Asset
Capital Structure	Ratio of Total Liability to the Total Assets
External Customer Satisfaction (Reputation)	Averaged Growth in Revenue in Major Sector
Internal Customer Satisfaction (Shareholder Value)	P/E Ratio = Price / Earnings

CHAPTER 3

METHODOLOGY

3.1 Background

Artificial Intelligence (AI) models, in particular the hybrid fuzzy neural networks, can be used to train and test market and event-related data. Sometimes referred to as Soft Computing, which is a collection of methodologies like fuzzy system, neural networks and genetic algorithm, designed to tackle imprecision and uncertainty involved in a complex nonlinear system (Buragohain & Mahanta, 2008). In the modelling process, these models discover the rules or relations between different variables and the outcome, even if such relations are sometimes unknown to researchers. Since these methods automatically learn from historical data, they can easily learn the non-linear relations among independent and dependent variables. They can make decisions like humans by adapting themselves to the situations and taking correct decisions automatically for future similar situations (Kharb et al., 2014). They have a better performance in comparison to traditional methods and most importantly, having the ability to conform to the new knowledge (Asgari et al., 2016 ; Boer et al., 2001 ; Kuo et al., 2010 ; Saghaei & Didehkhani, 2011). Recent reviews on artificial intelligence indicate that the number of its engineering applications is increasing (Dote & Ovaska, 2001). The evolution of soft computing techniques has helped in understanding the various aspects of nonlinear systems and thereby making it possible to model them, easier analysis and control as well as predict their future response (Zadeh, 1994). There are four major components constituting soft computing; fuzzy system, neural network, evolutionary computing and possibility reasoning. Soft computing is concerned with the integration of these components to model the human intelligence and reasoning ability (Cheng et al., 2007 ; Özkan & İnal, 2014).

3.2 The Adaptive Neuro-Fuzzy Inference System - ANFIS

The nonlinear universal function approximation property of Fuzzy Inference Systems (FIS) and Artificial Neural Networks (ANNs) qualifies them to be powerful candidates for identification and control of nonlinear dynamical systems (Lutfy, Noor, & Marhaban, 2011). The well-known Adaptive Neuro-Fuzzy Inference System (ANFIS) is a form of artificial intelligence models. It is a fuzzy inference system applied in the form of a neuro-fuzzy system with crisp functions in consequents as in the Takagi-Sugeno type fuzzy system (Mombeini & Yazdani-Chamzini, 2014). Among the fuzzy neural models, the ANFIS model is chosen in this instance for its strong modelling capability and computational flexibility, and hence its suitability for system modelling of complex, dynamic, and nonlinear relations, which is common in real case scenarios that include financial market behaviour (Azadeh et al., 2011). The unique forecasting features of ANFIS make this technique more popular in comparison with the traditional forecasting techniques. These can be due to the existing advantages in two methods: Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) that form its structure (Mombeini & Yazdani-Chamzini, 2014). In addition to the advantages of self-learning, adaptation, parallel processing, and generalization that are resulted from the use of the fuzzy reasoning (Zhang, Chai, & Wang, 2011).

Being a combination between ANN and FIS, the ANFIS, developed by (Jang, 1993), uses the learning capability of the ANN to derive the fuzzy "if-then" rules with appropriate membership functions worked out from the training pairs (Khoshnevisan, Rafiee, Omid, & Mousazadeh, 2014). This specific feature enhances the ability to automatically learn and adapt (Petković et al., 2014) on the basis of the smoothness characteristics and mathematical components each for set of input data (Valizadeh & El-Shafie, 2013). The soft computing models were used for processing different systems: in modelling, predicting and controlling in various engineering systems (Petković et al., 2014). Some of ANFIS applications in engineering includes automatic control, pattern recognition, human-machine interaction, expert systems, modelling, medical diagnosis and economics.

3.3 Advantages of ANFIS

In neuro-fuzzy systems, neural networks are incorporated into fuzzy systems which can acquire knowledge automatically by learning algorithms of neural networks (Kharb et al., 2014). The relations between input and output variables are represented by means of fuzzy “if–then” rules with unclear predicates (Mombeini & Yazdani-Chamzini, 2014). ANFIS represents a useful intelligent neuro-fuzzy technique that has many applications, such as:

1. Modelling and controlling of ill-defined and uncertain systems (Amirkhani, Nasirivatan, Kasaeian, & Hajinezhad, 2015);
2. The solution of function approximation problems (Buragohain & Mahanta, 2008);
3. Used with random data sequences with highly irregular dynamics (B. R. Chang & Tsai, 2009);
4. Can help find the mapping relation between the input and output data through hybrid learning to determine the optimal distribution of membership functions (M. S. Chen, Ying, & Pan, 2010);
5. Uses the rules in the rule base of fuzzy theory to describe the complex relations between the variables and re-use the learning ability of neural network (Fang, 2012).

Neuro-fuzzy system adds the advantage of reduced training time not only due to its smaller dimensions but also because the network can be initialized with parameters relating to the problem domain itself (Azadeh et al., 2011). It also represents connection of numerical data and linguistic representation of knowledge and characterized by transparency as fuzzy systems and learning ability as neural networks. ANFIS is a network of nodes and directional links associated with a learning rule, it is called adaptive because some, or all, of the nodes have parameters which affect the output of the node (Abirami, Ramalingam, & Palanivel, 2013), and also it has a network learning ability. The parameters can be adapted, hence the system is called adaptive neural fuzzy inference system (Negnevitsky, 2005). The main aim of using hybrid models is to decrease the risk of failure by integrating different models to obtain more accurate and precise results. The results of hybrid models performance shows improvements in prediction (Mombeini & Yazdani-Chamzini, 2014).

3.4 Fuzzy Systems and Neural-Networks

Since ANFIS combines between fuzzy systems and neural-networks, both of them have their own advantages as well as drawbacks, which limit its usefulness for certain situations, and not for others. The concept of fuzzy systems as described by (Zadeh, 1965), it provides means for making decisions based on ambiguous, imprecise or incomplete data (M. Y. Chen, 2013). The primary mechanism of fuzzy systems is based on conditional "if-then" rules, called fuzzy rules, which use fuzzy sets as linguistic terms in antecedent and conclusion parts. A collection of these fuzzy "if-then" rules can be determined from human experts or alternatively can be generated from observed data (Kharb et al., 2014). It has ability to represent comprehensive linguistic knowledge (given for example by a human expert and perform reasoning by means of rules) and the capability to approximate any nonlinear function on a compact set to arbitrary accuracy, which makes it a universal approximator (Echanobe, Campo, & Bosque, 2008 ; Zhang et al., 2010). Through the fuzzy inference, ordinary crisp input data produces ordinary crisp output, which is easy to understand and interpret (M. Y. Chen, 2013). Fuzzy system has been demonstrated as an effective tool to deal with a variety of complex nonlinear systems with unavailable states or completely unknown functions (Zhang et al., 2010).

The main advantage of the three different categories of fuzzy systems (i.e., Mamdani, Takagi–Sugeno, and evolving Takagi–Sugeno) is the easiness to interpret knowledge in the rule base (Kharb et al., 2014). However, one of the crucial drawback of the fuzzy inference system that it doesn't provide a mechanism to automatically acquire and/or tune those rules thus there are no standard methods for transforming human knowledge or experience into a rule base (M. Y. Chen, 2013 ; Fang, 2012). In addition to that, the fuzzy systems still have issues with the selection of appropriate Membership Functions (MF) and how to tune the rule base and the membership functions to the desired performance (Lutfy et al., 2011).

On the other hand, Artificial Neural Networks (ANN) are the systems that get inspiration from biological neuron systems and mathematical theories for learning. They are adaptive systems that can be trained and tuned from a set of samples. Once they are trained, they are characterized by their learning ability, parallel-distributed structure and can deal with new input data by generalizing the acquired knowledge (Kharb et al., 2014). ANNs service different purposes for classification, cluster and prediction (Wang, Chang, & Tzeng, 2011).

Neural network models have been used extensively to simulate human thinking mode or biological nervous system. Moreover, they have been developed to deal with repeated processes of learning, with the possibility of the output variables inquiring from the input variables, such as financial ratios and market information (Fang, 2012). However, the black-box nature is considered to be the most influential drawback of the neural network (M. Y. Chen, 2013 ; Cheng et al., 2007 ; Kharb et al., 2014 ; Lutfy et al., 2011). ANN is considered over-equipped fitness and cannot explain the causal relation between the variables shortcomings, so there are still restrictions in the estimation process (Fang, 2012). It suffers from the lack of knowledge representation power (Lutfy et al., 2011). Using neural network, many researchers have developed methods to extract rules, which are then used to explain the reasoning behind a given neural network output. These rules do not capture the learned knowledge well enough (Piramuthu, 1999). The ANN model still has a major limitation at extreme events (Najah, El-Shafie, Karim, & El-Shafie, 2014). Finally, it also has issues in lacking of the proper structure and size to solve a specific problem (Lutfy et al., 2011).

Therefore, (Jang, 1993), combined both algorithms of fuzzy theory and neural network in the proposed Adaptive Neural-Fuzzy Inference System (ANFIS) for the processing capabilities of any systems' uncertainties and imprecisions to adjust the parameters of the model and overcome drawbacks with both methods. Its architecture is based on fuzzy inference system for the network model based on combined with the characteristics of self-organizing neural network (Fang, 2012). ANN is capable to model all types of existing complexity and nonlinearity in the structure of the data under consideration. Likewise, FIS (corresponds to a fuzzy model of Takagi-Sugeno) is successful in face of uncertain data and can consider the human knowledge in modelling (Mombeini & Yazdani-Chamzini, 2014).

Some of the ANFIS characteristics are (Azadeh et al., 2011 ; Lutfy et al., 2011 ; Zhang et al., 2010):

1. It utilizes the self-learning, adaptiveness, parallel processing and generalization abilities of neural networks, and human-knowledge-representation abilities of fuzzy systems;

2. Using a given input–output dataset, it is a hybrid learning rule which creates a FIS whose membership function parameters are adjusted using a backpropagation algorithm alone or a combination of a backpropagation algorithm with least squares method. This allows the fuzzy systems to learn from the data being modelled to optimize the premise and the consequent parameters of the ANFIS network, respectively;

3. ANFIS can adapt the parameters of the membership functions quickly and optimize them depending on the input data. Both of them (FIS and ANN) have a predominant visibility in many forecasting problems as they do not require rigid conditions of the operational model of the problem.

The main advantage of a neural fuzzy network is its ability to model the characteristics of a given problem (known as system modelling) using a high level linguistic model instead of low-level complex mathematical expressions (Cheng et al., 2007). The embedded fuzzy system in a neural fuzzy network can self-adjust the parameters of the fuzzy rules using neural network learning algorithms to achieve the desired results. In addition, the “black-box” nature of the integrated neural network is resolved as the intuitive “if-then” fuzzy rules can be used to interpret the weights and linkages of the connectionist structure (Cheng et al., 2007), therefore, fuzzy systems and neural-networks are both complementary paradigms.

The success of ANFIS can be attributed to the embedded fuzzy system in a neural fuzzy network can self-adjust the parameters of the fuzzy rules using neural network learning algorithms to achieve the desired results. (B. R. Chang & Tsai, 2009 ; Cheng et al., 2007 ; Jang, 1993). (Fang, 2012) has listed many examples where the ANFIS has been successfully applied, such as: bank credit early warning system, the diagnosis of disease, the reservoir real-time operating system, water resources research, ocean engineering, motor control, industrial manufacturing, and electric power system and options evaluation.

Similar to the ANN with its classification application (Cheng et al., 2007 ; Zhang et al., 2011), Adaptive Neuro-Fuzzy Inference System (ANFIS) has been efficiently used for function approximation, clustering, pattern recognition and regression (Özkan & İnal, 2014). More specifically, toady, ANFIS has been successfully applied to classification tasks, data analysis, rule-based process controls, pattern recognition problems and the likes of them (Buragohain & Mahanta, 2008 ; Fang, 2012 ; Özkan & İnal, 2014). Intelligence analysis gives researchers the ability to model both experimental design and data in a number of different forms than the statistical approaches (Abbasi & Mahlooji, 2012 ; Sedighi et al., 2011).

3.5 ANFIS Structure

ANFIS is a graphical network of multilayer feed-forward network using neural network learning algorithms and fuzzy reasoning to map an input space to an output space (F. J. Chang & Chang, 2006). It is similar to a fuzzy inference system except for the fact that it uses back-propagation to minimize errors (M. Y. Chen, 2013). The network is comprised of nodes and with specific functions, or duties, collected in layers with specific functions (Terzi, Keskin, & Taylan, 2006).

The neural fuzzy systems are considered based on the Tagaki– Sugeno–Kang fuzzy rules, where the output of each fuzzy rule is a linear combination of input variables plus a constant term, and the final output is the weighted-average of each rule’s output (Buragohain & Mahanta, 2008). A fuzzy inference system is composed of five functional blocks as shown in Figure 3.1.

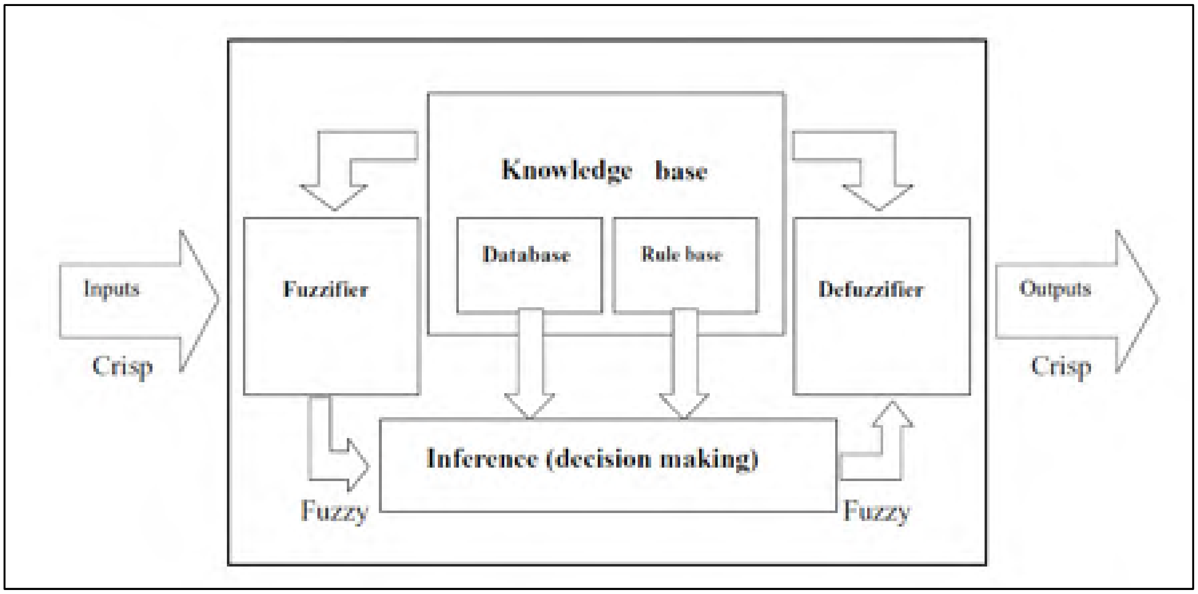

Figure 3.1 Fuzzy Inference System
Taken from Cheng et al. (2007)

The five functional blocks are:

1. A **rule base** consisting of a set of "if-then" fuzzy rules;
2. A **database** that defines the membership functions of the fuzzy sets used in the fuzzy rules;
3. An **inference unit** that performs the decision-making process based on the "if-then" fuzzy rules and the inputs;
4. A **fuzzifier** that transforms the crisp inputs into degrees of match with input fuzzy sets;
5. A **de-fuzzifier** that transforms inferred fuzzy results into crisp outputs.

Usually, the rule base and the database are jointly referred to as the knowledge base.

To provide a better understanding, consider the following example (Buragohain & Mahanta, 2008) by assuming a fuzzy inference system that has two inputs x_1 and x_2 and one output f, when $f(x_1, x_2)$ is a constant, a zero order Sugeno fuzzy model is formed, which may be considered to be a special case of Mamdani fuzzy inference system where each rule consequent is specified by a fuzzy singleton. Functions f_1 and f_2 are usually of first order, that is, f_1 and f_2 are linear functions with respect to the inputs and thus a first order Sugeno fuzzy model is formed but it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. The use of higher order functions has been reported also in the literature. Figure 3.2 illustrates the inference process for the first-order Sugeno fuzzy model. The first-order has become a common practice on ANFIS implements in the past studies (Zhang et al., 2011). The two-rules Sugeno fuzzy inference system may be stated as (Buragohain & Mahanta, 2008):

$$\begin{gathered} For\ rule\ R_k\text{: } If\ x_1\ is\ A_1^k\ and\ .\ .\ .\ x_i\ is\ A_i^k\ and.\ .\ .\ \ x_{n1}\ is\ A_{n1}^k \\ Then\ \ y\ \ is\ f_k(x_1,.\ .\ .,x_i,.\ .\ .\ ,x_{n1}) \end{gathered} \tag{3.1}$$

where

x_1 = the i^{th} input to the fuzzy system;

A_i^k= the input label of x_i that is attached to rule R_k;

y = output of the fuzzy system; and

f_k = function of the input variables based on fuzzy rule R_k.

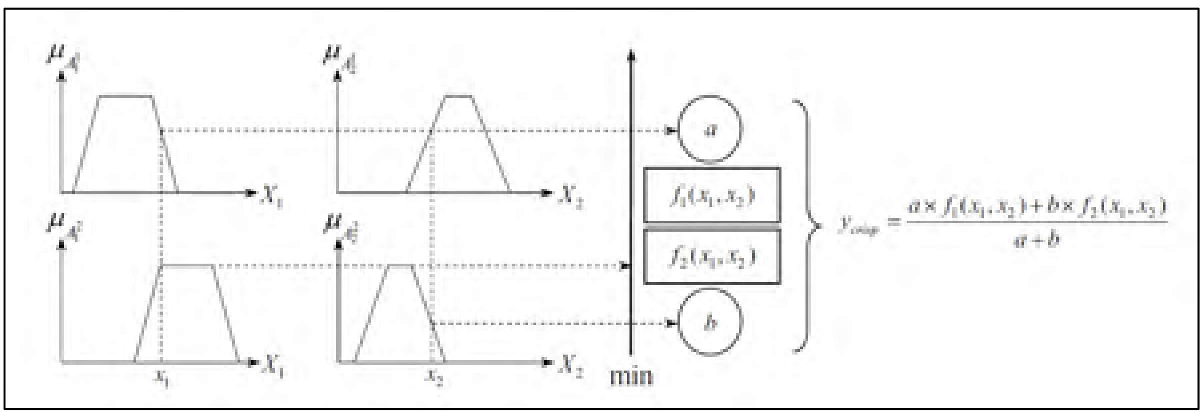

Figure 3.2 TSK fuzzy model
Taken from Cheng et al. (2007)

3.6 ANFIS Layers

ANFIS operates in a manner similar to both ANN and FIS. In both ANN and FIS, the input passes through the input layer (via the input membership function) and the output is shown in output layer (via the output membership function) (M. Y. Chen, 2013). ANFIS has a hybrid learning rule algorithm, which integrates the gradient descent method and the least square methods to train parameters. In the forward pass of the algorithm, functional signals go forward until Layer 4 and the consequent parameters are identified by the least squares method to minimize the measured error. In the backward pass, the premise parameters are updated by the gradient descent method (Özkan & İnal, 2014). Since this type of advanced fuzzy logic uses neural networks, a learning algorithm can be used to change the parameters until an optimal solution is found. Therefore, ANFIS uses either back-propagation or a combination of least squares estimation and back-propagation to estimate the membership function parameters (M. Y. Chen, 2013). The individual functioning of five-layers of the equivalent ANFIS structure are described below, noting that the inputs and outputs are not considered part of the network structure (Cheng et al., 2007).

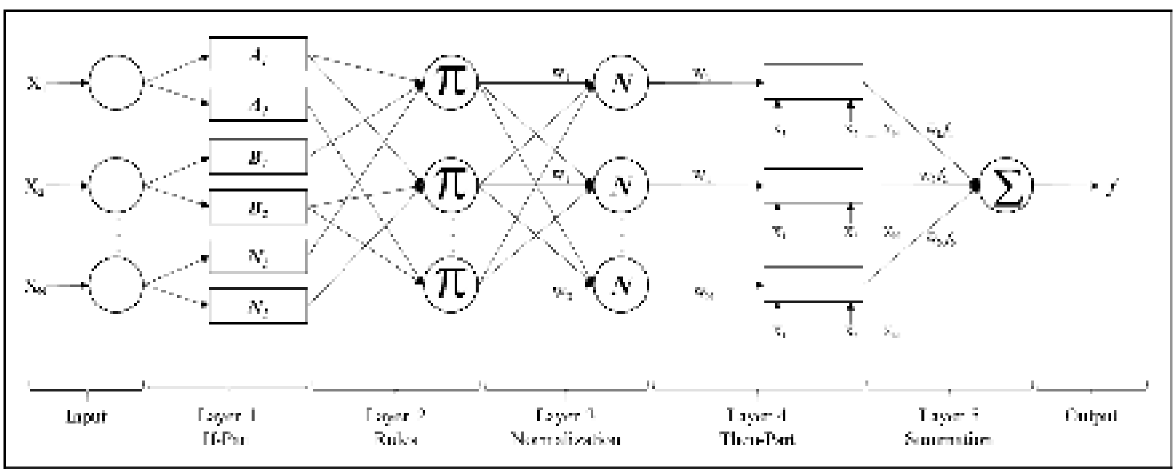

Figure 3.3 ANFIS architecture

Those layers as shown in Figure 3.3 are (Buragohain & Mahanta, 2008 ; M. Y. Chen, 2013 ; Cheng et al., 2007 ; Terzi et al., 2006 ; Zhang et al., 2011):

Layer 1: this layer consists of the linguistic terms (fuzzy sets), where each node is called an input linguistic node and corresponds to one input linguistic variable of the ANFIS network. Every node in this layer acts as a membership function, $\mu A_i^j\ (x_i)$ and its output specifies the degree to which the given x_i satisfies the quantifier A_i^j. Every node i in this layer is adaptive with a node function and each node function can be modeled by fuzzy membership function. The existing functions are triangular, trapezoidal, bell, and Gaussian, respectively. In this paper, the best forecast performance of membership function was chosen by comparing the performance of each membership function to others. Parameters in this layer are referred to as precondition parameters, and the nodes directly transmit input forecasts to the next layer. This layer can be expressed as:

$$O_i^1 = \mu\, A_i\,(x) \tag{3.2}$$

Where x is the input to node i, A_i is the linguistic variable associated with this node function and $\mu\, A_i$is the membership function of A_i. Usually $\mu\, A_i(x)$ is chosen as:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(x - {c_i}/{a_i}\right)^2\right]^{b_i}} \tag{3.3}$$

or

$$\mu_{A_i}(x) = exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \tag{3.4}$$

where x is the input and $\{a_i, b_i, c_i\}$ is the premise parameter set.

Layer 2 of the ANFIS network is the fuzzy rule base that models the underlying characteristics of the numerical training data. Every node in this layer is a fixed node, which calculates the firing strength (Wi) of a rule via multiplication of the incoming signals. The output of each node is the product of all the incoming signals to it and is given by the following equation.

$$O_i^2 = Wi = \mu\, A_i(x) \times \mu\, B_i(y), \qquad i = 1, 2 \tag{3.5}$$

Layer 3: every node in this layer is labelled by N, and it calculates the normalized firing strength of a rule. The i^{th} node in this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all the rules' firing strengths. The result would be the normalized firing strengths. The output of this layer will be called the "normalized firing strengths", and expressed as:

$$O_i^3 = \overline{Wi} = \frac{Wi}{W1 + W2}, \qquad i = 1, 2 \tag{3.6}$$

Layer 4: every node in this layer is an adaptive node with a node function given by the following equation:

$$O_i^4 = \overline{Wi}\ f_i = \overline{Wi}\,(p_i x + q_i y + r_i), \qquad i = 1, 2 \tag{3.7}$$

Where $\overline{Wi}$ is the output of Layer 3 and $(p_i + q_i + r_i)$ and is the consequent parameter set. Each node i in this layer is a square node with a node function. Parameters in this layer are referred to as consequent parameters by node function.

Layer 5: because each rule would compute an inferred output (crisp for ANFIS) based on the input stimulus, the final network output is the aggregation of all the computed inferred outputs. This layer comprises of only one fixed node that calculates the overall output as the summation of all incoming signals.

$$O_i^5 = overall\ output = \sum_i \overline{Wi}\ f_i = \frac{\sum_i Wi\ f_i}{\sum_i Wi} \tag{3.8}$$

From the proposed ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output *f* in Figure 3.3 can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w_1}\, f_1 + \overline{w_2}\, f_2$$
$$= (\overline{w_1} x) p_1 + (\overline{w_1} y) q_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2} y) q_2 + (\overline{w_2}) r_2 \quad (3.9)$$

f is linear in the consequent parameters ($p_1, q_1, r_1, p_2, q_2, r_2$). In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm (Hagan, Demuth, Beale, & Jesus, 1995 ; Haykin, 1999).

In summary, ANFIS only supports Sugeno type systems and these must have the following properties:

1. Be first or zeroth order Sugeno type systems;
2. Have a single output, obtained using weighted average de-fuzzification. All output MFs must be the same type and either be linear or constant;
3. Have no rule sharing. Different rules cannot share the same output MF, namely the number of output MFs must be equal to the number of rules;
4. Have unity weight for each rule. The main restriction of the ANFIS model is related to the number of input variables. If ANFIS inputs exceed five, the computational time and rule numbers will increase, so ANFIS will not be able to model output with respect to inputs.

3.7 Building the Model

3.7.1 Data collection

The yearly firms' data were used in this research to develop different forecasting models, and combination of Stepwise Regression Analysis and ANFIS methods were implemented to demonstrate the appropriateness and capability of the forecasting model. In Step 1, the

Stepwise Regression Analysis using SPSS Software was applied to extract the most significant input variables for each of the output measure. Analysis was conducted for datasets from 2006-2014 individually, averaged over two years and averaged over three years. Afterwards, in Step 2, the defined input-output pairs from earlier step was used as the basis for ANFIS forecasting models. Using MATLAB Fuzzy Logic Toolbox and Statistics and Machine Learning Toolbox, different forecasting models were developed to recognize the non-linear relation among the variables.

The research analysed historical data of international publicly listed Architecture, Engineering and General Contractor firms (AEC). Listed international firms normally require the inclusion of highly capable TMT, and such firms are thought to be high discretion/highly prudent, characteristics that affects both managerial attention patterns and the relation between attention and strategic choice (Levy, 2005). Furthermore, as publicly-traded firms, they are required to record archives with the Securities and Exchange Commission which enables access to the appropriate performance and demographical information according to certain standards and procedures (Tihanyi et al., 2000).

Two main databases were used to collect the data, Bloomberg real-time market and economic database and ENR (Engineering News and Record). Those databases are sometimes referred to as Fact Books, which are collections of publicly available data containing information specific to each of the firms studied. Those books contain a number of reports, articles and analyses prepared by analysts, journalists, or researchers studying the particular firm of interest (Joyce & Slocum, 2012). Fact books are useful for extracting information for different measures and attributes including firm performance as well as TMT demographical information, and provide information with a high degree of reliability (Yee & Cheah, 2006). Many studies have been conducted utilizing fact books as their prime source of information. In addition to that, some other articles combine Fact Books with other means of data collection, such as firms' archival data (Caligiuri et al., 2004 ; Camelo-Ordaz et al., 2005 ; Camelo et al., 2010 ; Clark & Soulsby, 2007 ; Khan et al., 2013 ; Naranjo-Gil et al., 2008).

For the firm to be included in the sample, it had to satisfy various guidelines, those are:

1. The firm should be publicly traded in its home country;
2. The firm should be ranked in ENR lists, either 225 Top International Design Firms and/or 250 Top International Contractors;
3. The firm had a fiscal year-end of December 31, which allowed appropriate reporting on all financial records;
4. All required accounting, company and TMT data to be available.

Two additional guidelines were also considered when developing the ANFIS forecasting models, those are: the firm should be continuously publicly listed in its home country market during the period 2006 – 2014, and the firm should also be continuously ranked in ENR lists for the same period. These two later guidelines will enable defining the sample size for the time series forecasting model.

From all (417) companies explored initially by ENR list, the sample was reduced to n =70 based on above guidelines. Some challenges were examined during data collection, which led to the reduction of the sample size, those can be summarized as follow:

1. Given that most construction companies are not publicly owned (Vorasubin & Chareonngam, 2007), out of (417) firms listed in both ENR lists, only (102) are publicly listed;
2. Missing or incomplete information for many TMT members, more specifically for those firms that are having large number of TMTs. The sample size has been reduced from (102) to (74);
3. Certain financial data were not available for some firms, reducing the number the sample to (70).

The sample range (2006 – 2014) has been carefully defined to suit the measurement methods for the selected variables. Although the ENR lists provide data on firms back to 2001, however, in order to satisfy the selected measurement methods for variables, the datasets only go back to 2006. For example, Past Performance (a controlled variable) is measured by

2 years lagged Return on Asset, which is limiting the range of the study. Similarly, the Economy Dynamism (another controlled variable), is measured by standard error of the regression slope coefficient divided by the mean value of sales over a five-years period (i.e., 2001 to 2005). Therefore, the sample range can only go from (2014 to 2006). In total, (457) data vectors are distributed in the collected sample (70 firms distributed over a period of 2014 to 2006). Table 3.1 below provides distribution of the total sample.

Table 3.1 Sample distribution

Dataset (Year)	**No. of Firms**
2014	70
2013	64
2012	60
2011	54
2010	50
2009	48
2008	45
2007	35
2006	31
Total	457 Data vectors

Table 3.2 provides summary on the total number of firms as well as the regions of origin for those firms. The (70) firms are spread over (19) different regions, with United States and Japan having the highest number of collected data (13 firms in each country, where both countries are representing around 37% of the overall data).

Table 3.2 Sample distribution by region

Region	No. of Firms	Region	No. of Firms
United States (US)	13	India (IN)	2
Australia (AU)	4	China (CH)	8
Netherlands (NA)	1	Japan (JP)	13
Canada (CN)	3	New Zealand (NZ)	1
United Kingdom (LN)	3	Germany (GR)	1
France (FP)	3	Thailand (TB)	1
Spain (SM)	6	South Korea (KS)	2
Sweden (SS)	1	Turkey (TI)	1
Finland (FH)	1	Austria (AV)	1
Italy (IM)	4		
Total Regions	19 Regions	Total Number of Firms	70 Firms

3.7.2 Data Recording

Before inserting data in the record sheet, several steps were taken to ensure data are presented in the needed format. For illustration, two examples are provided below, Table 3.3 shows the detailed TMT information recoding collected for one year (i.e., 2014) for a company that is located in France (coded here as FP-Example). In the second example, Table 3.4 provides the same information however recorded for a company that is located in Japan (coded here as JP-Example) for year (2010). Although the information on all firms are publicly available (both for ENR and Bloomberg), however due to confidentiality preference, the name of firms is kept un-announced in this research. Table 3.5 shows the detailed variables calculations. It should be noted also that all the inputs and output data are measured dimensionless and ratio based.

Table 3.3 Example 1 of data recording: Firm (FP-Example) – for the year 2014

Board Members*	Year of Birth	Age**	Year of Jointing Org.	Total Years in Org.**	Year of Joining Board	Total Years in Board**	Education ***	Function ****	Industry Experience *****
1	1954	60	1996	18	1998	16	2	1+3	1
2	1944	70	2000	14	2000	14	4	0	0
3	1962	52	2007	7	2007	7	8	0	0
4	1962	52	2007	7	2007	7	8	0	0
5	1946	68	2007	7	2007	7	2	0	1
6	1949	65	2008	6	2008	6	2	0	1
7	1946	68	2008	6	2009	5	8	0	1
8	1959	55	2013	1	2013	1	2	0	0
9	1952	62	2013	1	2013	1	8	0	0
10	1958	56	2014	0	2014	0	4	0	0
11	1959	55	1972	42	2014	0	2	0	1
12	1959	55	1976	38	2014	0	2	0	1
13	1966	48	1999	15	2014	0	8	0	1
14	1956	58	2011	3	2011	3	8	0	0

Table 3.4 Example 2 of data recording: Firm (JP-Example) – for the year 2010

Board Members*	**Year of Birth**	**Age****	**Year of Jointing Org.**	**Total Years in Org.****	**Year of Joining Board**	**Total Years in Board****	**Education** ***	**Function** ****	**Industry Experience** *****
1	1955	55	1979	31	2010	0	8	5+8	1
2	1953	57	1978	32	2005	5	2	8	1
3	1958	52	1982	28	2009	1	5	7+8	1
4	1955	55	1977	33	2009	1	2	8	1
5	1951	59	1975	35	2009	1	2	0	1
6	1951	59	1972	38	2008	2	2	8	1
7	1948	62	2006	4	2009	1	4	8	1
8	1950	60	1973	37	2008	2	8	0	1
9	1946	64	1970	40	2006	4	2	5	1
10	1949	61	1974	36	2005	5	8	8	1
11	1952	58	1975	35	2010	0	4	0	1
12	1950	60	1976	34	2010	0	8	0	1
13	1947	63	1971	39	2007	3	8	0	1
14	1949	61	1984	26	2005	5	2	0	1
15	1936	74	2004	6	2004	6	2	0	1

* Names hidden for confidentiality;
** Calculated from year 2014 for Table 3.3, and year 2010 for Table 3.4;
*** Eight categories: 1 = Science, 2 = Engineering, 3 = Math, 4 = Business, 5 = Economics, 6 = Law, 7 = Arts, 8 = Others;
**** For Table 3.3, nine categories: 1 = Chairman, 2 = Vice Chairman, 3 = Chief Executive Officer, 4 = Chief Financial Officer, 5 = Chief Operating Officer, 6 = Vice President, 7 = Secretary, 8 = General Counsel, 9 = Executives;
For Table 3.4, eight categories: 1 = Chairman, 2 = Vice Chairman, 3 = Chief Executive Officer, 4 = President, 5 = Chief Financial Officer, 6 = Chief Operating Officer, 7 = Chief Information Officer, 8 = Executives;
***** Has previous Industry Experience = 1, Do not have prior experience = 0.

Table 3.5 Detailed variables calculations

Variable	Method of Measurement	(JP-Example)	(FP-Example)
Input Variables			
Age Diversity	Coefficient of Variation $C_v = \frac{\sigma}{\mu}$ ………… (3.2)	0.081194782	0.111755965
TMT Org. Tenure		0.349755878	1.072864227
TMT Tenure		0.844371342	1.045309033
TMT Educational Diversity	Blau's Diversity Index $B = 1 - \sum_{i=1}^{k} P_i^2$ ………….. (3.1)	0.648888889	0.612244898
TMT Functional Diversity		0.813148789	0.991111111
Industry Experience	proportion of members with previous experience in construction	0	0.5
Controlled Variables			
TMT Size	Total Number of Board members	15	14
Economy Dynamism[(a)]	standard error of the regression slope coefficient divided by the mean value of sales over a three-years period	1.86691E-06	8.96867E-06
Degree of Internationalization [(a)]	ratio of international revenue to total organization revenue	0.840297122	0.379416913
Degree of Diversification[(b)]	Blau's Diversity Index $B = 1 - \sum_{i=1}^{k} P_i^2$ (3.1)	0.96875	0.984375
Past Performance[(a)]	2 years lagged firm's Return on Asset	6.6613	3.1395

Table 3.5 (continuation) Detailed variables calculations

Variable	Method of Measurement	(JP-Example)	(FP-Example)
Output Variables			
Profitability* + **	Profit Margin = Net Profit After Tax / Total Revenue	7.463484494	0.052947874
Liquidity*	Current Ratio = Current Asset / Current Liability	0.545579471	1.125047319
Cash Flow Stability*	Asset Turnover Ratio = Ratio of Annual Revenue to Total Asset	0.009195265	0.822922418
Capital Structure*	Ratio of Total Liability to the Total Assets	0.435470926	0.764112327
External Satisfaction*	Averaged Growth in Revenue in Major Sector	1.457326892	1.011075099
International Satisfaction*	Price / Earnings Ratio	17.5245	10.1812

* Obtained from stock market;
** Obtained from ENR database - eight Categories: 1 = Architect, 2 = Engineer, 3 = Contractor, 4 = Environment, 5 = Geo-Technical, 6 = Landscape, 7 = Planner, 8 = Other.

3.8 Model Setting

ANFIS is based on the input–output data pairs of the system under consideration. The size of the input–output dataset is very crucial when the data availability is much less and the generation of data is a costly affair. Under such circumstances, optimization in the number of data used for learning is of prime concern (Amirkhani et al., 2015). Since a simple ANFIS structure is always preferred (Petković et al., 2014), in this research, the number of data pairs employed for training and testing were selected by the application of the statistical tool known as Stepwise Regression Analysis. By employing the proposed two step approach, the match between the Input and Output variables for learning in the ANFIS network were reasonably identified, and thereby computation time and complexity were reduced.

3.8.1 Step 1: Stepwise Regression Analysis: Defining Input-Output Pairs

The stepwise regression is designed to obtain the most parsimonious set of predictors that are most effective in forecasting the output variables. Two rounds of Stepwise Regression Analysis have been adopted to select the most significant variables as model input variables. A total of (16) different datasets were processed those are:

1. Individual years from 2006 to 2014 (nine sets);
2. Datasets that are averaged over two years (four sets);
3. Datasets that are averaged over three years (three sets).

Averaged datasets were considered as they may provide many advantages. It may smooth any potential aberrations associated with a single year's performance (Carpenter, 2002), and will also smooth the fixed time effect that any one year by itself could produce on the dependent variable (Rivas, 2012) and to reduce bias of single year outliers (B. B. Nielsen & Nielsen, 2013). Some studies have used an averaged observation of two years on RoA (Angriawan, 2009 ; Carpenter, 2002 ; B. B. Nielsen & Nielsen, 2013 ; Ruigrok et al., 2013) while others have applied averaged observations over three year (Certo et al., 2006 ; Kale & Arditi, 2003). Employed by a growing number of organizational researchers, (Hambrick et al., 1996), this method permits consolidated use of the full dataset, producing results that reflect the average effect of the input variables over the full study period (Levy, 2005). The research has employed those different data arrangements to explore in fully the significant relations between the input-output pairs.

Two rounds of Stepwise Regression Analysis were performed to define the significant relation between the input-output pairs. Typically, traditional forecasting methods are linear and fail when the data they model is highly nonlinear (B. R. Chang & Tsai, 2009). To better model irregular dynamic behaviour, intelligence analysis gives researchers the ability to model both experimental design and data in a number of different forms than the statistical approaches (Abbasi & Mahlooji, 2012 ; Sedighi et al., 2011). In particular, ANFIS networks are finding extensive use for financial forecasting.

3.8.2 Step 2: Forecasting Models

The first-order Sugeno fuzzy model has become a common practice on ANFIS implementations in past studies (Buragohain & Mahanta, 2008 ; Cheng et al., 2007 ; Petković et al., 2014). Thus, the research used the same model in this step to construct, train and test multi input – multi output ANFIS structures.

MATLAB Fuzzy Logic Toolbox was used to generate the training dataset for the different ANFIS models. For each output, different forecasting models were constructed by using the input-output pairs as defined in Step 1. Each model was also assessed using three different membership functions: Generalised Bell-Shaped, Spline Curve Π-shaped and Triangular-Shaped membership functions. The prediction capabilities for all models were evaluated through Mean Absolute Percentage Error (MAPE).

The ANFIS system will identify the input data to be sent for training and testing based on the occurrence of an event. The training dataset is used to train the ANFIS model (to build the model and to identify the rules) whilst the testing dataset is subsequently used to evaluate the performance of the trained ANFIS model (to check and validate the model, which sometimes referred to as the memory recall in the terminology of neural fuzzy models). The training and testing data are mutually exclusive, that is data used for training would not be used for subsequent testing. Data are randomly selected in each time the model is running.

The research started by defining the most appropriate membership function, then three forecasting strategies were implemented in constructing different models, and those are:

1. **Strategy 1 and Strategy 2:** Two-Level Categorical Classification models, using cross-section data (year dependent). In this approach, models were trained and evaluated using nine different datasets (yearly data from 2006 to 2014). It provides forecasting model that is cross industry in an individual year. Models were constructed using two strategies, those are; Majority Vote Classifier model, and a Majority Vote Classifier combined with boxplot outlier elimination;

2. **Strategy 3:** Time-Series models, that are company dependent, constructed using the time series data for all firms with complete data (from 2006 to 2014). On those nine years' data, eight years are used for training (2006 to 2013) and the remaining is used for testing purposes. Similar procedure is found in previous scholars (Cheng et al., 2007). A total of 15 firms (with completed data from 2006 to 2014) were used to forecast time series output values for each of those firms individually.

Usually training dataset contains 70–90% of all data and remaining data are used for the testing dataset (Azadeh et al., 2011), in this research, random selection of data for training and testing based on (70/30) ratio. Figure 3.4 is a better illustration of the research methodology.

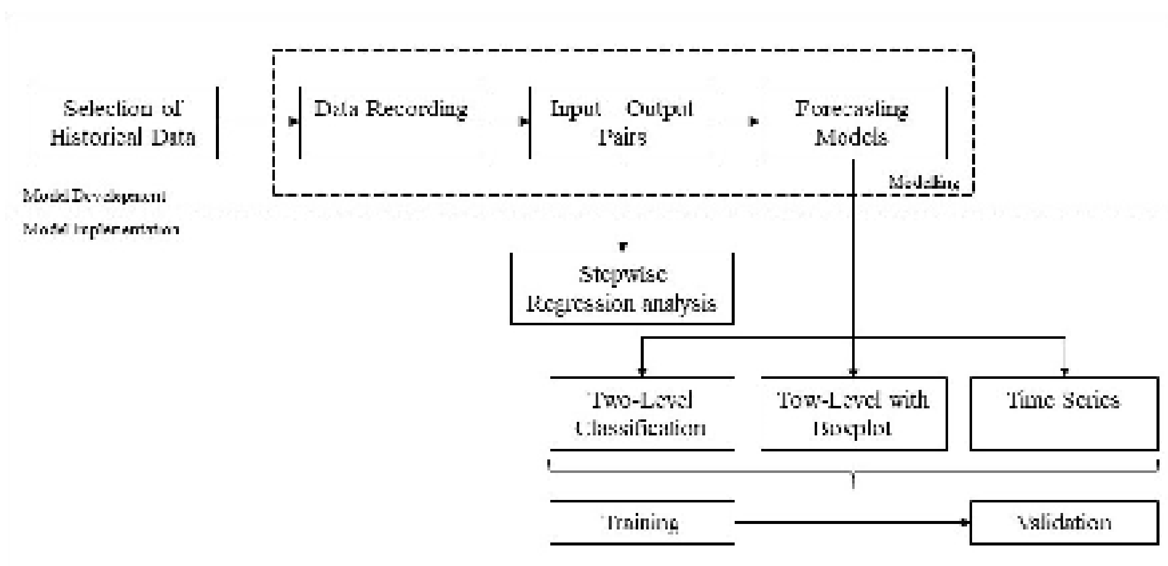

Figure 3.4 Research methodology

CHAPTER 4

RESULTS AND DISCUSSION

Modelling of systems is fundamental importance in almost all fields. This is because models enable us to understand a system better, simulate and predict the system behaviour and hence help us in designing new controllers and analyse existing ones (Amirkhani et al., 2015). However, probability and statistical programming approaches cause a significant problem in considering qualitative factors (Vahdani, Iranmanesh, Mousavi, & Abdollahzade, 2012). In addition, some of the attributes and variables that are suggested in this study are subjective based, and those methods require arbitrary aspiration levels and cannot accommodate subjective attributes. Fuzzy Set Theory allows simultaneous treatment of precise and imprecise variables. For this study, ANFIS was proposed to be the basis for developing different forecasting models.

The research analyses Architecture, Engineering and Construction (AEC) firms as listed in ENR (Engineering News and Records). The datasets consist of annual historical database describing international AEC firms that are publicly traded from different regions. The overall data is representing a period of nine different years (2006 to 2014) with a total of (457) data vectors and were obtained from different fact books. Information on Top Management Team, and their related variables (input variables) were collected from the firm's information listed in the stock market, additionally, missing information were completed from firms published reports. While output variables (organization outcome) were derived from either Bloomberg Terminal or Engineering News and Record database. Several intermediate steps have been taken before data being presented in the record sheet (refer to Chapter 2 and 3 for further details). Input variables include: TMT Age Diversity, TMT Organization Tenure, TMT Tenure, TMT Educational Diversity, TMT Functional Diversity and Industry Experience. While the Output variables include: Profitability, Liquidity, Cash Flow Stability, Capital Structure, External Satisfaction – Reputation and Internal Satisfaction – Shareholder Value. The analysis was carried in two steps, and those are:

1. **Step 1:** Defining input-output pairs: using stepwise regression analysis;
2. **Step 2:** Building the forecasting models: using three different strategies, those are:
   a. **Strategy 1:** Two-Level Catalogue Classification: Majority Vote Classifiers method;
   b. **Strategy 2:** Two-Level Catalogue Classification with outliers' elimination: Majority Vote Classifiers method combined with boxplot technique;
   c. **Strategy 3:** Time-Series forecasting.

Prior to developing the forecasting models, the best membership function was evaluated using cross-firms ANFIS models, afterwards, the prediction capabilities for all forecasting modes were evaluated.

4.1 Introduction

Probability and statistical tools have been used in different managerial studies. It includes many linear and nonlinear methods that were used for system forecasting. However, several problems limit the advantage of those tools, including: poorly defined situation, and having to use data with low precision (Buragohain, 2008). Those limitations are somehow inherited in this research causing difficulties in understanding the system belabour:

1. The literature on Top Management Team demographics correlation with organization outcome was not defined precisely;
2. The "black-box" nature of the relation among the different data variables is difficult to be determined.

The self-adaptive data driven neural networks were successfully used in the sense that it can approximate any arbitrary continuous function even with very little knowledge on the structural relation among the different determined variables. In some instances, tools such as (Bayesian curve fitting, Autoregressive integrated moving average method and extrapolation techniques) were used to check if any implicit information that may be embedded in the available data can be extracted for use in the forecasting model. In this research, a combination of fuzzy logic, neural networks and statistical methods were adopted to deduce the relation between the explanatory variables (TMT variables) and response variables (organization outcome) and to demonstrate the appropriateness and capability of the forecasting models. Identifying significant input-output pairs was first applied using stepwise regression analysis (Step 1), and then the best membership function was defined using the ANIFS model. Afterwards, three strategies of different models were applied (Step 2). Modelling of Top Management Team and organization outcome variables was based on real data that were obtained from annual fact books. The input-output pairs were processed in Step 1, and the selection was based on a threshold of P-value (≤0.05) combined with highest score of the Adjusted Determination Coefficient (adjusted R^2). The forecasting models were validated by the difference between the predicted compared to the measured output using Mean Absolute Percentage Error (MAPE). The details of these processes, the results obtained with dataset and discussion are presented in the following subsections.

4.2 Models performance evaluation criteria and benchmark

4.2.1 Step 1: Stepwise Regression Analysis

The selection of input-output pairs was processed in two rounds of stepwise regression analysis. The outcome of Round 1 was run for a second round to confirm the results and confirm the pairs selection. The interpretation of the assumptions was facilitated by descriptive and graphical analysis. Selection was based on the largest R^2 with minimum changes to the adjusted R^2. Pairs were deemed statistically significant if their respective P-value is equal or less than 0.05, while they were defined as marginally significant if their P-value is equal or less than 0.08.

4.2.2 Step 2: Forecasting Models

The accuracy of the forecasting models has been evaluated by two sets of data samples, those are: training (datasets that express the effectiveness of learning, used to build the model), and testing (datasets that measure the generalisation capability of the network, used to check and validate the model, sometimes referred to as the memory recall in the terminology of neural fuzzy models). Usually training dataset contains 70–90% of all data and remaining data are used for the testing dataset. In this research, the models were built to randomly select data for training and testing based on (70/30) ratio. The models' system will identify the input data to be sent for training and testing based on the occurrence of an event. The training and testing data are mutually exclusive that is data used for training would not be used for subsequent testing.

The number of effective data pairs reduces with the different cross-section data samples. The highest number of data pairs are in the (Year 2014 where n = 70), while the smallest are in the (Year 2006 where n = 31). Table (4.1) represents the number of data pairs for the samples. It also shows the split of data between training and testing for each year.

Table 4.1 Number of data pairs

Dataset (Year)	**Total No. of Firms**	**Training (70% of dataset)**	**Testing (30% of dataset)**
2014	70	49	21
2013	64	45	19
2012	60	42	18
2011	54	38	16
2010	50	35	15
2009	48	34	14
2008	45	32	13
2007	35	25	10
2006	31	22	9

Once the structures for the three strategies have been constructed and trained, three accuracy evaluation criteria were used, and those are:

1. **Mean Absolute Percentage Error (MAPE):** sometime known as Mean Absolute Percentage Deviation (MAPD). It is a measure of prediction accuracy of a forecasting model and usually expresses the accuracy as percentage. It can be expressed by following formula:

$$M = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{4.1}$$

where A_t is the actual value and F_t is the forecasted value. The difference between A_t and F_t is divided by the actual value A_t again. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points n. Multiplying by 100 makes it a percentage error. The percentage provided by (MAPE) is determine the "goodness of fit" between outputs of the model and the system given the same input;

2. **Visualizing the performance of the model:** several visualization techniques have been used in this research such as: plots of the predicted and observed, Error distribution plot, scatter plots, ANFIS surface, etc. Together with accuracy percentage, those techniques are valuable assessment of the models using simple plots. It can give an indication of under and over-fitting data and will illustrate the model performance;

3. **Accuracy Level Benchmark:** as it has been detailed in previous section of this report (Introduction and Chapter 1), forecasting in the management studies are rare. Moreover, the focus of most related studies is on exploring the relation between different contextual TMT demographics and the organizational performance. Forecasting can be found in different business related trades; however, benchmark was rare in the context of this research.

   In some financial studies, a forecasting accuracy was accepted at a level of:

   a. (Fang, 2012) with accepted accuracy = (91.8%) to forecast financial crisis;
   b. (Zanganeh, Rabiee, & Zarei, 2011) used ANFIS for bankruptcy forecasting and with accepted accuracy = (92.5%);
   c. (Giovanis, 2010) forecasted financial distress periods using ANFIS with accepted accuracy = (96.6%).

On the other hand, other studies have accepted a lower accuracy rate, for example:

a. (Atsalakis, Skiadas, & Braimis, 2007) used ANFIS to predict the trend of exchange rate, with accuracy level (63%) stating that any system that can predict the trend more than 50% would be profitable;
b. Finally, (Yang, 2010) accepted accuracy level = (56%).

In the absence of a comparable benchmark that suit the context of this research, the results have been presented by grouping them in different accuracy categories. Those categories will provide significant insights into distinguishing between the output variables that could be forecasted at an acceptable accuracy level, and those that are not. For validating the accuracy of each model, the testing data (30% of dataset) were used to compare between the Actual reading (collected data) with the Forecasted reading (produced by the model). The different between both readings is recorded and then placed in its related categories. For example, if the accuracy (difference in two readings between Actual and Forecasted) is more than 90%, it will be placed in Category 1, while if the accuracy is between 80% and 89% then it belongs to Category 2, and so forth. The same procedure will be repeated in all datasets (from 2006 to 2014 for all output variables). Afterwards the total number of recordings in each category is summed and converted as a percentage of total number of tested data. Table (4.2) shows the category accuracy level that has been utilized in this study to evaluate the performance of different forecasting models. The same procedure is applied to all output variables in all datasets.

Table 4.2 Categories of accuracy levels

Category	Accuracy Level
Category 1	≥ 90%
Category 2	89 – 80%
Category 3	79 – 70%
Category 4	69 – 60%
Category 5	59 – 50 %
Category 6	49 – 40%
Category 7	39 – 30%
Category 8	< 30%

Those accuracy level tables are providing a tool to examine whether an output variable can be forecasted at an acceptable level or not. For each forecasting strategies, the same tables and comparison are produced.

4.3 Model Setting: Step 1: Statistical Tool: Stepwise Regression Analysis

Most traditional statistical forecasting models, such as the geometry average method, saturation curve method, least-squares regression method, and the curve extension method, are designed based on the configuration of semi-empirical mathematical models. The structure of these models is simply an expression of cause-effect or an illustration of trend extension in order to verify the inherent systematic features that are recognized as related to the observed database (Dyson & Chang, 2005). Regression Analysis Technique of least squares was used in many previous studies of TMT in evaluating the relation between TMT composition and organization outcome (Auden et al., 2006). The technique of least squares is particularly useful and objective when analysing historical data (Srijariya, Riewpaiboon, & Chaikledkaew, 2008).

Regression analysis is a statistical tool for the investigation of relations among the variables. Usually, the researcher seeks to ascertain the causal effect of one variable upon another, they also typically assess the degree of confidence that the true relation is close to the estimated relation “statistical significance”. In the multiple linear regression model, Y has normal distribution with mean (Alexopoulos, 2010), where:

$$Y = \beta_0 + \beta_1 X_1 + \dots + \beta_\rho X_\rho + \sigma(Y) \tag{4.2}$$

The model parameters $\beta_0 + \beta_1 + \dots + \beta_\rho$ and σ must be estimated from data.

β_0 = intercept;

$\beta_1 \dots \beta_\rho$ = regression coefficients;

$\sigma = \sigma_{res}$ = residual standard deviation (or the error).

The purpose of regression is to predict Y on the basis of X or to describe how Y depends on X (regression line or curve). The $X_i(X_1, X_2, \dots, X_k)$ is defined as “predictor”, “explanatory” or “independent” variable, while Y is defined as “dependent”, “response” or “outcome” variable.

Linear regression models present a mean of structuring data around a particular form of analysis (Srijariya et al., 2008). However, in this research, Stepwise regression analysis was used as a special case of multiple linear regression analysis to define the input-output pairs. Stepwise regression is an automated tool used in the exploratory stages of model building to identify a useful subset of predictors. The process systematically adds the most significant variable or removes the least significant variable during each step. A forward selection approach was processed, which involves starting with no variables in the model, testing the addition of each variable using a chosen model fit criterion, adding the variable (if any) whose inclusion gives the most statistically significant improvement of the fit, and repeating this process until none improves the model to a statistically significant extent.

In this study, a cross-sectional analysis was designed to identify the input-output pairs. The input (independent), controlled and output (dependent) variables were regressed over two rounds. Data were checked for recording errors, then, stepwise regression models using 16 different datasets were assessed, those datasets are for each individual year from 2006 to

2014 (nine datasets), averaged over two years (four datasets) and averaged over three years (three datasets) as illustrated in Table (4.3).

Table 4.3 Stepwise Regression Analysis datasets

Datasets	Year		Datasets	Year
Dataset 1	2014		Dataset 9	2006
Dataset 2	2013		Dataset 10	Average of (2013/2014)
Dataset 3	2012		Dataset 11	Average of (2011/2012)
Dataset 4	2011		Dataset 12	Average of (2009/2010)
Dataset 5	2010		Dataset 13	Average of (2007/2008)
Dataset 6	2009		Dataset 14	Average of (2012/2013/2014)
Dataset 7	2008		Dataset 15	Average of (2009/2010/2011)
Dataset 8	2007		Dataset 16	Average of (2006/2007/2008)

Three descriptive characteristics were explored, these being the mean (μ), the standard deviation (σ) which measures the width or variability around the Mean (the central value) and the skewness (characterizes the degree of asymmetry – or rather, lack of asymmetry – of the distribution around the mean). Those three characteristics can provide understanding of the behaviours of the output variables in all of their datasets. Tables (4.4) and (4.5) provide the descriptive statistics of output variables in all 16 datasets. For normal distribution (bell curve, or Gaussian distribution), if the skewness = 0, the data is perfectly symmetrical, but an exactly zero is quite unlikely for real-world data. Studies suggest that if skewness is less than -1 or greater than +1, then the distribution is highly skewed, if skewness is between -1 and -0.5 (skewed left) or between +1 and +0.5 (skewed right) then the distribution is moderately skewed, and if skewness is between -0.5 and +0.5, then the distribution is approximately skewed.

The datasets in this research were found to have different degrees of skewness. Cash Flow Stability, Capital Structure and External Satisfaction datasets were mostly highly skewed (either left or right), Profitability, Liquidity and Internal Satisfaction were mostly moderately skewed, and some were approximately skewed (e.g., Profitability for datasets 2007 and 2006, Liquidity dataset of 2009, and Internal Satisfaction in datasets of 2009 and 2008). Tables (4.4) and (4.5) below details the descriptive statistics (Mean, Standard Deviation and Skewedness) for output variables in all datasets.

Table 4.4 Descriptive statistics of the output variables

Dataset	**Profitability**			**Liquidity**			**Cash Flow Stability**		
	μ	σ	Skewness	μ	σ	Skewness	μ	σ	Skewness
2014	0.119	0.045	0.77	0.828	0.376	0.648	0.817	0.402	0.991
2013	0.119	0.048	0.512	0.828	0.356	0.79	0.787	0.335	0.708
2012	0.117	0.045	0.279	0.804	0.353	0.487	0.753	0.330	1.23
2011	0.119	0.048	0.435	0.803	0.358	0.317	0.794	0.311	0.656
2010	0.118	0.045	0.394	0.768	0.330	0.076	0.752	0.250	0.261
2009	0.114	0.042	0.383	0.771	0.306	-0.072	0.776	0.317	-0.017
2008	0.112	0.033	0.263	0.812	0.286	0.429	0.725	0.380	0.751
2007	0.109	0.031	-0.026	0.797	0.321	0.588	0.767	0.297	0.952
2006	0.104	0.028	0.013	0.711	0.320	0.56	0.704	0.289	1.37
2013-2014	0.121	0.046	0.598	0.842	0.344	0.865	0.812	0.351	1.153
2012-2011	0.119	0.046	0.432	0.795	0.332	0.123	0.771	0.277	0.779
2010-2009	0.116	0.043	0.382	0.769	0.314	-0.004	0.763	0.274	0.174
2008-2007	0.109	0.031	0.033	0.779	0.288	0.591	0.741	0.275	0.665
2012-2013-2014	0.120	0.046	0.323	0.826	0.326	0.751	0.792	0.317	1.042
2009-2010-2011	0.116	0.043	0.326	0.780	0.315	-0.104	0.781	0.262	0.303
2006-2007-2008	0.109	0.028	0.178	0.744	0.263	0.493	0.726	0.259	1.101

Table 4.4 (continuation) Descriptive statistics of the output variables

Dataset	Capital Structure			External Satisfaction			Internal Satisfaction		
	μ	σ	Skewness	μ	σ	Skewness	μ	σ	Skewness
2014	0.6348	0.0992	-0.461	0.9364	0.083	-1.846	0.339	0.216	0.114
2013	0.6411	0.1055	-1.01	0.9378	0.087	-2.079	0.312	0.225	0.404
2012	0.645	0.092	-0.663	0.9332	0.084	-2.075	0.317	0.221	0.328
2011	0.6471	0.090	-0.598	0.9272	0.092	-1.907	0.306	0.218	0.34
2010	0.6532	0.092	-0.483	0.9389	0.072	-2.288	0.299	0.194	-0.118
2009	0.6396	0.137	-2.741	0.936	0.062	-2.044	0.31	0.199	-0.09
2008	0.6319	0.142	-2.676	0.9404	0.060	-1.517	0.314	0.193	0.009
2007	0.63	0.109	-1.064	0.9307	0.067	-0.951	0.300	0.184	0
2006	0.6228	0.119	-1.322	0.9027	0.106	-1.408	0.29	0.204	0.44
2013-2014	0.6444	0.090	-0.264	0.9384	0.078	-1.839	0.329	0.218	0.265
2012-2011	0.6422	0.089	-0.639	0.9328	0.083	-2.005	0.314	0.221	0.329
2010-2009	0.6474	0.109	-1.603	0.937	0.069	-2.197	0.308	0.192	-0.174
2008-2007	0.6236	0.127	-1.917	0.9319	0.062	-0.883	0.309	0.189	-0.06
2012-2013-2014	0.6463	0.087	-0.381	0.9356	0.080	-1.906	0.328	0.217	0.278
2009-2010-2011	0.6495	0.095	-0.806	0.936	0.073	-2.025	0.311	0.190	-0.185
2006-2007-2008	0.629	0.116	-1.735	0.924	0.071	-1.001	0.303	0.182	0.022

4.3.1 Round 1 Results

The Stepwise Regression Analysis using SPSS Software was used to extract the most significant input variables for each of the output variables. To control for TMT effect on organization outcome, the regression analyses were performed in a stepwise manner. For each dependent variable, Sub-Model 1 includes only the control variables (TMT Size, Economy Dynamism, Degree of Internationalization, Degree of Diversification and Past Performance). On the other hand, Sub-Model 2 includes (in addition to the controlled variables) the effects of TMT characteristics (Input Variables: Age Diversity, Organization Tenure, TMT Tenure, TMT Educational Diversity, TMT Functional Diversity and Industry Experience). The pairs selection was based on the largest R^2 with minimum changes to the adjusted R^2. The interpretation of the assumptions was facilitated by descriptive and graphical analysis. Pairs were deemed statistically significant if their respective P-value equal or less than 0.05, while they were marginally significant if their P-value equal or less than 0.08.

Table (4.5) shows the results of stepwise regression analysis – Round 1 of output variable 1 (Profitability), where (dataset: 2012) was found to be marginally significant (0.07), and selected input variable is (Age Diversity).

Table 4.5 Stepwise regression analysis – Round 1: Profitability

Output Variable: Profitability										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2012	0.155	0.054	65.16%	2.99568	0.198	0.238	0.126	47.06%	2.87993	0.07
2006	0.118	-0.114	196.61%	10.7206	0.766	0.31	0.08	74.19%	9.74169	0.287
2012-2011	0.069	-0.057	182.61%	5.11714	0.742	0.184	0.048	73.91%	4.85444	0.259
2012-2013-2014	0.056	-0.057	201.79%	4.31508	0.778	0.143	0.017	88.11%	4.16119	0.358

Table (4.6) shows the results of the stepwise regression analysis – Round 1 of output variable 2 (Liquidity), where datasets (dataset: 2014, dataset: 2009, dataset: 2008, dataset: 2007, dataset: 2006) were found to be significant (0.023, 0.001, 0.001, 0.002 and 0.003 respectively), and selected input variables are (Functional diversity, Educational Diversity and TMT Tenure).

Table 4.6 Stepwise regression analysis – Round 1: Liquidity

Output Variable: Liquidity										
Dataset (Year)	Sub-Model 1 (Controlled Variables)					Sub-Model 2 (Independent Variables)				
	R^2	Adj. R^2	% of Change	Std. Error	Sign.	R^2	Adj. R^2	% of Change	Std. Error	Sign.
2014	0.171	0.088	48.54%	0.21607	0.085	0.251	0.159	36.65%	0.20753	0.023
2009	0.285	0.177	37.89%	0.20567	0.041	0.494	0.399	19.23%	0.17575	0.001
2008	0.433	0.339	21.71%	0.28124	0.003	0.529	0.432	18.34%	0.26082	0.001
2007	0.504	0.392	22.22%	0.16997	0.006	0.608	0.496	18.42%	0.15463	0.002
2006	0.336	0.161	52.08%	0.18665	0.138	0.632	0.509	19.46%	0.14269	0.003
2010-2009	0.33	0.228	30.91%	0.19556	0.017	0.468	0.368	21.37%	0.17694	0.002
2008-2007	0.464	0.342	26.29%	0.23112	0.012	0.563	0.438	22.20%	0.21354	0.004
2009-2010-2011	0.311	0.207	33.44%	0.20088	0.025	0.411	0.3	27.01%	0.18862	0.006
2006-2007-2008	0.438	0.282	35.62%	0.2241	0.048	0.655	0.533	18.63%	0.18085	0.003

Table (4.7) shows the results of the stepwise regression analysis – Round 1 of output variable 3 (Cash Flow Stability), where datasets (dataset: 2014, dataset: 2012, dataset: 2007, dataset: 2006 and dataset: Avr. 2011/2012) were found to be significant (0.013, 0.002, 0.01, 0.037 and 0.001 respectively). Some other datasets recorded an infinite significance, so they were excluded. The selected input variables are (Functional diversity, Educational Diversity, Industry Experience, and Age Diversity).

Table 4.7 Stepwise regression analysis – Round 1: Cash Flow Stability

Output Variable: Cash Flow Stability										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2014	0.09	-0.001	101.11%	0.74125	0.432	0.272	0.183	32.72%	0.66977	0.013
2012	0.201	0.106	47.26%	0.75321	0.083	0.387	0.297	23.26%	0.6679	0.002
2011	0.311	0.221	28.94%	0.68771	0.012	0.482	0.398	17.43%	0.60466	0
2010	0.234	0.122	47.86%	0.72559	0.092	0.509	0.42	17.49%	0.58949	0
2009	0.213	0.094	55.87%	0.84661	0.143	0.516	0.425	17.64%	0.67449	0
2007	0.356	0.21	41.01%	1.05948	0.067	0.52	0.383	26.35%	0.93583	0.01
2006	0.269	0.077	71.38%	1.07208	0.268	0.491	0.321	34.62%	0.91965	0.037
2012-2011	0.276	0.178	35.51%	0.71174	0.03	0.454	0.363	20.04%	0.62627	0.001
2010-2009	0.254	0.141	44.49%	0.76653	0.073	0.531	0.444	16.38%	0.61698	0
2009-2010-2011	0.299	0.193	35.45%	0.7286	0.032	0.546	0.46	15.75%	0.5959	0

Table (4.8) shows the results of the stepwise regression analysis – Round 1 of output variable 4 (Capital Structure), where datasets (dataset: 2014, dataset: 2013, dataset: 2007 and dataset: Avr. 2006/2007/2008) were found to be significant (0.016, 0.004, 0.009 and 0.033 respectively). DataSet: 2007 was excluded, while dataset: 2009 (0.062), dataset: 2006 (0.054) and dataset: Avr. 2007/2008 were considered as marginally significant. The selected input variables are (Organization Tenure, TMT Tenure and Educational Diversity).

Table 4.8 Stepwise regression analysis – Round 1: Capital Structure

Output Variable: Capital Structure										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2014	0.169	0.086	49.11%	0.15502	0.09	0.264	0.173	34.47%	0.14741	0.016
2013	0.274	0.195	28.83%	0.16328	0.01	0.338	0.25	26.04%	0.15758	0.004
2009	0.193	0.071	63.21%	0.17018	0.193	0.298	0.167	43.96%	0.16119	0.062
2008	0.348	0.24	31.03%	0.14507	0.02	0.553	0.46	16.82%	0.12222	0
2007	0.354	0.207	41.53%	0.16284	0.069	0.528	0.393	25.57%	0.14241	0.009
2006	0.203	-0.007	103.45%	0.19684	0.463	0.464	0.286	38.36%	0.16578	0.054
2008-2007	0.244	0.073	70.08%	0.17371	0.255	0.411	0.243	40.88%	0.15693	0.06
2006-2007-2008	0.249	0.04	83.94%	0.18714	0.352	0.517	0.347	32.88%	0.15438	0.033

Table (4.9) shows the results of the stepwise regression analysis – Round 1 of output variable 5 (External Satisfaction – Reputation), where two datasets only considered, Dataset: 2013 is statistically significant (0.036) and dataset: 2012 is marginally significant (0.07). The selected input variables are (Organization Tenure, TMT Tenure and Industry Experience).

Table 4.9 Stepwise regression analysis – Round 1: External Satisfaction

Output Variable: External Satisfaction										
Dataset (Year)	Sub-Model 1 (Controlled Variables)					Sub-Model 2 (Independent Variables)				
	R^2	Adj. R^2	% of Change	Std. Error	Sign.	R^2	Adj. R^2	% of Change	Std. Error	Sign.
2014	0.015	-0.083	653.33%	0.63825	0.978	0.148	0.043	70.95%	0.5998	0.229
2013	0.149	0.057	61.74%	0.32002	0.176	0.25	0.15	40.00%	0.30385	0.036
2012	0.149	0.047	68.46%	0.3736	0.221	0.238	0.127	46.64%	0.35771	0.07
2008	0.05	-0.108	316.00%	0.82955	0.899	0.171	-0.001	100.58%	0.78835	0.447
2013-2014	0.066	-0.04	160.61%	0.33251	0.684	0.161	0.044	72.67%	0.3188	0.246
2012-2013-2014	0.073	-0.038	152.05%	0.29094	0.658	0.206	0.089	56.80%	0.27251	0.13

Finally, Table (4.10) shows the results of the stepwise regression analysis – Round 1 of output variable 6 (Internal Satisfaction – Shareholder Value), where two datasets are statistically significant, dataset: 2011 (0.042) and dataset: Avr. 2011/2012 (0.008). While two datasets are marginally significant, dataset: 2013 (0.054) and dataset: 2008 (0.051). The selected input variables are (Organization Tenure, TMT Tenure and Age Diversity). Finally, summary of Round 1 findings are explained in Table (4.11) below.

Table 4.10 Stepwise regression analysis – Round 1: Internal Satisfaction

Output Variable: Internal Satisfaction										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2013	0.106	0.009	91.51%	16.31897	0.379	0.232	0.13	43.97%	15.28997	0.054
2011	0.11	-0.008	107.27%	33.177	0.469	0.285	0.17	40.35%	30.11976	0.042
2010	0.139	0.012	91.37%	843.4021	0.38	0.264	0.131	50.38%	791.2396	0.097
2008	0.228	0.095	58.33%	18.80021	0.164	0.343	0.202	41.11%	17.65032	0.051
2012-2011	0.099	-0.023	123.23%	17.92593	0.548	0.366	0.26	28.96%	15.24891	0.008
2010-2009	0.092	-0.046	150.00%	446.3593	0.652	0.228	0.083	63.60%	417.9137	0.187
2009-2010-2011	0.08	-0.059	173.75%	300.821	0.718	0.197	0.047	76.14%	285.3696	0.28

Table 4.11 Summary of Round 1 analysis significant input-output pairs

		Output Variables		
		Profitability	**Liquidity**	**Cash Flow Stability**
Input Variables	**Age Diversity**	Dataset: (2012)		Dataset: (2007)
	Organization Tenure			
	TMT Tenure		Dataset: (2006)	
	Educational Diversity		Datasets: (2009) +(2008)+(2007)	Datasets: (2012)+(2010/2011)
	Functional Diversity		Dataset: (2014)	Dataset: (2014)
	Industry Experience			Datasets: (2012)+(2011)+ (2010)+(2009)+(2006)+ (2011/2012)+(2009/2010)+ (2009/2010/2011)

Table 4.11 (continuation) Summary of Round 1 analysis: significant input-output pairs

		Output Variables		
		Capital Structure	**External Satisfaction**	**Internal Satisfaction**
Input Variables	**Age Diversity**			Dataset: (2013)
	Organization Tenure	Dataset: (2014)	Dataset: (2013)	Datasets: (2011)+ (2011/2012)
	TMT Tenure	Datasets: (2013)+(2006)+ (2006/2007/2008)	Dataset: (2012)	Datasets: (2011)+(2008)+ (2011/2012)
	Educational Diversity	Datasets: (2014)+(2009)+(2008)+(2007)+(2007/2008)		
	Functional Diversity			
	Industry Experience		Dataset: (2013)	

4.3.2 Round 2 Results

To ensure generalisability of the research findings as well as to confirm the outcome of Round 1 results (significant input-output Paris), a similar procedure but with only selected input variables was repeated as Round 2 of stepwise regression analysis. The selected input variables (from Round 1) for each dependent variable were regressed in the stepwise analysis for the different 16 datasets. Tables from (4.12) to (4.17) below show the result of Round 2 analysis for all output variables. In addition, Table (4.18) shows the summary of Round 2 for all dependent variables.

Table 4.12 Stepwise regression analysis – Round 2: Profitability

Output Variable: Profitability										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2013	0.155	0.054	65.16%	2.99568	0.198	0.238	0.126	47.06%	2.87993	0.07
2011	0.118	-0.114	196.61%	10.7206	0.766	0.31	0.08	74.19%	9.74169	0.287
2010	0.069	-0.057	182.61%	5.11714	0.742	0.184	0.048	73.91%	4.85444	0.259

Table 4.13 Stepwise regression analysis – Round 2: Liquidity

Output Variable: Liquidity										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2014	0.171	0.088	48.54%	0.21607	0.085	0.251	0.159	36.65%	0.20753	0.023
2009	0.285	0.177	37.89%	0.20567	0.399	0.494	0.399	19.23%	0.17575	0.001
2008	0.433	0.339	21.71%	0.28124	0.003	0.529	0.432	18.34%	0.26082	0.001
2007	0.504	0.392	22.22%	0.16997	0.006	0.504	0.392	22.22%	0.16997	0.002
2006	0.336	0.161	52.08%	0.18665	0.138	0.632	0.509	19.46%	0.14269	0.003
2010-2009	0.33	0.228	30.91%	0.19556	0.017	0.468	0.368	21.37%	0.17694	0.002
2008-2007	0.464	0.342	26.29%	0.23112	0.012	0.563	0.438	22.20%	0.21354	0.004
2009-2010-2011	0.311	0.207	33.44%	0.20088	0.025	0.411	0.3	27.01%	0.18862	0.006
2006-2007-2008	0.438	0.282	35.62%	0.2241	0.048	0.655	0.533	18.63%	0.18085	0.003

Table 4.14 Stepwise regression analysis – Round 2: Cash Flow Stability

Output Variable: Cash Flow Stability										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2014	0.09	-0.001	101.11%	0.74125	0.432	0.272	0.183	32.72%	0.66977	0.013
2012	0.201	0.106	47.26%	0.75321	0.083	0.387	0.297	23.26%	0.6679	0.002
2011	0.311	0.221	28.94%	0.68771	0.012	0.482	0.398	17.43%	0.60466	0
2010	0.234	0.122	47.86%	0.72559	0.092	0.509	0.42	17.49%	0.58949	0
2009	0.213	0.094	55.87%	0.84661	0.143	0.516	0.425	17.64%	0.67449	0
2007	0.356	0.21	41.01%	1.05948	0.067	0.52	0.383	26.35%	0.93583	0.01
2006	0.269	0.077	71.38%	1.07208	0.268	0.491	0.321	34.62%	0.91965	0.037
2012-2011	0.276	0.178	35.51%	0.71174	0.03	0.454	0.363	20.04%	0.62627	0.001
2010-2009	0.254	0.141	44.49%	0.76653	0.073	0.531	0.444	16.38%	0.61698	0
2009-2010-2011	0.299	0.193	35.45%	0.7286	0.032	0.546	0.46	15.75%	0.5959	0

Table 4.15 Stepwise regression analysis – Round 2: Capital Structure

Output Variable: Capital Structure										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2014	0.169	0.086	49.11%	0.15502	0.09	0.264	0.173	34.47%	0.14741	0.016
2013	0.274	0.195	28.83%	0.16328	0.01	0.338	0.25	26.04%	0.15758	0.004
2009	0.193	0.071	63.21%	0.17018	0.193	0.298	0.167	43.96%	0.16119	0.062
2008	0.348	0.24	31.03%	0.14507	0.02	0.553	0.46	16.82%	0.12222	0
2007	0.354	0.207	41.53%	0.16284	0.069	0.528	0.393	25.57%	0.14241	0.009
2006	0.203	-0.007	103.45%	0.19684	0.463	0.464	0.286	38.36%	0.16578	0.054
2008-2007	0.244	0.073	70.08%	0.17371	0.255	0.411	0.243	40.88%	0.15693	0.06
2006-2007-2008	0.249	0.04	83.94%	0.18714	0.352	0.517	0.347	32.88%	0.15438	0.033

Table 4.16 Stepwise regression analysis – Round 2: External Satisfaction

Output Variable: External Satisfaction										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2013	0.149	0.057	61.74%	0.32002	0.176	0.25	0.15	40.00%	0.30385	0.036
2012	0.149	0.047	68.46%	0.3736	0.221	0.238	0.127	46.64%	0.35771	0.07
2008	0.05	-0.108	316.00%	0.82955	0.899	0.05	-0.108	316.00%	0.82955	0.447

Table 4.17 Stepwise regression analysis – Round 2: Internal Satisfaction

Output Variable: Internal Satisfaction										
Dataset (Year)	**Sub-Model 1 (Controlled Variables)**					**Sub-Model 2 (Independent Variables)**				
	R^2	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**	**R^2**	**Adj. R^2**	**% of Change**	**Std. Error**	**Sign.**
2013	0.106	0.009	91.51%	16.31897	0.379	0.232	0.13	43.97%	15.28997	0.054
2011	0.11	-0.008	107.27%	33.177	0.469	0.285	0.17	40.35%	30.11976	0.042
2010	0.139	0.012	91.37%	843.4021	0.38	0.264	0.131	50.38%	791.2396	0.097
2008	0.228	0.095	58.33%	18.80021	0.164	0.343	0.202	41.11%	17.65032	0.051
2012-2011	0.099	-0.023	123.23%	17.92593	0.548	0.366	0.26	28.96%	15.24891	0.008
2010-2009	0.092	-0.046	150.00%	446.3593	0.652	0.228	0.083	63.60%	417.9137	0.187
2009-2010-2011	0.08	-0.059	173.75%	300.821	0.718	0.197	0.047	76.14%	285.3696	0.28

Table 4.18 Summary of Round 2 analysis: significant input-output pairs

		Output Variables		
		Profitability	**Liquidity**	**Cash Flow Stability**
Input Variables	**Age Diversity**	Dataset: (2012)		Dataset: (2007)
	Organization Tenure			
	TMT Tenure		Datasets: (2006)+ (2006/2007/2008)	
	Educational Diversity		Datasets: (2009)+(2008)+ (2007)+ (2009/2010+ (2007/2008)+ (2009/2010/2011)	Datasets: (2012)+ (2011/2012)
	Functional Diversity		Datasets: (2014)+ (2006/2007/2008)	Dataset: (2014)
	Industry Experience			Datasets: (2012)+(2011)+ (2010)+(2009)+(2006)+ (2011/2012)+(2009/2010)+ (2009/2010/2011)

Table 4.18 (continuation) Summary of Round 2 analysis: significant input-output pairs

		Output Variables		
		Capital Structure	**External Satisfaction**	**Internal Satisfaction**
Input Variables	**Age Diversity**			Dataset: (2013)
	Organization Tenure	Dataset: (2014)	Dataset: (2013)	Datasets: (2011)+ (2011/2012)
	TMT Tenure	Datasets: (2013)+(2006)+ (2006/2007/2008)	Dataset: (2012)	Datasets: (2011)+(2008)+ (2011/2012)
	Educational Diversity	Datasets: (2014)+(2009)+(2008)+(2007)+(2007/2008)		
	Functional Diversity			
	Industry Experience		Dataset: (2013)	

Although in Round 2 of stepwise regression analysis the significant relations were found in different datasets than those of Round 1, but the selected independent variables in Round 2 are found to be consistent with those in Round 1, which confirms the selection of input-output pairs for the next step of developing the forecasting models. Table (4.19) shows a comparison between the outcome of Round 1 and Round 2, and shows the final selected pairs.

Table 4.19 Comparison between Round 1 and Round 2

	Profitability		**Liquidity**		**Cash Flow Stability**	
	Input Variables	**Occurrence**	**Input Variables**	**Occurrence**	**Input Variables**	**Occurrence**
Round 1	Age Diversity	1	TMT Tenure	1	Age Diversity	1
			Educational Diversity	3	Educational Diversity	2
			Functional Diversity	1	Functional Diversity	1
					Industry Experience	8
Round 2	Age Diversity	1	TMT Tenure	2	Age Diversity	1
			Educational Diversity	6	Educational Diversity	2
			Functional Diversity	2	Functional Diversity	1
					Industry Experience	8

Table 4.19 (continuation) Comparison between Round 1 and Round 2

	Capital Structure		External Satisfaction		Internal Satisfaction	
	Input Variables	**Occurrence**	**Input Variables**	**Occurrence**	**Input Variables**	**Occurrence**
Round 1	Org. Tenure	1	Org. Tenure	1	Age Diversity	1
	TMT Tenure	3	TMT Tenure	1	Org. Tenure	2
	Educational Diversity	5	Industry Experience	1	TMT Tenure	3
Round 2	Org. Tenure	1	Org. Tenure	1	Age Diversity	1
	TMT Tenure	3	TMT Tenure	1	Org. Tenure	2
	Educational Diversity	5	Industry Experience	1	TMT Tenure	3

4.4 Model Setting: Step 2: Forecasting Models

4.4.1 Defining Membership Function

Constructing fuzzy models usually starts with choosing the number and type of membership functions. The research started by building a generic ANFIS model for the system under consideration for all output variables. Although it is a good practice to start with a triangle membership function (Funsten, 2015 ; Rustum, 2009), a multi input – multi output ANFIS have been evaluated with three different membership functions (Generalised Bell-Shaped, Spline Curve Π-shaped, and Triangular-Shaped membership functions). The forecasting capabilities for all of them were evaluated through Mean Absolute Percentage Error (MAPE). The smaller the value of (MAPE), the better the prediction capability.

Generalised Bell-Shaped provided an overall smaller MAPE compared to Spline Curve Π-shaped, and Triangular-Shaped membership functions. Figure (4.1) shows the prediction of External Satisfaction, while Figure (4.2) is for Internal Satisfaction using the three membership functions. Therefore, Generalised Bell-Shaped Membership Function (GbellMF) was used to develop subsequent forecasting models.

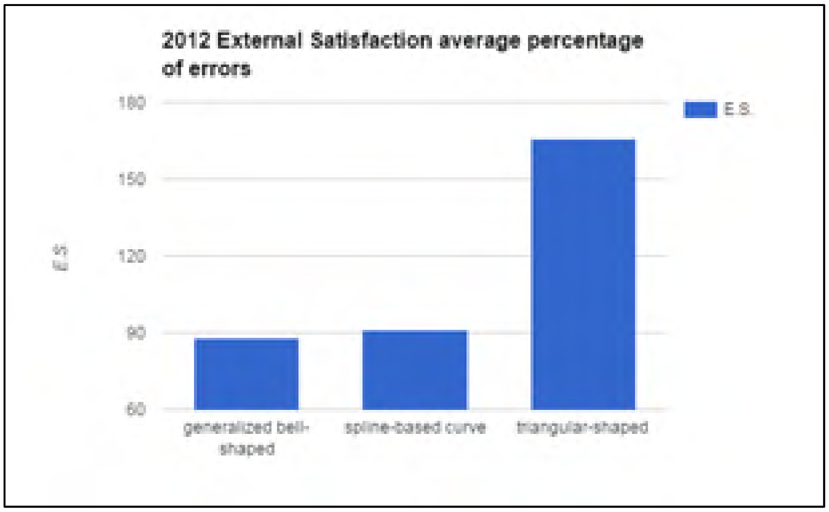

Figure 4.1 Average percentage of errors –
External Satisfaction (year 2012)

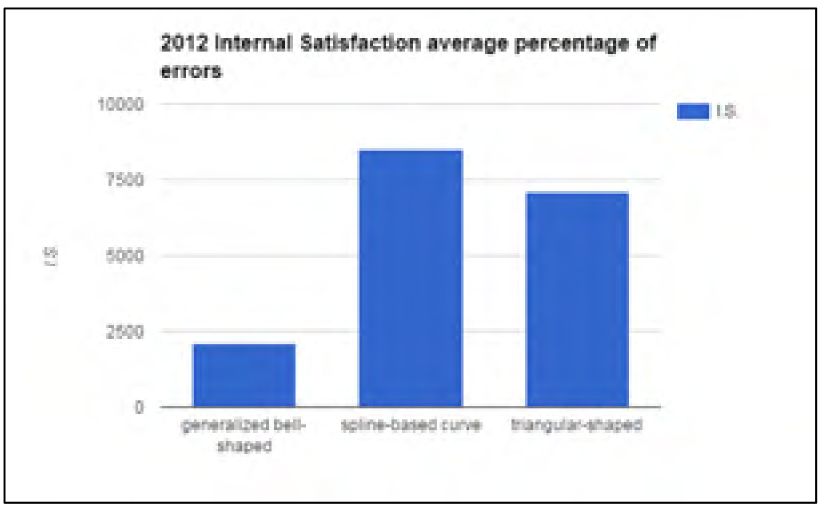

Figure 4.2 Average percentage of errors –
Internal Satisfaction (year 2012)

4.4.2 Strategy 1: Two-Level Catalogue Classification - Majority Vote Classifiers method

Due to the nature of TMT influence on organization outcome and measures employed in this research, many recent studies are recommending the use of intervals. For example, (Angriawan, 2009) noted that the analysis of diversity is preferable for interval data, while (Clark & Soulsby, 2007) are calling those intervals as a "strategic eras", and claim that those eras are not simply "occupied" by a stable TMT but marked by internal continuity in management values and strategic priorities and separated by discontinuity between contiguous eras. Therefore, analysis via intervals is more sensitive to the changes that may occur on organization output due to TMT influence. In this sub-section, the use of a Two-Level Catalogue Classification approach, known as Majority Vote Classifiers is suggested.

Many classification techniques have been used by researchers, examples of those include: Bayes Classifier, Plug in Classification Techniques (PICTs), Bagging Techniques, Boosting Techniques, and The Error Correcting Output Coding Classifier (ECOC). Among the various classification method, the Classical Majority Vote Problem (or sometimes known as Classical Majority Vote Learns “MaVLs”) has been a much studied topic for many years, especially by social scientists (Lam & Suen, 1997). For this research, it is expected that (MaVLs) classifiers will produce a better classifier forecasting than exact value forecasting, and two level classifiers that will superior to any of the individual classifier. The Majority Vote Classifiers have previously demonstrated an ability to produce very accurate classification rules. The method is based on the belief that the majority opinion of a group is superior to those of individuals provided the individuals have reasonable competence, which was validated later by the well-known Condorcet Jury Theorem (CJT) (Lam & Suen, 1997).

Assuming n independent people have the same probability P of being correct, and then the probability of the majority opinion being correct, denoted by $P_C(n)$, can be computed using the binomial distribution.

$$P_C(n) = \sum_{m=k}^{n} \binom{n}{m} p^m (1-p)^{n-m}$$

where the value of k is determined by

$$k = \begin{cases} \frac{n}{2} + 1 & if\ n\ is\ even, \\ \frac{n+1}{2} & if\ n\ is\ odd. \end{cases} \tag{4.3}$$

The following theorem, known as the Condorcet Jury Theorem (CJT), has provided validity to the belief that the judgment of a group is superior to that of individuals, provided the individuals have reasonable competence in the sense that they would make correct decisions with reasonably high probabilities p.

Theorem (CJT): Suppose n is odd and $n \geq 3$. Then the following are true:

1. If $p > 0.5$, then $P_C(n)$ is monotonically increasing in n and $P_C(n) \to 1$ as $n \to \infty$;
2. If $p < 0.5$, then $P_C(n)$ is monotonically decreasing in n and $P_C(n) \to 0$ as $n \to \infty$;
3. If $p = 0.5$, then $P_C(n) = 0.5$ for all n.

4.4.2.1 Majority Vote Classifiers

In this model, the first level of classification uses three different classifiers. In addition to ANFIS, two other methods have been used widely in financial studies. Decision Tree and K-Nearest Neighbours algorithm (Imandoust & Bolandraftar, 2013). They have been adopted in risk analysis, stock market, bank bankruptcies, currency exchange rate, trading futures, credit rating, loan management, bank customer profiling and money laundering analyses. Those three methods were selected because of their application in finance, as well as there are no pre-assumptions required for the data distribution (B. Chen, 2014).

In this research, those three rules were combined in a way to produce a classifier that is superior to any of the individual rules, and can be expressed as:

$h_1(X) = \text{ANFIS}$

$h_2(X) = \text{Decision Tree}$

$h_3(X) = \text{KNN}$

$$C(X) = mode\{h_1(X), h_2(X), h_3(X)\} \tag{4.4}$$

At each value of X classify to the class that receives the largest number of classifications (or votes). As an example of this method, consider the following situation (James, 1998): the predictor space (X) is divided into three regions. In the first region h_1 and h_2 classify correctly but h_3 is incorrect, in the second region, h_1 and h_3 are correct but h_2 incorrect and in the last region h_2 and h_3 are correct but h_1 is incorrect. If a test point is equally likely to be in any of the three regions, each of the individual classifiers will be incorrect one third of the time. However, the combined classifier will always give the correct classification. Of course, there is no guarantee that this will happen and it is possible (though uncommon) for the combined classifier to produce an inferior performance. This procedure can be extended to any number of classifiers. It is also possible to put more weight on certain classifiers. In general, a Majority Vote Classifier is consisting of votes from rules $h_1, h_2, \ldots . h_B$ as follows:

$$C(X) = arg \max_i \sum_{j=1}^{B} w_j I\big(h_j(X) = i\big) \tag{4.5}$$

4.4.2.2 Decision Tree

A decision tree is established as a graphical tool for the visualisation of relations in decision analysis, to help identify a strategy most likely to reach a goal (B. Chen, 2014). It is a representation of “if-then” statements for classification. An economic Decision Tree example is illustrated in Figure 4.3.

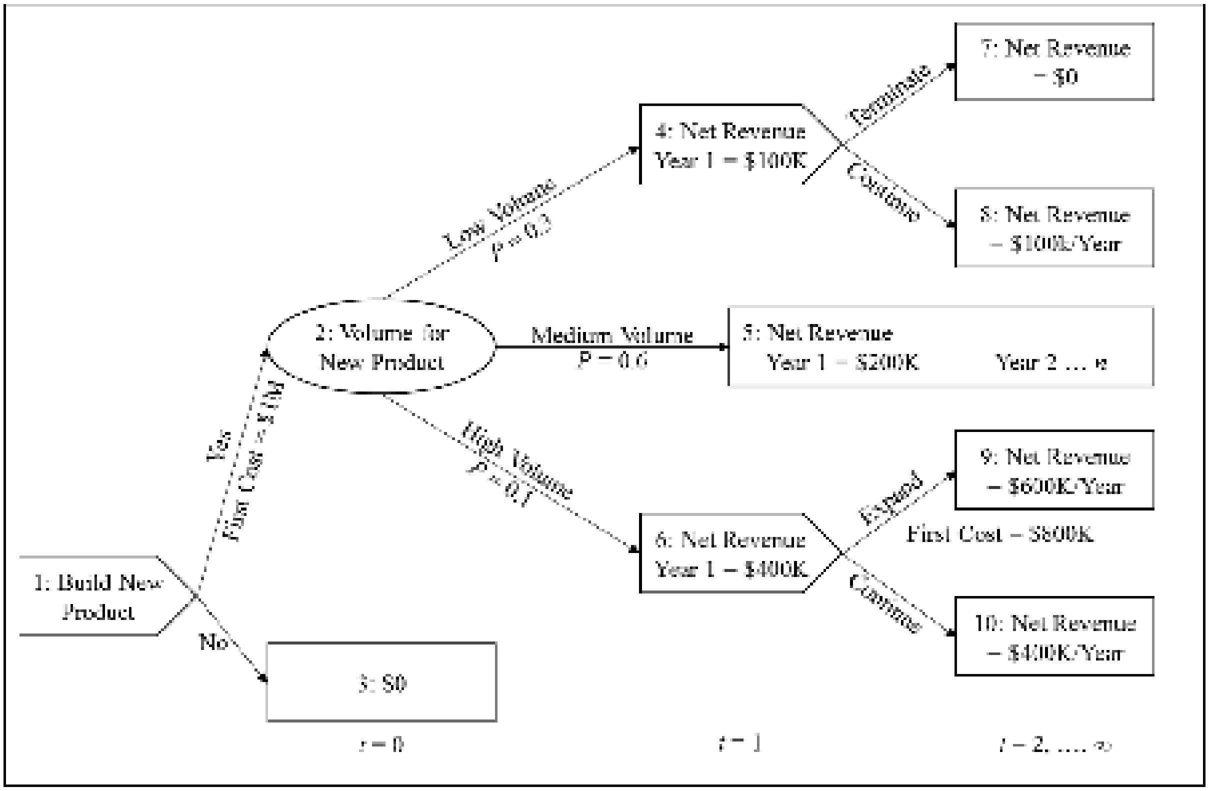

Figure 4.3 Economic Decision Tree example – new product
Taken from Newnan, Eschenbach, & Lavelle (2004)

A Decision Tree representative has three symbols:

1. Decision Nodes: decision maker chooses one of the available paths ( );
2. Chance Nodes: represent a probabilistic (chance) of event ( );
3. Outcome Nodes: show result for a particular path through the decision tree ( ).

Other details such as the probabilities and costs can be added on the branches that link the nodes. In the above example, if the sales volume is low, then the product may be discontinued early in its potential life. On the other hand, if sales volume is high, additional capacity may be added to the assembly line and new produce variations maybe added. Decision trees are useful and intuitive graphical tools for demonstrating relations that lead to faults with a hierarchical structure that aids human comprehension.

4.4.2.3 K-Nearest Neighbours (KNN)

The (KNN) is supervised learning that has been used in many applications in the field of data mining and pattern recognition. It is a very simple classification method; however, practice it tends to work well on a large number of problems (B. Chen, 2014). To use the method, KNN classification system using the training data will need to be created. After the system is created, testing data can be put into the system. The system will use the distance of n dimensional space to classify the testing data. For example, there are ten training data points and one testing data point in two-dimensional space. Five of them belong to group A and the other five belong to group B. To create the KNN classifier, the centre point of each group will be calculated. The KNN classifier will calculate the distances between the testing data point, the centre points of group A, and the centre point of group B. The testing data point will be classified as group A if the distance between testing data point and the centre point A is shortest. Otherwise testing data point will be classified as group B.

After the introduction of K-Nearest Neighbours rule the tool has been later refined with a more formal algorithm becoming more popular in mid 70s. Researchers are now offering an enhanced put effort to enhance the features of the KNN, such as rejection approaches during training and weight each training data point differently.

4.4.3 Results

As explained in pervious sections, the first level of classification uses three different classifiers. They are: K-Nearest Neighbours algorithm, Decision Tree and ANFIS. Data has been trained and tested in each classifier. The result of each classifier will cost a vote. If two or all three votes are going to the same category, then the resultant output will be that category. However, if each classifier vote for different categories then the dominant classifier will make the final decision.

Since there were nine different datasets (from 2006 to 2014), the following steps were used to construct the classification model:

1. Dataset were randomly separated into 70% for training, and 30% for testing;
2. A classification model was constructed for each of the output variables;
3. For each dataset, per output variable, the classification range was defined. Five equal size ranges (bin A to bin E) were generated;
4. Training output data were based on their values to assign a bin;
5. The different classification models were trained based on the bin information;
6. The testing group data were used to test the accuracy of the classifier.

MATLAB Fuzzy Logic Toolbox and Statistics, and Machine Learning Toolbox were used to develop the ANFIS models, KNN models and Decision Tree models. The same above procedure have been examined for the following different classification models:

1. Two levels catalogue classification (Decision Tree as a dominant classifier);
2. Two levels catalogue classification (KNN as a dominant classifier);
3. Two levels catalogue classification (ANFIS as a dominant classifier);
4. Classification by Decision Tree only;
5. Classification by KNN only;
6. Classification by ANFIS only.

Table (4.20) and Table (4.21) show example of defining a classification range (bin A to bin E) for two different years, 2006 and 2014. Bins from A to E are defined as:

1. Column 1 – To Column 2 = bin A;
2. Column 2 – To Column 3 = bin B;
3. Column 3 – To Column 4 = bin C;
4. Column 4 – To Column 5 = bin D;
5. Column 5 – To Column 6 = bin E.

Table 4.20 Classification range – bins for year 2006

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Profitability	-0.0031	10.2263	20.4557	30.685	40.9144	51.1438
Liquidity	0.5031	0.6243	0.7455	0.8667	0.9879	1.1091
Cash Flow Stability	0.0012	0.7945	1.5879	2.3813	3.1747	3.968
Capital Structure	0.4306	0.5661	0.7015	0.8369	0.9724	1.1078
External Satisfaction	0.7913	1.0808	1.3703	1.6598	1.9493	2.2388
Internal Satisfaction	4.9688	12.032	19.0952	26.1583	33.2215	40.2847

Table 4.21 Classification range – bins for year 2014

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Profitability	-9.8801	-4.0467	1.7868	7.6203	13.4537	19.2872
Liquidity	0.3256	0.5594	0.7931	1.0268	1.2606	1.4943
Cash Flow Stability	-0.0743	0.512	1.0982	1.6845	2.2707	2.857
Capital Structure	0.3035	0.4299	0.5563	0.6827	0.809	0.9354
External Satisfaction	0.3382	1.2006	2.0629	2.9253	3.7877	4.6501
Internal Satisfaction	0	17.9802	35.9604	53.9406	71.9208	89.901

Tables (4.22) to Table (4.27) shows the results of accuracy level for each one of the six classifiers. Table (4.22) shows the accuracy results when Decision Tree is the dominant classifier. Both Liquidity and Capital Structure were badly forecasted (most of the forecasting results are below 30%). While, Profitability are the best forecasted output in this case (around 55% of forecasted data points are above 90% accuracy, and 22% are between 80 and 89%).

Table 4.22 Classification results for Decision Tree as a dominant classifier

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	33.33%	0.00%	11.11%	0.00%	11.11%	33.33%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	22.22%	0.00%
70 - 79.9	11.11%	0.00%	22.22%	0.00%	11.11%	11.11%
60 - 69.9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
50 - 59.9	22.22%	0.00%	22.22%	0.00%	11.11%	11.11%
40 - 49.9	11.11%	0.00%	11.11%	0.00%	0.00%	33.33%
30-39.9	11.11%	33.33%	33.33%	11.11%	22.22%	0.00%
< 30	0.00%	66.67%	0.00%	88.89%	22.22%	11.11%

Table (4.23) provides summary of results when KNN is the dominant classifier, which shows the same results as per previous table. With the exception of Cash Flow Stability and Internal Satisfaction, the percentage of accuracy below 30% have been reduced.

Table 4.23 Classification results for KNN as a dominant classifier

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	33.33%	0.00%	11.11%	0.00%	11.11%	33.33%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	22.22%	0.00%
70 - 79.9	11.11%	0.00%	11.11%	0.00%	11.11%	11.11%
60 - 69.9	0.00%	0.00%	22.22%	0.00%	0.00%	0.00%
50 - 59.9	22.22%	0.00%	22.22%	0.00%	11.11%	22.22%
40 - 49.9	11.11%	11.11%	22.22%	0.00%	0.00%	11.11%
30-39.9	11.11%	33.33%	11.11%	0.00%	11.11%	22.22%
< 30	0.00%	55.56%	0.00%	100.00%	33.33%	0.00%

Table (4.24) shows results when ANFIS is the dominant classifier. The results are similar to the previous two methods; however, the accuracy in forecasting Cash Flow Stability has been reduced to around 55% of results that are below 30% accuracy level.

Table 4.24 Classification results for ANFIS as a dominant classifier

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	33.33%	0.00%	11.11%	0.00%	11.11%	33.33%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	11.11%	0.00%
70 - 79.9	11.11%	0.00%	11.11%	0.00%	22.22%	11.11%
60 - 69.9	11.11%	0.00%	11.11%	0.00%	0.00%	11.11%
50 - 59.9	11.11%	0.00%	11.11%	0.00%	11.11%	0.00%
40 - 49.9	11.11%	0.00%	33.33%	0.00%	11.11%	22.22%
30-39.9	11.11%	22.22%	22.22%	0.00%	22.22%	11.11%
< 30	0.00%	77.78%	0.00%	100.00%	11.11%	11.11%

When using Decision Tree, KNN and ANFIS as standalone methods, still Liquidity and Capital Structure could not be forecasted with good accuracy (although ANFIS shows a better accuracy in Capital Structure, 11% of data were with accuracy between 50-59%). Other output variables have been around the same accuracy levels. Although the number of forecasted data points with accuracy above 90% are less; however, still they are forecasted with no less than 80% accuracy.

Table 4.25 Classification results for Decision Tree only

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	33.33%	0.00%	11.11%	0.00%	11.11%	33.33%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	0.00%	0.00%
70 - 79.9	0.00%	0.00%	11.11%	0.00%	22.22%	11.11%
60 - 69.9	11.11%	0.00%	11.11%	0.00%	11.11%	0.00%
50 - 59.9	22.22%	0.00%	0.00%	0.00%	11.11%	11.11%
40 - 49.9	11.11%	0.00%	33.33%	0.00%	11.11%	33.33%
30-39.9	11.11%	33.33%	0.00%	11.11%	22.22%	0.00%
< 30	0.00%	66.67%	33.33%	88.89%	11.11%	11.11%

Table 4.26 Classification results for KNN only

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	33.33%	0.00%	11.11%	0.00%	11.11%	22.22%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	11.11%	0.00%
70 - 79.9	11.11%	0.00%	0.00%	0.00%	22.22%	11.11%
60 - 69.9	0.00%	0.00%	11.11%	0.00%	0.00%	11.11%
50 - 59.9	22.22%	0.00%	33.33%	0.00%	22.22%	0.00%
40 - 49.9	11.11%	0.00%	22.22%	0.00%	0.00%	33.33%
30-39.9	11.11%	55.56%	22.22%	0.00%	11.11%	22.22%
< 30	0.00%	44.44%	0.00%	100.00%	22.22%	0.00%

Table 4.27 Classification results for ANFIS only

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	0.00%	0.00%	11.11%	0.00%	0.00%	33.33%
80 - 89.9	22.22%	0.00%	0.00%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	0.00%	0.00%	22.22%	11.11%
60 - 69.9	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%
50 - 59.9	22.22%	11.11%	11.11%	0.00%	22.22%	11.11%
40 - 49.9	22.22%	0.00%	44.44%	0.00%	11.11%	11.11%
30-39.9	0.00%	11.11%	11.11%	11.11%	33.33%	0.00%
< 30	0.00%	77.78%	11.11%	88.89%	11.11%	33.33%

Figure (4.4) shows the output of the classification method using Decision Tree method, for Cash Flow Stability – year 2014. While Figure (4.5) shows the output of the same method in the same year but for Capital Structure. Figure (4.6) provides illustration of Majority Vote forecasting for Cash Flow Stability for the year 2014 using KNN as a classification method.

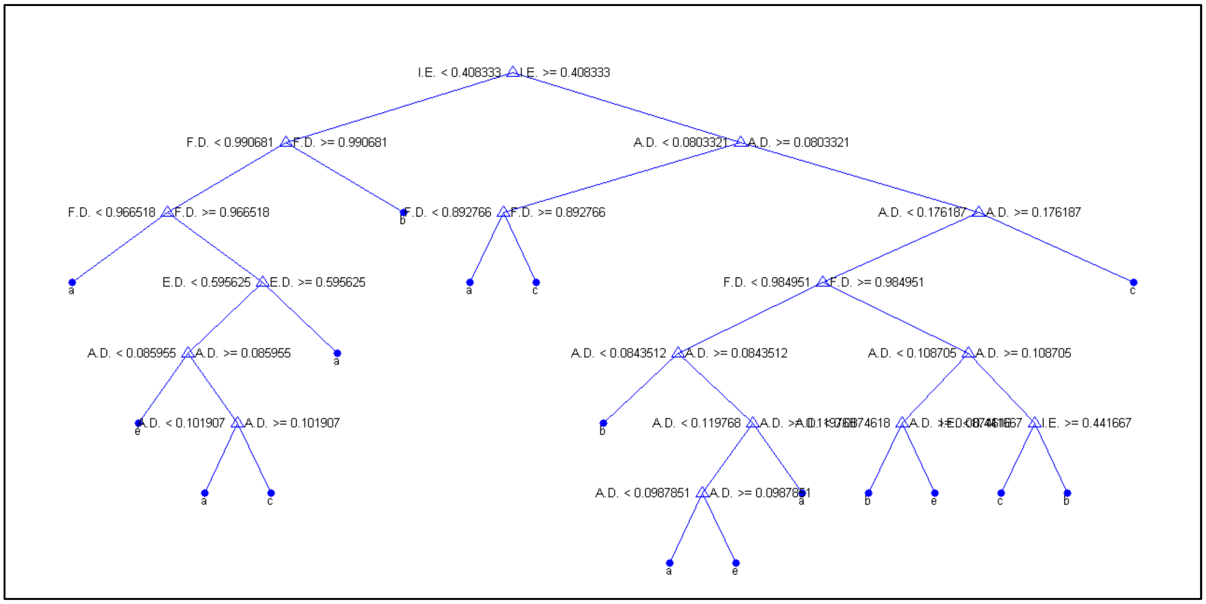

Figure 4.4 Decision Tree as a classifier for Cash Flow Stability for year 2014 with TMT Demographics: Age Diversity, TMT Education Diversity, TMT Function Diversity and Industry Experience

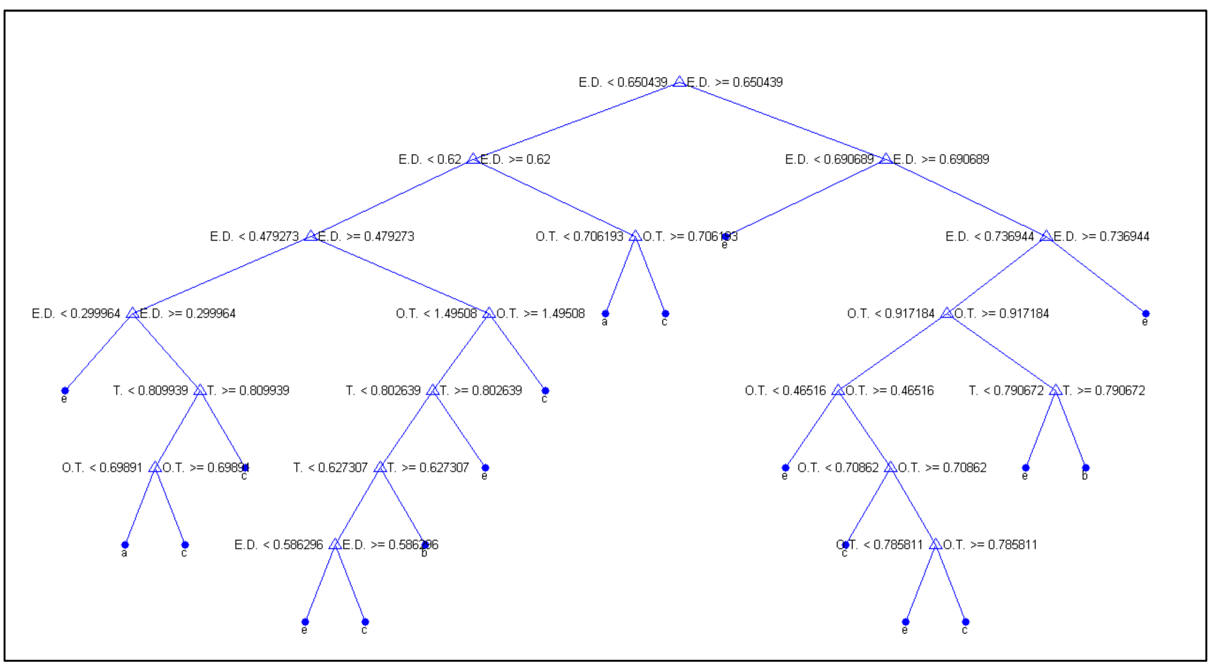

Figure 4.5 Decision Tree as a classifier for Capital Structure for year 2014 with TMT Demographics: TMT Tenure, TMT Organization Tenure and TMT Education Diversity

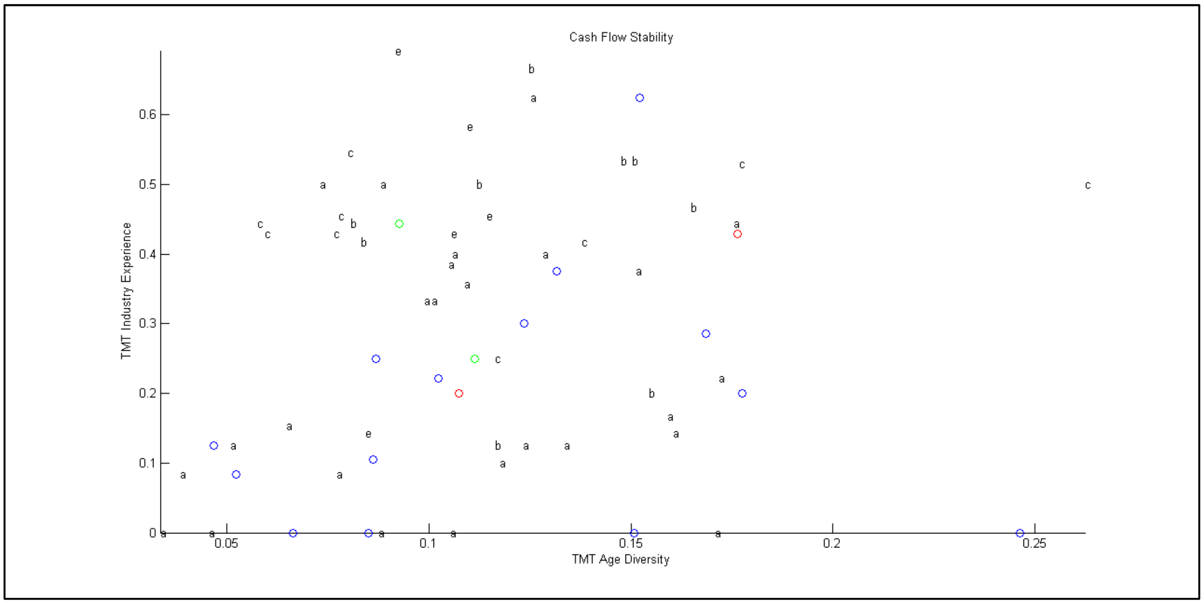

Figure 4.6 Cash Flow Stability 2D scatter plot of KNN: TMT Age Diversity and TMT Industry Experience plane

For the classifier, letters "a, b, c, d and e" on the graph are for training, while the forecasting are:

1. Blue colour to forecast data which belongs to bin "A";
2. Green colour to forecast data which belongs to bin "B";
3. Red colour to forecast data which belongs to bin "C";
4. Cyan colour to forecast data which belongs to bin "D";
5. Magenta colour to forecast data which belongs to bin "E".

4.5 Strategy 2: Two-Level Catalogue Classification with Boxplot

To ensure reliability of results, the same methods are tested again with eliminating outliers. Data distributions may influence the classification results, as the successful classification may be due to the highly-skewed data. In forecasting, outlier data affect the forecasting performance drastically. An outlier, is an observation point (sample value) that distant from other observations. Or in another meaning, differs notably from the mean of the measurement series. Outliers can occur in any distribution, and they often indicate variability in the measurement. They can be caused for many reasons such as electromagnetic interference, hostile measurement environment, defective installation, insufficient maintenance, or erroneous handling of the measurement system and intentional cover-up for lapses of the technician (Rustum, 2009). Outliers, being the extreme observations, may sometimes include the maximum or minimum of the sample (or both). However, a distinction should be established between true outliers and the sample maximum and minimum (since they are usually not far from other observations). To avoid such confusion, the well know boxplot techniques is applied.

4.5.1 Boxplot Method

Boxplot is a graphical representation of numerical data through their quartiles, five values. They are 25th percentile (known as Q1), the 50th percentile (the median), the 75th percentile (Q3), upper limit and lower limit. To find the upper and the lower limit, Inter-Quartile Range (IQR) will need to be found (subtracting Q3 – Q1) found. Then multiply IQR by 1.5, add this amount to the value of Q3 and subtract this amount from Q1 to get the upper and lower limit. Boxplots have lines extending vertically from the boxes (whiskers) indicating variability outside the upper and lower quartiers. They display variation in samples of a statistical population without making any assumption of the underlying statistical distribution.

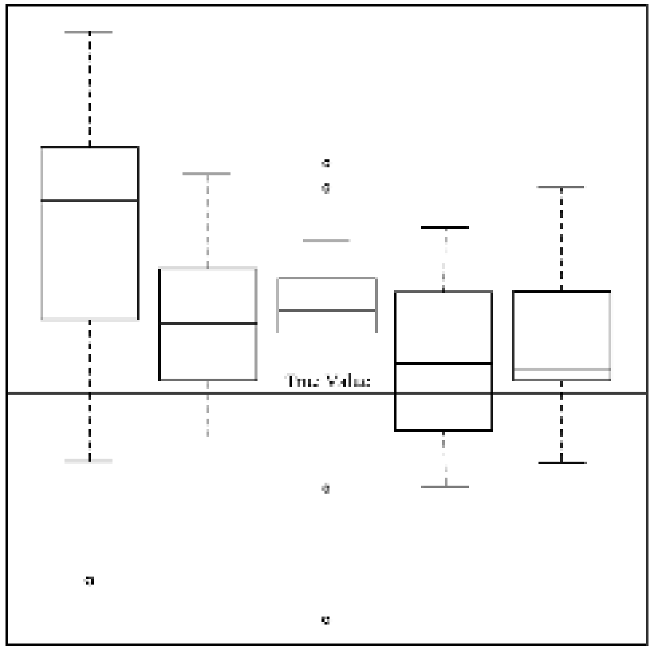

Figure 4.7 Example of boxplot displaying four
outliers in the middle column, as well as
one outlier in the first column

Researchers prefer to use boxplot because many outlier detection methods work only if the data has some specific distributed. For example, using Z score could find outliers in only in normally distributed data. However, a normal probability plot will need to be done to check the assumption of normality before using Z score to remove outliers. Moreover, most of the time researchers do not know whether the data is specifically distributed. Therefore, researchers like to use this universal approach to find outliers from any data.

Boxplots were used on all output variables of each year respectively. The outlier data was removed. (Note: if the company ‘A’ in year 2012 for the output Profitability was an outlier, company ‘A’ was removed only in 2012 Profitability specific model). After that, the same procedure in two-catalogue classification method was applied.

Figure 4.8 shows an example of the boxplot method applied to the output (Profitability) for the year 2014. Around 14.3% of the data were removed from Profitability in year 2014 using boxplot method.

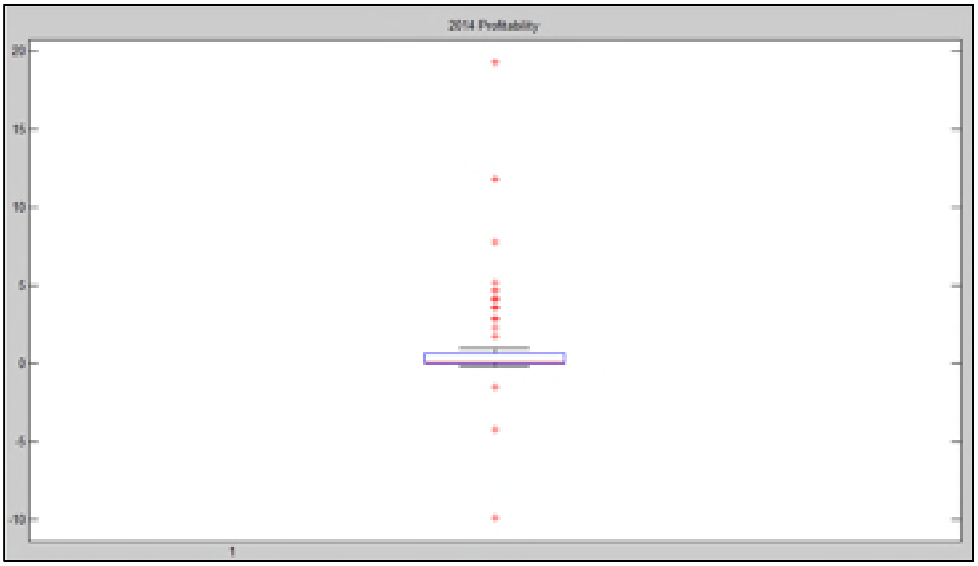

Figure 4.8 Boxplot graph for Profitability in year 2014

4.5.2 Results

First, boxplot method was applied to all datasets from 2006 to 2014. Table (4.28) shows the percentage of data points removed from each output variable, and from each year.

Table 4.28 Percentage of removed data using boxplot

Dataset	Profitability	Liquidity	Cash Flow Stability	Capital Structure	External Satisfaction	Internal Satisfaction	Average (%)
2014	27.1%	2.9%	0%	0%	7.1%	4.3%	6.9%
2013	18.6%	1.4%	1.4%	0%	5.7%	8.6%	6%
2012	20%	1.4%	1.4%	0%	5.7%	5.7%	5.7%
2011	15.7%	1.4%	0%	0%	7.1%	8.6%	5.5%
2010	7.1%	1.4%	0%	0%	5.7%	4.3%	3.1%
2009	15.7%	0%	0%	0%	4.3%	7.1%	4.5%
2008	11.4%	1.4%	1.4%	1.4%	7.1%	7.1%	5%
2007	11.4%	0%	0%	0%	7.1%	1.4%	3.3%
2006	1.4%	1.4%	1.4%	1.4%	7.1%	2.9%	2.6%
Average (%)	14.3%	1.3%	0.6%	0.3%	6.3%	5.6%	

The highest data removed were from Profitability (14.3% of data were removed), while the lowest was from Capital Structure (0.6%). On the other hand, boxplot method have removed around (6.9%) and (2.6%) of data from year 2014 and 2006, representing the highest and lowest removal respectively.

Then, since some data were eliminated, new classification range has been defined. Table (4.29) and Table (4.30) are examples for the new range of five bins (A to E) for the dataset of years 2006 and 2014.

Table 4.29 Classification range – bins for year 2006 after applying boxplot

	Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
Profitability	0.0032	1.0721	2.141	3.2099	4.2787	5.3476
Liquidity	0.5031	0.6243	0.7455	0.8667	0.9879	1.1091
Cash Flow Stability	0.0038	0.575	1.1462	1.7173	2.2885	2.8597
Capital Structure	0.3524	0.5035	0.6545	0.8056	0.9567	1.1078
External Satisfaction	1.0014	1.1288	1.2563	1.3837	1.5111	1.6386
Internal Satisfaction	4.9688	11.4679	17.967	24.4661	30.9652	37.4643

Table 4.30 Classification range – bins for year 2014 after applying boxplot

	Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
Profitability	-0.1853	-0.01	0.1652	0.3405	0.5158	0.691
Liquidity	0.3143	0.4849	0.6556	0.8263	0.9969	1.1676
Cash Flow Stability	-0.0743	0.512	1.0982	1.6845	2.2707	2.857
Capital Structure	0.2659	0.4035	0.5411	0.6786	0.8162	0.9538
External Satisfaction	0.3382	0.5829	0.8277	1.0724	1.3172	1.562
Internal Satisfaction	0	8.8533	17.7067	26.56	35.4134	44.2667

Afterwards, the same procedure that was used in Strategy 1 are followed again for the six classifiers. Tables (4.31) to Table (4.36) show the results detailing the accuracy level for each output variable.

Table 4.31 Classification results for Decision Tree as a dominant classifier – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	11.11%	0.00%	22.22%	0.00%	0.00%	0.00%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	33.33%	0.00%	0.00%	0.00%
60 - 69.9	22.22%	0.00%	22.22%	0.00%	0.00%	0.00%
50 - 59.9	0.00%	11.11%	22.22%	0.00%	0.00%	0.00%
40 - 49.9	11.11%	11.11%	0.00%	0.00%	22.22%	33.33%
30-39.9	11.11%	0.00%	0.00%	0.00%	44.44%	44.44%
< 30	11.11%	77.78%	0.00%	100.00%	33.33%	22.22%

Table 4.32 Classification results for KNN as a dominant classifier – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	11.11%	0.00%	22.22%	0.00%	0.00%	0.00%
80 - 89.9	22.22%	0.00%	0.00%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	0.00%	0.00%	0.00%	0.00%
60 - 69.9	11.11%	11.11%	55.56%	0.00%	0.00%	0.00%
50 - 59.9	0.00%	0.00%	11.11%	0.00%	0.00%	33.33%
40 - 49.9	11.11%	0.00%	11.11%	0.00%	33.33%	22.22%
30-39.9	11.11%	11.11%	0.00%	0.00%	11.11%	0.00%
< 30	11.11%	77.78%	0.00%	100.00%	55.56%	44.44%

Table 4.33 Classification results for ANFIS as a dominant classifier – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	11.11%	0.00%	22.22%	0.00%	0.00%	0.00%
80 - 89.9	11.11%	0.00%	0.00%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	22.22%	0.00%	0.00%	0.00%
60 - 69.9	22.22%	11.11%	33.33%	0.00%	0.00%	0.00%
50 - 59.9	0.00%	0.00%	22.22%	0.00%	0.00%	0.00%
40 - 49.9	11.11%	0.00%	0.00%	0.00%	11.11%	22.22%
30-39.9	22.22%	0.00%	0.00%	0.00%	33.33%	33.33%
< 30	0.00%	88.89%	0.00%	100.00%	55.56%	44.44%

Table 4.34 Classification results for Decision Tree only – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%
80 - 89.9	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	22.22%	0.00%	0.00%	0.00%
60 - 69.9	22.22%	11.11%	44.44%	0.00%	0.00%	0.00%
50 - 59.9	0.00%	0.00%	11.11%	0.00%	11.11%	33.33%
40 - 49.9	11.11%	0.00%	0.00%	0.00%	11.11%	33.33%
30-39.9	11.11%	0.00%	0.00%	11.11%	33.33%	22.22%
< 30	11.11%	88.89%	0.00%	88.89%	44.44%	11.11%

Table 4.35 Classification results for KNN only – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%
80 - 89.9	22.22%	0.00%	11.11%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	11.11%	0.00%	0.00%	0.00%
60 - 69.9	11.11%	11.11%	11.11%	0.00%	0.00%	0.00%
50 - 59.9	0.00%	0.00%	44.44%	0.00%	0.00%	33.33%
40 - 49.9	11.11%	11.11%	11.11%	0.00%	33.33%	22.22%
30-39.9	11.11%	11.11%	0.00%	0.00%	11.11%	11.11%
< 30	11.11%	66.67%	0.00%	100.00%	55.56%	33.33%

Table 4.36 Classification results for ANFIS only – using boxplot

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	22.22%	0.00%	11.11%	0.00%	0.00%	0.00%
80 - 89.9	0.00%	0.00%	11.11%	0.00%	0.00%	0.00%
70 - 79.9	22.22%	0.00%	0.00%	0.00%	0.00%	0.00%
60 - 69.9	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%
50 - 59.9	22.22%	0.00%	33.33%	0.00%	11.11%	0.00%
40 - 49.9	0.00%	0.00%	33.33%	0.00%	11.11%	0.00%
30-39.9	11.11%	11.11%	0.00%	11.11%	22.22%	0.00%
< 30	11.11%	88.89%	0.00%	88.89%	55.56%	100.00%

Although the overall accuracy of the new classification approach is lower; however, it did not differ significantly from the previous strategy. Some examples are:

1. When Decision Tree is the dominant classifier, it can be noticed that the percentage of forecasted outputs with accuracy level less than 30% has been increased. This percentage is increased in Profitability to 11%, and with Internal Satisfaction where 100% of all forecasted data are now with accuracy lower than 30%;

2. The same can be also noticed when using ANFIS alone as a classifier, the forecasting of Profitability and Liquidity (level of accuracy is lower than 30%) has been increased from 0% to 11% and from 77% to 88% respectively;
3. With Internal Satisfaction, the percentage of data points with forecasting accuracy more than 90% has dropped to 0% from (33%);
4. It can also be noticed that Capital Structure and External Satisfaction are the worst among all outputs in terms of forecasting accuracy.

The exception to that can be noticed mainly with Cash Flow Stability. The percentage of data points with accurate forecasting (more than 90% accuracy) has been increased for this output variable in all six classifiers. It was increased from 11% to 22% in three classifiers (when Decision Tree, KNN and ANFIS are dominant classifiers), while it stayed the same (11%) in the remaining classifiers. The same behaviour is also noticed with Profitability when ANFIS is used alone. The percentage of data points with accurate forecasting (more than 90% accuracy) has been increased to 22%.

4.6 Strategy 3: Time-Series Forecasting using ANFIS

In order to have a comprehensive view of the TMT predictability power, Strategy 3: time series model is constructed trained and tested using ANFIS. Since complete records are required for the time series forecasting model (from 2006 to 2014 – nine years), among the whole datasets (70 firms) only (15) complete data records (firms) with no missing values were found. Like other models (Strategy 1 and Strategy 2), it is necessary to divide the dataset into training and testing subsets. The division is achieved by selecting representative sets for both training and testing data. Of these nine data points, records from 2006 to 2013 were used for model training, while the record of 2014 was used for model testing. Strategy 3 is using multi input – multi output ANFIS models to forecast an exact future value for each output variable.

As it can be seen from Table (4.37), applying time series analysis have increased the percentage of forecasting at 90% accuracy. In both Liquidity and Capital Structure, could not be forecasted at that level in Strategies 1 and 2. However, in time series analysis, forecasting of those two output variables with 90% accuracy have now been achieved (around 26% of data points).

Table 4.37 Results of time series forecasting using ANFIS

	% of Testing Data Points in each Accuracy Level					
Accuracy Level (%)	**Profitability**	**Liquidity**	**Cash Flow Stability**	**Capital Structure**	**External Satisfaction**	**Internal Satisfaction**
≥ 90	20.00%	26.67%	20.00%	26.67%	13.33%	6.67%
80 - 89.9	6.67%	26.67%	20.00%	20.00%	6.67%	13.33%
70 - 79.9	0.00%	0.00%	13.33%	0.00%	6.67%	6.67%
60 - 69.9	0.00%	13.33%	6.67%	0.00%	6.67%	6.67%
50 - 59.9	6.67%	6.67%	0.00%	0.00%	0.00%	6.67%
40 - 49.9	6.67%	0.00%	13.33%	6.67%	6.67%	6.67%
30-39.9	6.67%	0.00%	6.67%	0.00%	26.67%	6.67%
< 30	53.33%	26.67%	20.00%	46.67%	33.33%	46.67%

Below are two examples, the ANFIS surface graph and rules are shown for External Satisfaction (Figure 4.9 and Figure 4.10). Same graphs are also presented for Liquidity (Figures 4.12 and Figure 4.13). Additionally, the ANFIS rules for both examples are also presented below in Figure 4.10 and 4.14 respectively.

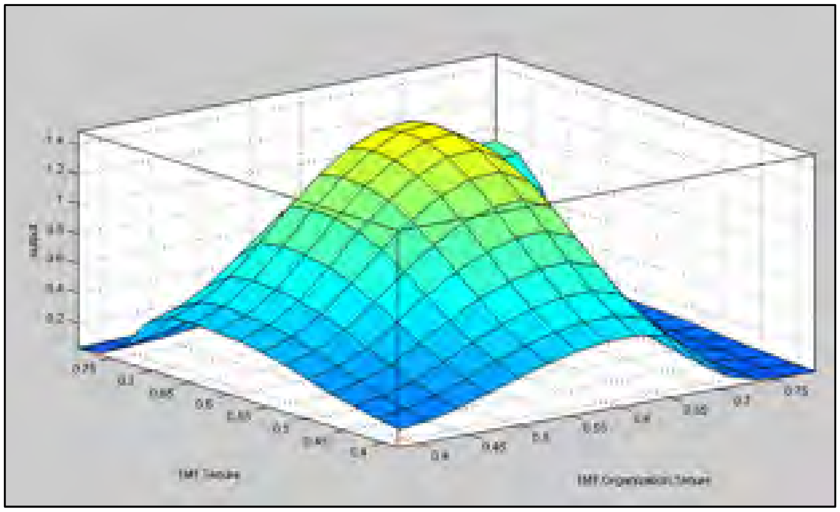

Figure 4.9 ANFIS surface for forecasting External Satisfaction:
input variables are TMT Tenure and
TMT Organization Diversify

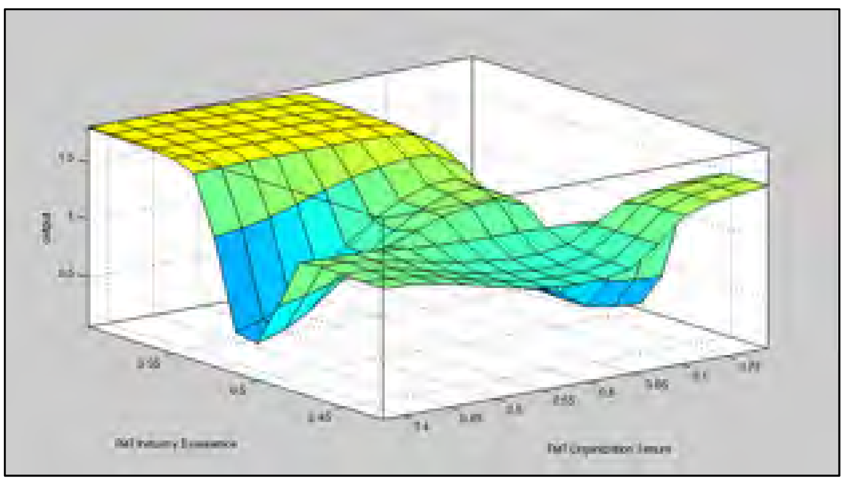

Figure 4.10 ANFIS surface for forecasting External Satisfaction:
input variables are Industry Experience and
TMT Organization Diversify

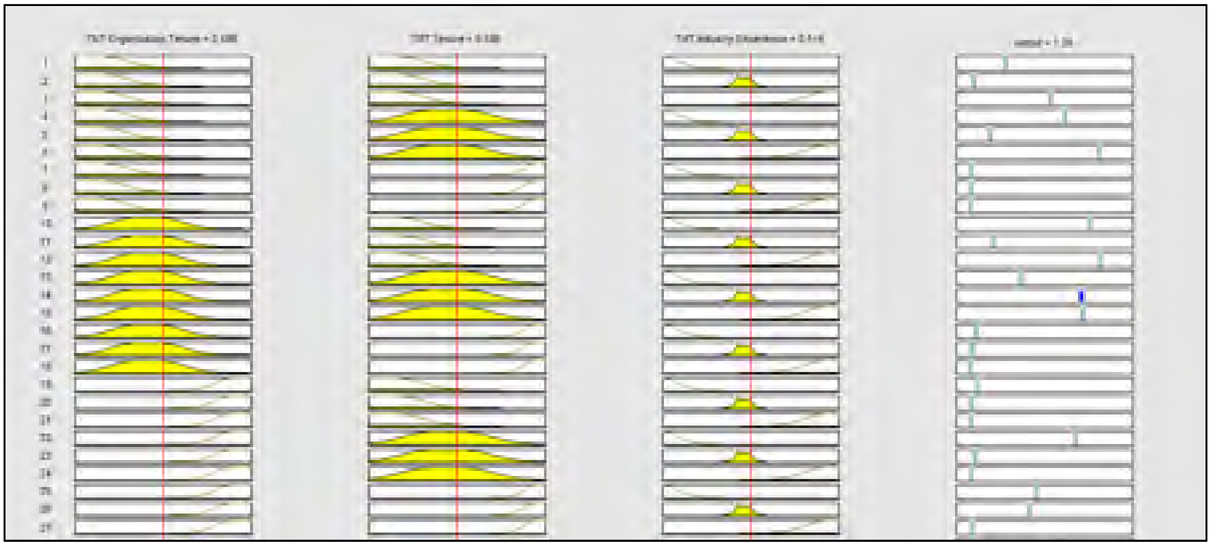

Figure 4.11 ANFIS rules for External Satisfaction

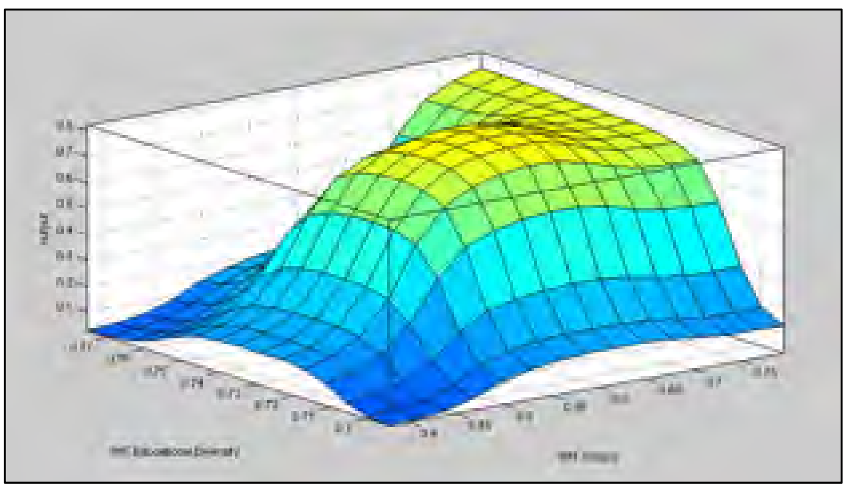

Figure 4.12 ANFIS surface for forecasting Liquidity:
input variables are TMT Tenure and TMT Educational Diversify

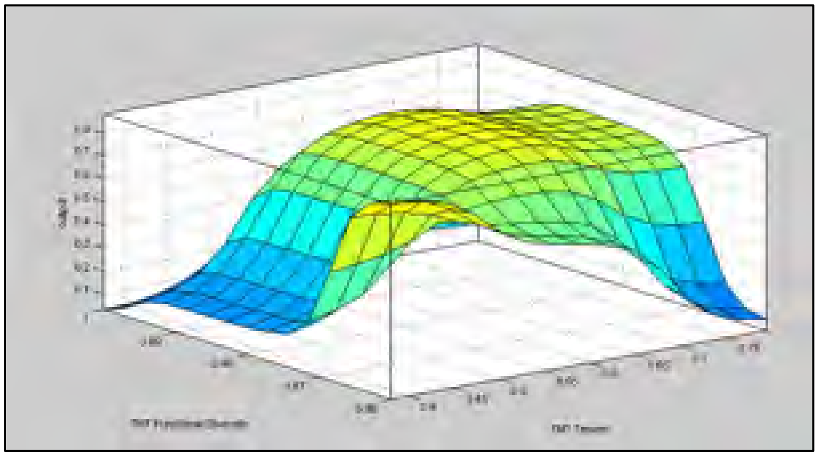

Figure 4.13 ANFIS surface for forecasting Liquidity:
input variables are TMT Tenure and TMT Functional Diversify

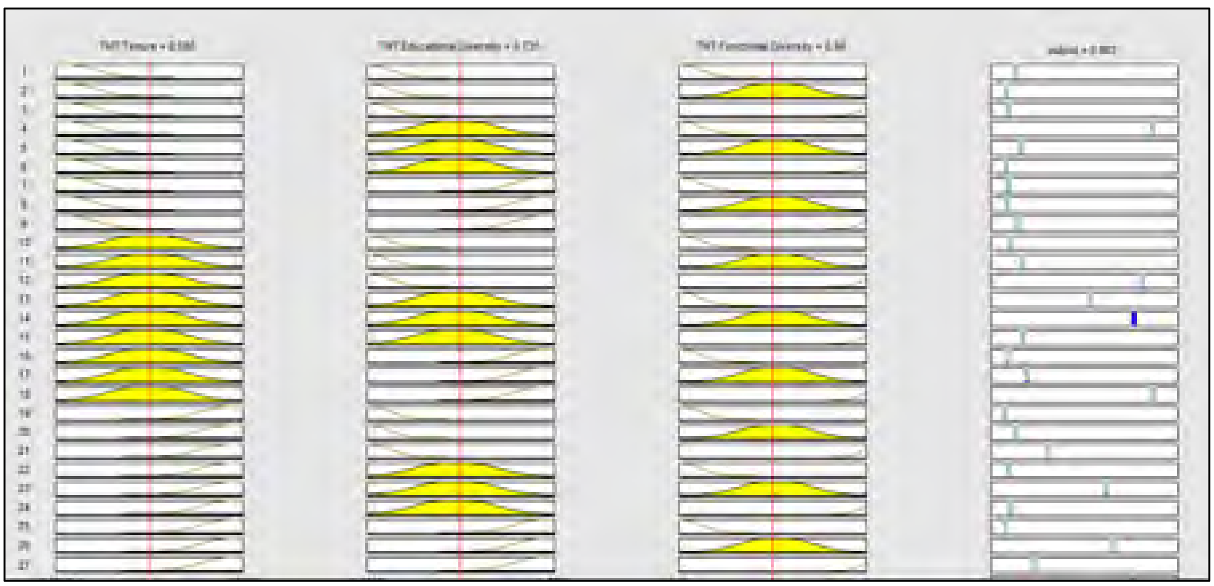

Figure 4.14 ANFIS Rules for Liquidity

Table (4.38) provides an indication of the overall allocation of majority of forecasted testing dataset for each of the output variables, i.e. in which accuracy level was the majority of the testing dataset. Finally, Table (4.39) represent an overall summary of forecasting accuracy for the three different strategies. In this table, the accuracy level of 80% was compared as a minimum. Generally, time series analysis provided better results for three output variables (Liquidity, Cash Flow Stability and Capital Structure). While Classification Strategy 1 have provided marginally better results to forecast the other three output variables (Profitability, Internal Satisfaction and External Satisfaction).

Table 4.38 Overall allocation of major testing datasets

Accuracy Level (%)	**Profitability**			**Liquidity**			**Cash Flow Stability**		
Strategy	1*	2**	3***	1	2	3	1	2	3
≥ 90%									
89 – 80%									
79 – 70%									
69 – 60%									
59 – 50 %									
49 – 40%									
39 – 30%									
< 30%									

Accuracy Level (%)	**Capital Structure**			**External Satisfaction**			**Internal Satisfaction**		
Strategy	1	2	3	1	2	3	1	2	3
≥ 90%									
89 – 80%									
79 – 70%									
69 – 60%									
59 – 50 %									
49 – 40%									
39 – 30%									
< 30%									

* Strategy 1: Majority Vote Classifier;
** Strategy 2: Majority Vote Classifier with Boxplot;
*** Strategy 3: Time Series.

Table 4.39 Results comparison between three strategies

Accuracy Level (%)	Profitability			Liquidity			Cash Flow Stability		
Strategy	1*	2**	3***	1	2	3	1	2	3
≥ 90	33.33%	11.11%	20.00%	0.00%	0.00%	26.67%	11.11%	22.22%	20.00%
80 - 89.9	11.11%	22.22%	6.67%	0.00%	0.00%	26.67%	0.00%	0.00%	20.00%
Total	44.44%	33.33%	26.67%	0.00%	0.00%	53.34%	11.11%	22.22%	40.00%
Accuracy Level (%)	**Capital Structure**			**External Satisfaction**			**Internal Satisfaction**		
Strategy	1	2	3	1	2	3	1	2	3
≥ 90	0.00%	0.00%	26.67%	11.11%	0.00%	13.33%	33.33%	0.00%	6.67%
80 - 89.9	0.00%	0.00%	20.00%	22.22%	0.00%	6.67%	0.00%	0.00%	13.33%
Total	0.00%	0.00%	46.67%	33.33%	0.00%	20.00%	33.33%	0.00%	20.00%

* Strategy 1: Majority Vote Classifier;
** Strategy 2: Majority Vote Classifier with Boxplot;
*** Strategy 3: Time Series.

The best three forecasted organization outcomes are (Liquidity, Cash Flow Stability and Capital Structure), where 53%, 40% and 46% respectively of all data points were forecasted at 80% accuracy level as a minimum. From Step 1 of the research methodology, those organization outcome variables were forecasted using the following TMT demographics (input variables):

1. **Liquidity:** TMT Tenure, TMT Education Diversity and TMT Functional Diversity;
2. **Cash Flow Stability:** TMT Education Diversity, TMT Functional Diversity, Age Diversity and Industry Experience;
3. **Capital Structure:** TMT Tenure, TMT Education Diversity and TMT Organizational Tenure.

As a result, three TMT demographics could provide a good forecasting basis for organization outcome. Those are: TMT Tenure, TMT Education Diversity and TMT Functional Diversity. The frequency of those three TMT demographics has provided a good accuracy level (more than 80%) for at least two organization outcomes.

4.7 Discussion

Because organizations are reflections of the members of their upper echelons, many scholars have studied the relation between Top Management Team (TMT) composition and performance, more specifically organization outcome. However, the inconsistency between the different propositions of various studies has led to confusion and multiple possible conclusions. Consequently, this research is not tackling the same stream of literature. The main objective of this study is to explore whether future organization outcome can be forecasted in the context of Top Management Team demographics, and which of those TMT demographics are useful tools for future forecasting. While majority of prior scholars has studied the TMT diversity and its impact on organization performance, the findings of this research is filling the gap of exploring the predictability power to TMT.

The research results on three of the organization outcome (Liquidity, Cash Flow Stability and Capital Structure), postulates a high forecasting accuracy when TMT Tenure and TMT Educational Diversity are used. Furthermore, TMT Functional Diversity has also been utilized in two of those three outputs (Liquidity and Cash Flow Stability). It demonstrates that those three TMT variables can provide a good forecasting tool for organization outcome (Liquidity, Cash Flow Stability and Capital Structure). The relation between those input variables and organization outcome is fully supported by many previous researches (more details are in Chapter 3). To the contrary, although previous literature had illustrated the relationships between (Age Diversity, TMT Organization Tenure and Industry Experience) and organization outcome, the research findings could not validate their predictability benefits for organization outcome.

Several crucial implications from the results arise, specifically in three main areas, those are:

1. The results show that three organization outcome variables could be forecasted with acceptable accuracy, those are; Liquidity, Cash Flow Stability and Capital Structure. While the results could not provide good accuracy levels for the remaining outcome variables;

2. The accurately forecasted outcome variables, have been forested by mainly three out of the six TMT demographics, which are: TMT Educational Diversity, TMT Functional Diversity and TMT Tenure;

3. Time series forecasting had provided a better accuracy among the other two methods, and it was found to be more suitable for the context of this research.

Those three main findings are consistent with other studies, and below is a detailed discussion on them:

4.7.1 Organization Outcome Variables

Since construction firm performance is confirmed as being multidimensional in nature (Vorasubin & Chareonngam, 2007), the proposed operationalization of organization outcome in this research was based on an integrated and multidimensional perspective. A combination of six different organization outcomes has been presented and tested, however, the research findings are only validating three of those six outcomes: Liquidity, Cash Flow Stability and Capital Structure, while the other three (Profitability, External Satisfaction – Reputation and Internal Satisfaction – Shareholder Value) couldn't be validated. In fact, the findings are consistent with recent studies.

Although the research has studied and measured Profitability as a short-term variable (net profit after tax as a percentage of total sales), different studies is considering the stability of Profitability is a measure of a long-term stability of firm performance. Profitability growth rate on the long term examines the change of a firm's business content, its operating performance, diversification strategy and competition in the construction industry (Choi & Russell, 2005). Due to the nature of construction industry, knowing the right business mix is necessary, measure the market volatility and measure fluctuation are all necessary, and can be defined by profitability. Therefore, Profitability is considered as a long-term measure in construction industry; however, the span of the research longitudinal data may not have allowed the full exploration of that variable.

Moreover, in the construction industry, several intangible resources and capabilities have been considered to provide a competitive advantage and value creation to clients (Abidin & Pasquire, 2007 ; Wethyavivorn et al., 2009). From a Resource-Based View (RBV), both External Satisfaction (measured as reputation) and Internal Satisfaction (measured as shareholder value) are considered as two key resources lead to competitive advantage. They are a measure of how construction firms are effective in managing their operations (Seaden et al., 2003). Those strategic assets lead to sustainable (long-term) competitive advantages and were characterized in RBV studies as valuable, scarce, difficult to trade, difficult to imitate and difficult to substitute (Vorasubin & Chareonngam, 2007). Because of the nature of these characteristics, many scholars have suggested that firms still performed differently due to a particular asset called organization capabilities which were the firm's mechanism of transforming its intangible resources in delivering services (Eisenhardt & Martin, 2000 ; Stalk, Evans, & Shulman, 1992 ; Teece, Pisano, & Shuen, 1997). Capability here is defined as a firm's capacity to deploy integrated resources and competencies to operate the business (Seaden et al., 2003). Additionally, many studies have shown that factors affecting competitiveness of construction firms differed from country to country due to both capability of local firms as well as environmental factors including industry demand, political factors, and international competitors.

Additionally, construction firm performance is confirmed as being multidimensional in nature (Vorasubin & Chareonngam, 2007). The research results are consistent with many recent studies where they consider Profitability, External Satisfaction and Internal Satisfaction as dynamic type of firm performance, while the research methodology is based on a multidimensional operationalization of firm performance. A multidimensional firm performance approach have been used since this research is considering multiple and different time persistence of measures (Devinney, Yip, & Johnson, 2010 ; Richard et al., 2009), however, the three mentioned variables are with dynamic nature where they measure the objective of senior management to manage for sustained performance that leads to superior returns for shareholders in the long term (Yip, Devinney, & Johnson, 2009). Although those three variables are specifically designed to capture the facets of organizational outcome, alone, they are insufficiently holistic to tackle the multidimensionality of organization outcome (Deng & Smyth, 2014).

The selection of operationalization items in this research is meant to capture the different performance spans (short, medium and long) terms. However, due to the limited accessibility to: longitudinal data (only nine years of complete data were available), sample size (maximum number of firms = 70) and the combination in the samples from different regions, have probably partially explaining the results on Profitability, External Satisfaction and Internal Satisfaction.

4.7.2 TMT Job-Related Demographics

As mentioned above, three TMT demographics have been scientifically associated with the forecasted outcome variables. TMT Educational Diversity, TMT Functional Diversity and TMT Tenure. On the other hand, the remaining demographics were not useful and could not forecast the other outcome variables. Those are: TMT Age Diversity, TMT Organization Tenure and Industry Experience. The results revealed that those were not a good forecasting tool of the organization future outcome. Many explanations could be provided for the results:

1. **TMT Educational Diversity, TMT Functional Diversity and TMT Tenure**

The research results are consistent with the Organizational Demographic Theory, and with many other recent studies. Researchers distinguish between different types of TMT demographical characteristics and are now splitting them into two sub-groups: job-related and non-job-related. The functional background, educational background, and team tenure of the TMT constitute the job-related (S. Nielsen, 2010). Non-job related demographics such as, age, race, and gender are visible and silent (Pelled, 1996). The same demographic division had also been the subject of many other diversity literatures. For example (Lau & Murnighan,

1998) introduced a conceptual division that separate a TMT into subgroups and structure diversity within a team naming it “Faultline”. It has the same concept of executives sub-grouping into task-oriented Faultline (similar to job-oriented) and bio-demographic Faultline (similar to non-job oriented);

2. **Demographic Faultline’s**

Additionally, (Hutzschenreuter & Horstkotte, 2013) argue that that demographic Faultline’s within a TMT impact its ability to process information and coordinate diversification, and thereby impact firm performance. Depending on Faultline’s’ underlying characteristics, (Milliken & Martins, 1996), and (Pelled, 1996) theoretical works have distinguishes two types of Faultline’s: task-related Faultline’s (e.g., differences in educational background and in length of tenure) and bio-demographic Faultline’s (e.g., differences in age and nationality).

Task or Job related demographics are based on acquired characteristics that serve as indicators of knowledge and perspectives relevant to particular tasks (Hambrick & Mason, 1984 ; Jackson & Ruderman, 1995). Therefore, the study findings are supporting this line of research. Those characteristics significantly shape managerial opinions about their job, company, and the business environment. Therefore, this study argues that heterogeneity of educational field, functional background, and team tenure results in substantive, job-related, and non-personal conflicts.

The research findings are consistent with prior research which have suggested that high job-related diversity variables are more relevant to organizational outcomes than other related diversity variables, i.e., low job-related (Simons, Pelled, & Smith, 1999). High job-related diversity of the top executives is particularly relevant in organizational settings because top executives’ career backgrounds affect their cognitive structures, skills, knowledge and competencies (Gunz & Jalland, 1996);

3. **Industry Experience**

There are two reasons that could explain the results of Industry Experience. First, all firms in the research sample are from international construction firms, whereas the executives of those types of firms are experienced and skilled to manage the amount of risk to which their firms are exposed. Firms engaged with international businesses are exposed to various types of risks, such as: international risks, foreign location risk, international revenue exposure risk and mode of entry risk (S. Nielsen, 2010). The type of experiences required for TMT in international firms are related to exploit economies of scope (Hill, Hitt, & Hoskisson, 1992 ; Markides & Williamson, 1994 ; Teece, 1980), increase and exploit market power and cross subsidize businesses (Caves, 1981 ; Scherer & Ross, 1980), shifting resources, such as capital and labor, between business areas (Hill & Hoskisson, 1987) and product expansion and subsidiary establishment (Hutzschenreuter & Horstkotte, 2013). Those types of international challenges require TMTs to deal with a new external environment.

Researchers such as (Reeb, Kwok, & Baek, 1998) reported that internationalization carries multiple risks to a firm. In addition to many political, economic, social, and technological unknowns that could translate into significant risks. Volatile foreign exchange rates, incompatible culture, or unfavorable legal environment structured to protect the interest of host country companies are just a few examples of the potential setbacks that can adversely affect a global operation (Yee & Cheah, 2006). Top managers will need to address new industry-specific environmental elements and issues, and to acquire knowledge about specific characteristics and business logics of the product areas added to the firm portfolio (Prahalad & Bettis, 1986). Therefore, TMT's at international firms are more likely to have international business not specific industry experience.

Secondly, at the executive (board level), it is argued that experienced managers with intimate knowledge of the firm are needed (Kor, 2003) not those with specific industry experience. In looking at TMT competence, managers with experience-based tacit knowledge of firm resources who know one another's skills, limitations, and habits are able to build on the firm's idiosyncratic resources bundle by matching its material, human, or intangible resources with new growth opportunities. Thus, the availability of that type of experienced managers facilitates the coordination work of international firms and its integration to the parent firm.

In this study, International exposure of the firm was controlled by measuring Degree of Internationalization in each firm (ratio of international revenue to total organization revenue); however, executives' international experience has not been considered. Whereas, as discussed above, for the context of the selected sample, the international business experience is more important than industry specific experience, which can explain the low accuracy levels of Industry Experience Variable to forecast future organization outcome.

4.7.3 Time Series Results

To gain a comprehensive understanding of the TMT predictive power, three strategies were considered in this research, and those are:

1. **Strategy 1:** Two-Level Catalogue Classification: Majority Vote Classifiers method;
2. **Strategy 2:** Two-Level Catalogue Classification with outliers' elimination: Majority Vote Classifiers method combined with boxplot technique;
3. **Strategy 3:** Time-Series forecasting: using ANFIS method.

The three strategies have performed differently during the training and testing. Similarities could be found between Strategies 1 and 2, however, time series analysis (Strategy 3) provided better results for some output variables. As discussed exhaustively in Chapter 4, the basic idea behind neuro-fuzzy combination is to design a system that uses a fuzzy system to represent knowledge in an interpretable manner and have the learning ability of neural network to adjust its membership functions and parameters in order to enhance the system performance. Using this technique makes it possible to adjust the rules of forecasting from data by using neural network learning algorithms. Additionally, longitudinal research, is assisting researchers to better understand the causal relations between these TMT and performance variables (Certo et al., 2006). That kind of data structure has become increasingly popular in studies of strategic management and has several advantages (Glunk et al., 2001). It can improve statistical estimates by capturing effects for an entire sample (Domowitz, 1988), and it also enables the results to take both structural changes and cyclical fluctuations into consideration (Frangouli, 2002). Therefore, it improves both the econometric specifications and the parameter estimation because there is more information, more variability, less collinearity among the variables and more efficiency.

Strategy 1 provided a forecasting model based on Two-Level Catalogue Classification using a Majority Vote Classifiers method. On the other hand, Strategy 2 have considered a boxplot to eliminate any outliers in the output variables. Except for two output variables (External Satisfaction and Internal Satisfaction), the results between two strategies are almost identical. Strategy 2 have provided an overall lower forecasting accuracy compared to Strategy 1. The reason might be due to the data distribution, where a possible cause is that all data (before elimination) are belonging to one classification bin. In other words, the successful prediction may be due to the highly-skewed data. However, Strategy 3 – time series forecasting has provided a better performance. In general, the performance of the time series is good in some output variables (i.e., Liquidity, Cash Flow Stability and Capital Structure). In particular, the forecasting accuracy was more than 80%, which is close to that obtained for the validation as explained earlier. However, much more satisfying is that the model could better forecast with 90% accuracy for those output variables than the other two strategies. The percentage of data with 80% accuracy level for Liquidity around 53% in time series Model, while the other two strategies could not provide such accuracy. For Cash Flow Stability, the percentage of data with more than 80% accuracy was 40% for time series, while it was 11% and 22% for strategies 1 and 2 respectively. Finally, time series could accurately forecast around 46% of data with accuracy level more than 80% in Capital Structure, while both strategies 1 and 2 forecast accuracy was lower than 80%. It was clear that ANFIS as a time series forecasting tool can produce significant reductions in error rates.

4.8 Study Limitations

Despite all effort made to anticipate and control for possible complications, this study has several limitations, and those can be highlighted by the following:

1. **Sample Size**

Sample size might be considered small. In order to establish consistency in the study results, some certain guidelines have been employed (refer to Chapter 3 for details). From an initial (417) international construction firms listed in ENR, only 70 firms were considered for this study. (102 are only publicly listed, and complete data could be collected for only 70 firms). The sample range covers nine years (2006 to 2014), data of year (2014) had the highest number of sample size (n = 70) while year (2006) had the lowest sample size (n = 31). Those will be later divided into training and testing subset (70/30). Furthermore, in the research time series analysis was conducted for 15 firms that had complete longitudinal data (2006 to 2014) which are eight data points for training and one for testing. It was noticed that data in construction firms are not easily available due to: most of the international construction firms are not publicly owned, and historical data on ENR are only available from (2001) inwards for both top international design firms and top international contractors. Other data could have been provided from firms, which are, either not publicly listed or firms that are not international, however, it would have violated the data collection guidelines established for this research;

2. **Diversified Regions**

The sample of this study consists of firms from (19) different regions. Although data collection procedure was consistent with all regions, the construction industry is usually regarded as a localized industry, and a reflection of the country's macroeconomic situation (H. L. Chen, 2010) thus, diversification among (19) different regions may limit the understanding of results and may give some misleading generalisation.

More specifically, sociocultural norms may influence whether attention is paid to particular differences and the importance attached to specific characteristics (Wiersema & Bird, 1993). The information on TMT and its variables are subject to the norms and governance system of each individual region. For example, the research has defined the TMT as board members since they are responsible of taking the most strategic and influential decision of behalf of the firm shareholder (refer to the Introduction and Chapters 1), however in some regions the role of board members is considered less strategic. For example, in the German governance system the board of any company is replaced with a two-tiered concept (Hutzschenreuter & Horstkotte, 2013). A management board (Vorstand) and a separate supervisory board. Members of the (Vorstand) represent the firm and are legally and collectively responsible for managing the firm with the Chief Executive Officer (CEO) acting as primus inter pares.

Another example is in Taiwan (H. L. Chen, 2011), where the standard regulatory structure of corporations is a multi-structure that consists of shareholders, supervisors, and a board of directors (Chiang & He, 2010 ; Wu, 2008). Supervisors are designed to oversee the board of directors and to audit the managerial execution of business activities, however, they are not in charge of managing the company. The board of directors' monitors managers and performs the functions of management. Additionally, the functions of the board of directors has been enhanced by the appointment of independent directors. Corporate Governance Best-Practice Principles for TSEC/GTSM Listed Companies (2002) in Taiwan announce that every public company applying for listing "shall appoint independent directors in accordance with its articles of incorporation not less than two in number and not less than one-fifth of the total number of directors". Independent director is someone that shall not be an employee of the company, a shareholder or has a financial or business relation with the company;

3. **TMT Size**

Moreover, measuring TMT diversity is known to be size-dependent (Carpenter, 2002) larger teams can be more diverse by definition, and also, the size of the board varies across geographical borders. The average board size in Australia, the United States, and the United Kingdom is around 10 members. In comparison, a board size of 40 members is not uncommon for Japanese firms (Rebeiz & Salameh, 2006). In addition to that, the differences between regions in the functional orientation of firms. That orientation can be captured by two elements, the number of executive committees, and the role of TMT in those committees.

In this study, the average number of board members between regions has been differing largely. There are also differences in the average number of executive committees as well as the average TMT tenure between regions. For example, in USA sample, the average numbers are (8.2, 10 and 9.5) for average number of TMT members, average number of executive committees and average TMT tenure, while, in South Korea sample, the average numbers are (9.1, 6 and 2.7) respectively. Another example is Italy with average numbers are (10.7, 4.7 and 4.6). Although TMT size was controlled in this study (the total number of executives on the board), still some other related variables such as the number of executive committees and the TMT tenure make it difficult to conclude whether significant statistical associations should be attributed to heterogeneity or to the unobserved effects of TMT size (Carpenter et al., 2004).

While several measures have been added to control the abovementioned limitations (e.g., two control variables: to measure the TMT size, and to control for economy dynamism, in addition to the measurement of the functional diversity within each firm), studies have shown that a country's norms and its system influence what top managers' abilities (Hambrick, 2007 ; Hutzschenreuter & Horstkotte, 2013). Therefore, future researchers are encouraged to carefully select the study sample in the below two aspects:

a. **Selection of Industry**

Listed construction industry require the inclusion of highly capable TMT due to its high discretion / high prudent, a characteristic that affects both managerial attention patterns and the relation between attention and strategic choice (Kale & Arditi, 2003 ; Levy, 2005). However, future researchers may select an industry with more stable nature and accessible data. Future researchers can select either fairly stable or relatively uncertain industries. Prior studies have provided some insight into distinguishing between both types. Stable industries such as food, furniture, industrial machines, and petroleum industries, while other industries such as the aerospace, computer, motor vehicles, pharmaceutical, semiconductor, surgical and medical, and telecommunications industries have been described as relatively uncertain (Cannella et al., 2008). Selection between those industries may provide a better understanding of the predictability power of TMT by avoiding any uncertainty level that might exist due to the industry fluctuation.

Additionally, in order to ensure careful consideration of causality, future studies in the field of TMT need to incorporate longitudinal studies to allow conclusions regarding causality and provide more robust results (Finkelstein & Hambrick, 1996 ; Herrmann & Datta, 2005 ; Ruigrok et al., 2013). However, the limited availability of data in AEC industry has limited that option. Therefore, researchers are encouraged to find an additional source of data that will ensure having enough longitudinal span;

b. **Sample from one region versus multi regions**

In recent studies, theoretical and empirical evidences demonstrate that differences between regional and country-level has become more important over time (Ruigrok et al., 2013). It is suggested that future studies should distinguish between home, regional and international exposure. Future studies should provide a more complete analysis on organization outcome prediction at three different levels. Researchers are encouraged to explore the use of hierarchal analysis of different levels (home, region and international) to forecast organization outcome, whereas it may provide consistency in measuring TMT variables. Such analysis may also provide an opportunity to examine how organization outcome forecasting can be moderated by the difficulties, opportunities and complexities the organization is facing at different levels;

4. **TMT Nationality**

Additionally, the study of the TMT cultural, ethnical and nationality background may also have impact on the firm outcome. Prior studies had studied the effect of TMT nationality at different aspects:

a. The decision for foreign market entry (S. Nielsen, 2010);
b. Its influence on corporate performance (Carpenter, 2002 ; B. B. Nielsen & Nielsen, 2013);
c. The integration and depth of information use within the TMT as a team (Dahlin et al., 2005);
d. Its relationship with firm-level internationalization (foreign sales ratio, foreign assets ratio, foreign subsidiaries ratio, and foreign employees' ratio) (Caligiuri et al., 2004);
e. Therefore, researchers are encouraged to explore in further details the influence of TMT cultural, ethnical and nationality background in predicting the organization outcome.

CONCLUSIONS AND RECOMMENDATIONS

The results of this research provide several opportunities for future studies. This section summarizes those opportunities in three different categories, future extensions, theoretical extensions and methodological extensions. Afterwards, a general conclusion is provided.

5.1 Future Research

5.1.1 Theoretical Extensions – Redefining Diversity

Williams and O'Reilly (1998) define diversity as ''any attribute that another person may use to detect individual differences''. Moreover, several studies have concluded that diversity literature in organizations is confusing and difficult to understand and synthesize. Previous studies have observed many other forms of diversity that might operate in Top Management Teams (Angriawan, 2009). Diversity has been used to refer to many types of differences among people.

In most literature, TMT diversity variables had been measured either by Blau's Index (e.g., Educational Diversity and Functional Diversity – for categorical type of variables) or by Coefficient of Variations (e.g., Age Diversity, Organizational Tenure and TMT Tenure – for numerical type of variables). However, recent studies are suggesting redefining the concept of diversity as a mean of multidimensional construct. Some researchers have suggested that theoretical refinement of the conceptualization of diversity is necessary before selection of an index (Solanas, Selvam, Navarro, & Leiva, 2012).

Diversity, is a growing concept in organizational literature defined as the distribution of differences among the members of a unit (i.e., organization) with respect to a common attribute (Harrison & Klein, 2007 ; Swart, 2010). It is a function of the group size and the distribution of members within a group across the respective properties. However, this interesting theme is not an easy one because diversity occurred to be a difficult topic for scientists to research and for organizations to manage (Jackson & Ruderman, 1995 ; Swart, 2010). It has been considered as a complex construct because of its multidimensionality and not a one meaning concept. In that vein, (Harrison & Klein, 2007) typologies are considered as one of the well-known construct in diversity literature. It consists of three diversity types: Variety, Separation, and Disparity. To elaborate on the difference between the three typologies, an example provided by (Harrison & Klein, 2007) is summarized below. Consider three research teams where each team consists of eight members. The teams study how patients experience medical treatment in hospitals.

The members of Team "V – as in Variety" differ in their disciplinary backgrounds. One is a psychologist, another is a human factor engineer, and the others include a macroeconomist, sociologist, anthropologist, linguist, hospital administrator, and practicing physician. Members of Team "S – as in Separation" differ in their attitude toward a particular research paradigm. Half of the team's members revere richly descriptive, interpretive inquiry, the other half disparage it. Finally, the members of Team "D – as in Disparity" vary in their research eminence or rank. One member of the team is a highly-accomplished professor who is renowned for having formulated seminal theories of patient interactions with health care professionals; the other members of the team are getting their first behavioural science research experience.

Although diversity is obvious in all teams, the content and likely outcomes of diversity differ across the teams. In Team V, perceiving diversity as variety is based on differences in kind, source, or category of relevant experience and knowledge among a group of employees. In this example, team member diversity in disciplinary background reflects variety: together, team members bring a multiplicity of information sources to bear on the research question. In Team S, perceiving diversity as separation refers to differences in position or opinion on value, attitude, or belief among a group of employees. In this example, diversity in team members' endorsement of qualitative research reflects separation: team members hold opposing positions on a task- or team-relevant issue. Finally, in Team D, perceiving diversity as disparity is known as differences in socially valued assets or resources like status and salary among a group of employees, diversity is associated with disparity: one member of the team is superior to the other team members in research expertise, and presumably in status as well.

The three teams not only differ in the type of diversity they represent but also in the attribute of diversity present in each team (attitude toward disciplinary background, qualitative research and member prestige). Figure 5.1 provides a graphic illustration of these three types of diversity.

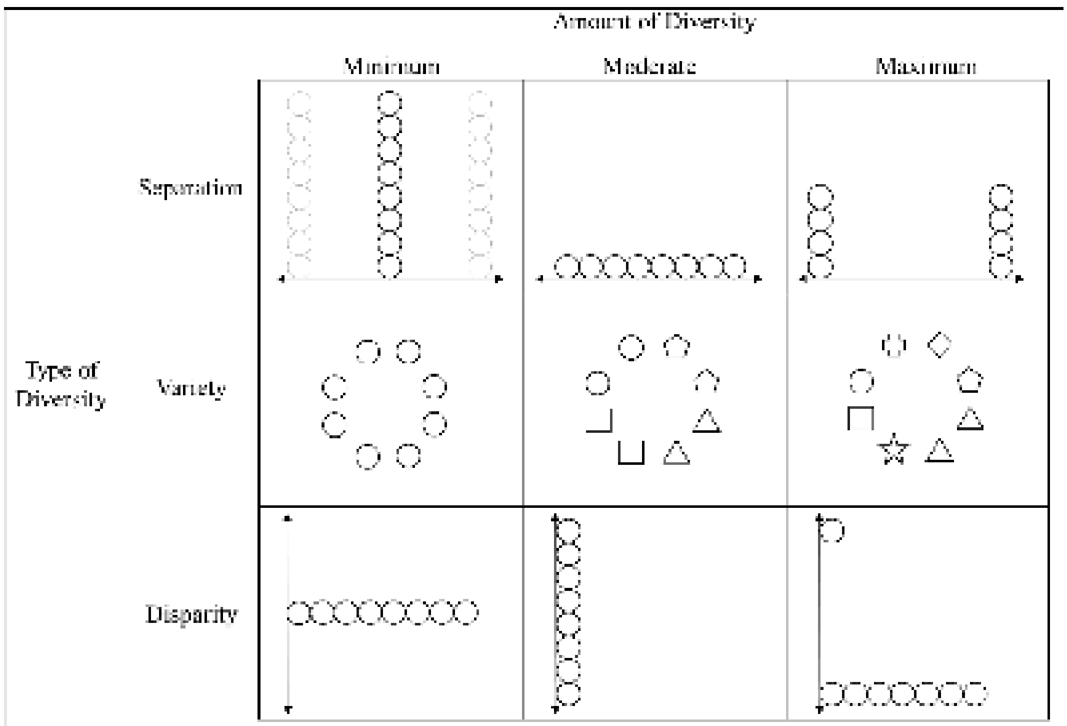

Figure 5.1 Pictorial representation of types of three meaning of diversity
Taken from Harrison & Klein (2007)

Additionally, diversity typology also has implications for research design. It can also lead to methodological errors and mistaken research conclusions. Table 5.1 below provides an explanation of the appropriate operationalization for each type of diversity (Harrison & Klein, 2007 ; Solanas et al., 2012).

Table 5.1 Operationalization of diversity type
Adapted from Harrison & Klein (2007)

Diversity Type	Index	Assumed Scale of Measurement
Separation	Standard Deviation	Interval
	$\sqrt{[\Sigma(S_i - S_{mean})^2/n]}$ (5.1)	
	Mean Euclidean Distance	Interval
	$\Sigma\sqrt{[\Sigma(S_i - S_j)^2/n]}/n$ (5.2)	
Variety	Blau's Diversity Index	Categorical
	$1 - \sum P_k^2$ (5.3)	
	Teachman (entropy)	Categorical
	$-\Sigma[p_k . ln(p_k)]$ (5.4)	
Disparity	Coefficient of Variation	Ratio
	$\sqrt{[\Sigma(D_i - D_{mean})^2/n]}/D_{mean}$ (5.5)	
	Gini Coefficient	Ratio
	$(\Sigma\lvert D_i - D_j\rvert)/(2. N^2. D_{mean})$ (5.6)	

Researchers often leave theoretical concepts about organizational demography unmeasured, through which they create a "black box" filled with non-tested and vague theories (Lawrence, 1997). A similar black box concept is also known in the context of Upper Echelon Theory. The majority of research in this area has used demographic variables as proxies for underlying cognitive capabilities and processes, thereby "black-boxing" cognitive variables of interest (Carpenter & Fredrickson, 2001 ; Levy, 2005).

However, similarities could be noticed between the diversity literature and Upper Echelon Theory. In diversity construct, it can be divided into the primary and secondary dimension (Loden & Rosener, 1990). The primary dimension is based on, for example, gender, sexual orientation, age, physical abilities/qualities, and ethnicity. Because these relatively unchanging aspects are very observable, this dimension can be regarded as extrinsic. Those are equivalent to the TMT observable demographics in the Upper Echelon Theory. The secondary dimension includes attributes like communication style, religion, geographical location, and work experience. This dimension can be described as intrinsic due to the less observable quality of the attributes. Which are equivalent to the team processes mechanism in the Upper Echelon Theory (including communication quality, communication frequency, social integration, inter dependence, and consensus).

While most of the recent diversity typologies literature is focused on employees at their unit (i.e., organization), utilizing those typologies could provide valuable extension in the context of the Upper Echelon Theory. It is acknowledged that the challenge with diversity is complicated due to many reasons (Harrison & Klein, 2007 ; Jackson & Ruderman, 1995 ; Solanas et al., 2012 ; Swart, 2010):

1. Few clear findings derived from scientific research;
2. Findings related to diversity are difficult to synthesize because diversity literature is highly variant for reasons such as:
   a. Varied theoretical perspectives used to guide diversity research;
   b. Few consistent findings and cumulative insights have emerged;
3. Most of the recent studies were constrained to descriptive analysis and thus no conclusions are made about the statistical properties of the indices as estimators.

However, it is suggested that the construct of diversity in the context of upper echelons requires closer examination and refinement. This distinction has been rarely addressed in TMT research (Boone & Hendriks, 2009). Therefore, future researchers in TMT studies are encouraged to no longer treat diversity as an overall measure. Each of the three typologies (Variety, Separation, and Disparity) could produce distinct outcomes. They could have different effects on an organization explained by organizational outcomes (Harrison & Klein, 2007). Such theoretical extension is believed to provide more attention to the structure of TMT to improve understanding of TMT processes.

5.1.2 Methodological Extensions

1. **Construction Industry Diversification**

The industry diversification has been controlled in this study; however, the consequence of diversifying can be examined for the individual firm with respect to its long-term growth or profit. Numerous studies both within and outside the construction management literature have sought to establish the impact of diversification on the performance of the firm. Even so, little agreement exists amongst researchers on the subject (Palich et al., 2000). Construction researchers generally support specialization rather than diversification. An investigation into the possible reasons for the differences in profitability between firms conducted by (Akintoye & Skitmore, 1991) showed that the degree and type of diversification is a major factor. Furthermore, there are several studies that show that a firm's institutional environment may affect the performance of its diversification efforts. Therefore, a natural extension of this study is for researchers to study and describe the variability of impact on organization outcome in terms of industry diversification. In the context of this study, the diversification can be established in different perspective:

a. Diversification of enterprise (i.e., being architect, engineer, a general contractor or with any other speciality);
b. Diversification in scope, following ENR categories (i.e., Architects, Engineer, Contractors, Environment, Geo-Technology, Landscaping, Planner and other specialties and subspecialties). It shall provide great understanding of the inherited variability within construction industry;
c. Diversification in terms of business areas such as: civil engineering, building, property development, estate development and construction product manufacture (David Langford & Male, 2001);
d. Diversification in terms of related businesses, such as: housing development, property development and material production (Ibrahim & Kaka, 2007);
e. Finally, diversification can be in terms of unrelated businesses, such as: forestry and logging, sales of motor vehicles, hotel and restaurant business, broadcasting and financial institutions (Cho, 2003).

Studying the different diversification in construction could provide better understating to the diversity extent within the industry, and the effect this has on the performance of the firm. Confirmatory Factor Analysis (CFA) can be used in that sense, e.g., (Daily, Johnson, & Dalton, 1999). CFA enables researchers to assess whether these disparate definitions constitute a single factor (i.e., one latent construct) (Certo et al., 2006);

2. **Temporal Lagging Structure**

Although past performance was controlled in this study (lagged two years' average of Return on Assets), a temporal order of measure structure should be also considered in future studies. Studies suggest a lagging structure of the data to allow enough time to assess the implications of change and to show the effect on firm's performance. Such structure is referred to as the Temporal Ordering of Measures (Levy, 2005).

Top Management Teams' decisions and actions (which reflect Top Management Teams' perspective of organizational output), is claimed to have an impact on firm performance after a period of time (Rivas, 2012). Researchers anticipate time lags in the relations among TMTs, strategic choices, and firm financial performance. For instance, the decision to include TMT members with international work experience in order to further internationalize firms' operations is unlikely to be immediately apparent in firms' financial performance. This relation is likely best tested over a period of several years (Certo et al., 2006). It is also argued that lagging is required to allow enough time for potential Top Management Team effects to manifest themselves as a group (Levy, 2005), and in recognition that the effects of top management on organizational outcomes are less than immediate. It will also ensure and avoid causality of the studied relation (Hambrick, 2007 ; B. B. Nielsen & Nielsen, 2013). Lagging structure is beneficial in many instances, those are:

a. To mitigate or control potential endogeneity problems, and to safeguard against a potential reverse causality (Rivas, 2012);
b. To allow time for governance features to reveal their impacts on strategic decisions (Carpenter & Fredrickson, 2001);

c. Will ensure that antecedent variables temporally precede the dependent variable (Hambrick, 2007).

Future studies may consider a lagging structure between input – output variables, however, the lagging structure differs in literature depending on the TMT tenure. Lag structure lagging period is usually determined by the average tenure for boards (Rivas, 2012 ; Wally & Becerra, 2001). In the context of this study, a cross-sectional data was used with a semi-lagged dependent variable (to control Past Performance) to derive the research results. A complete lagging structure could not be applied in this study due to the sample structure (sample is from different regions with different average TMT tenure) and limited accessibility to data. Therefore, future studies can incorporate a lagging concept in the analysis with more coherent sample;

3. **Selection of Variables**

Finally, another important limitation regarding operationalization of input and output variables involves the selection of those variables. TMT demographics is a central concept in this research theoretical assumptions and it is important to mention that by using the TMT diversity variable (i.e., input variables), the research did not measure the TMT performance directly (black box nature), but instead tried to capture those team characteristics that are with demographic representation. As suggested by (Hambrick, 2007), future research should attempt to develop a theoretical model, which can be tested to determine the effectiveness of team performance measures. The realization that team performance differs with demographic composition is an important first step to the development of such a theoretical model (Auden et al., 2006). This has led, within the Upper Echelon Theory, to a new line of inquiry proposing that organizational decisions and outcome cannot be explained by the composition of the TMT alone; the analysis also requires consideration of the processes and situations deriving from the relations among TMT members (Camelo et al., 2010).

5.2 Main Conclusion

Three levels of challenges are usually contributed to the complexity of Top Management Team studies. Some researchers consider diversity within TMTs is traditionally based on single characteristics, that is, they have examined the dispersion of individual members along one characteristic independently from others (Joshi & Roh, 2009). Others have considered that TMT as individuals have multiple attributes on which they may differ, and the diversity along multiple characteristics may interact and jointly influence team outcomes (Harrison & Klein, 2007). Moreover, the internal black box nature of TMT processes and interaction has added a third complexity level to studying executives in the context of organizational outcome. Previous literature has found conflict and inconsistent relations between Top Management Team demographics and organization performance. No single conclusion can be drawn from the literature on the exact effect of TMT on firm performance. Indeed, several studies have contributed to the overall appreciation of the Top Management Team influence on firm performance, however, previous studies clearly lack the elements of exploring the future predictability power of TMT. As stated in different literature, researchers studying upper echelon should change their approaches. They should examine the empirical regularities they have found. There is also a possibility that the Upper Echelons Theory might not have the degree of empirical support that its advocates express (Angriawan, 2009). Thus, this study is contributing to the debate of TMT diversity by using a multi-regional international AEC firms' dataset in the period from 2006 to 2014. The study has focused on exploring the forecasting dimensions of different TMT demographics on Organization outcome constructs.

The study overcomes the lack of previous research in the Upper Echelon Theory by considering TMT demographics and organization outcome are multi-dimensional constructs. Multi input (TMT demographics) – multi output (organization outcome) structures have been constructed, trained and tested. TMT demographics as explored in the literature and were measured by a mean of diversity between the members of the TMT (i.e., board members). On the other hand, the methodology has been designed to explore TMT demographics influence on each output variables. Each of the Organization Outcome constructs (short-term span: Profitability and Liquidity, medium term span: Cash Flow Stability and Capital Structure, and long-term span: External Satisfaction and Internal Satisfaction) has been forecasted separately by defining its specific input-output pairs (Step 1 of methodology). Afterwards, three forecasting strategies has been evaluated (Majority Vote Classifiers with and without boxplot, and time series model).

The research results generally support the study objectives, they suggest that composition of TMT can assist in forecasting some dimensions of organization outcome. The findings of this study highlight the importance of the composition of a firm's Top Management Team. A TMT is a bundle of attributes that includes a mixture of managerial talents, abilities and most importantly, demographics. These capabilities should not only complement each other, but also the envisage the future of organization outcome. Three main conclusions can be drawn from this research:

1. The results of fuzzy set theory have provided good forecasting results. More specifically, time series approach using ANFIS has provided better forecasting results than other two methods. The percentage of data points with accurate forecasting (above 90%) have been increased when applying ANFIS with longitudinal design. The other two strategies (Majority Vote Classifiers with and without boxplot) have provided lower accuracy results;

2. On the other hand, the research found that not all types of TMT demographics have the same forecasting power on organization outcome. Three of the studied TMT demographics (input variables) were good future predictors for organization outcome. As supported by literature, job-related demographics (explained in Section 4.7.2) were more useful in predicting the future of organization outcome. More specifically, TMT Educational Diversity, TMT Functional Diversity and TMT Tenure were type of demographics that could be useful in forecasting. To the contrary, non-job demographics (TMT Age Diversity and TMT Organizational Tenure) in addition to the Industry Experience appears not to provide useful forecasting tools;

3. The research has provided an operational concept for organization outcome in construction industry. Although outcomes with short and medium spans have been forecasted satisfactory (i.e., Liquidity, Cash Flow Stability and Capital Structure), Profitability and other long span outcome could not be forecasted with the same accuracy. The suggested operationalization is a multi-construct approach while those three un-predictable outcomes are with dynamic nature, hence, a different methodology would be required for their forecasting.

This research contributes to the management literature by providing an examination of the upper echelons impact on forecasting the organization outcome. The research results have confirmed the possibility of forecasting the future organization outcome in the context of TMT demographics. Moreover, with the results of this research, the suitability of soft-computing analysis tools to model the unknown structure of TMT demographics is examined. Because Multi Input – Multi Output (MIMO) systems typically have inherent nonlinear couplings and uncertainties, using traditional model-based solutions for MIMO problems results in a computational burden that increases exponentially with the number of variables (Huang & Yu, 2016). The main impetus for using ANFIS in the proposed framework comes from the fact that developed intellectual capital models use crisp values to measure knowledge assets. The context of the input variables in this research takes place under ambiguities, uncertainties, and vagueness. This challenge calls for a method that can adopt with unknown structures and inexact nature. Therefore, ANFIS is a convenient and flexible tool for dealing with such ambiguity, uncertainty, and vagueness.

A final important comment to be highlighted is the involvement of any moderating variable. TMT demographics is a central theoretical concept in this study, and to be able to measure the TMT impact directly, some moderating variables have not been introduced. The realization that TMT's influence may differ with demographic composition indicate that additional research is needed to include certain context of the TMT characteristics (more specifically the job-related demographic). Researcher may attempt to develop theoretical models, which consider different moderating variables at different levels (individuals, firm and regional levels).

All of these observations, together with the confirmation of study objectives provide motivation to continue deeply into the forecasting phenomenon of TMT demographics. It creates a fruitful opportunity for future researchers in order to solve the mentioned limitations and to achieve reliable empirical results within the literature of Top Management Teams, business forecasting and operationalization of organization outcome.

LIST OF REFERENCES

Abbasi, B., & Mahlooji, H. (2012). Improving response surface methodology by using artificial neural network and simulated annealing. *Expert Systems with Applications*, *39*(3), p.p. 3461-3468.

Abidin, N. Z., & Pasquire, C. L. (2007). Revolutionize value management: A mode towards sustainability. *International Journal of Project Management*, *25*(3), p.p. 275-282.

Abirami, S., Ramalingam, V., & Palanivel, S. (2013). Species classification of aquatic plants using PSVM and ANFIS. *Pattern Recognition and Image Analysis*, *23*(2), p.p. 278-286.

Akalu, M. M. (2001). Re-examining project appraisal and control: developing a focus on wealth creation. *International Journal of Project Management*, *19*(7), p.p. 375-383.

Akintoye, A. S., & Skitmore, M. R. (1991). Profitability of UK construction contractors. *Construction Management & Economics*, *9*(9), p.p. 311-325.

Alexopoulos, E. (2010). Introduction to Multivariate Regression Analysis. *Hippokratia*, *14*(Suppl 1), p.p. 23-8.

Allison, P. D. (1978). Measures of Inequality. *American Sociological Review*, *43*(6), p.p. 865-880.

Amirkhani, S., Nasirivatan, S., Kasaeian, A. B., & Hajinezhad, A. (2015). ANN and ANFIS models to predict the performance of solar chimney power plants. *Renewable Energy*, *83*, p.p. 597-607.

Angriawan, A. (2009). *Top Management Team Heterogeneities and Firm Performance: The Moderating Role of Board Composition*. Southern Illinois University Carbondale.

Asgari, M. sadat, Abbasi, A., & Alimohamadlou, M. (2016). Comparison of ANFIS and FAHP-FGP methods for supplier selection. *Kybernetes*, *45*(3), p.p. 474-489.

Athanassiou, N., & Douglas, N. (1999). The Impact of U.S. Company Internationalization on Top Management Team Advice Networks: A Tacit Knowledge Perspective. *Strategic Management Journal*, *20*(1), p.p. 83-92.

Athanassiou, N., & Nigh, D. (2000). Internationalization, Tacit Knowledge and the Top Management Teams of MNCs. *Journal of International Business Studies*, *31*(3), p.p. 471-487.

Atsalakis, G. S., Skiadas, C. H., & Braimis, I. (2007). Probability of trend prediction of exchange rate by ANFIS. Dans *XIIth Applied Stochastic Models and Data Analysis (ASMDA2007) International Conference*. Chania, Crete, Greece, p.p. 12-19.

Auden, W. C., Shackman, J. D., & Onken, M. H. (2006). Top management team, international risk management factor and firm performance. *Team Performance Management*, *12*(7/8), p.p. 209-224.

Azadeh, A., Asadzadeh, S. M., Saberi, M., Nadimi, V., Tajvidi, A., & Sheikalishahi, M. (2011). A Neuro-fuzzy-stochastic frontier analysis approach for long-term natural gas consumption forecasting and behavior analysis: The cases of Bahrain, Saudi Arabia, Syria, and UAE. *Applied Energy*, *88*(11), p.p. 3850-3859.

Azzone, G., Masella, C., & Bertele, U. (1991). Design of Performance Measures for Time-based Companies. *International Journal of Operations & Production Management*, *11*(3), p.p. 77-85.

Blau, P. (1977). *Inequality and Heterogeneity: A Primitive Theory of Social Structure*. (S.l.) : Free Press.

Boer, L. de, Labro, E., & Morlacchi, P. (2001). A review of methods supporting supplier selection. *European Journal of Purchasing and Supply Management*, *7*(2), p.p. 75-89.

Boone, C., & Hendriks, W. (2009). Top Management Team Diversity and Firm Performance: Moderators of Functional-Background and Locus-of-Control Diversity. *Management Science*, *55*(2), p.p. 165-180.

Brignall, T. J., Fitzgerald, L., Johnston, R., & Silvestro, R. (1991). Performance Measurement in Service Businesses. *Management Accounting*, *69*(10), p.p. 34-36.

Buragohain, M. (2008). *Adaptive Network based Fuzzy Inference System (ANFIS) as a Tool for System Identification with Special Emphasis on Training Data Minimization*. Indian Institute of Technology Guwahati.

Buragohain, M., & Mahanta, C. (2008). A novel approach for ANFIS modelling based on full factorial design. *Applied Soft Computing Journal*, *8*(1), 609-625.

Caligiuri, P., Lazarova, M., & Zehetbauer, S. (2004). Top managers' national diversity and boundary spanning: Attitudinal indicators of a firm's internationalization. *Journal of Management Development*, *23*(9), p.p. 848-859.

Camelo-Ordaz, C., Hernández-Lara, A. B., & Valle-Cabrera, R. (2005). The relationship between top management teams and innovative capacity in companies. *Journal of Management Development*, *24*(8), p.p. 683-705.

Camelo, C., Fernández-Alles, M., & Hernández, A. B. (2010). Strategic consensus, top management teams, and innovation performance. *International Journal of Manpower*, *31*(6), p.p. 678-695.

Cannella, A. A., Park, J. H., & Lee, H. U. (2008). Top Management Team Functional Background Diversity and Firm Performance: Examining the Roles of Team Member Colocation and Environmental Uncertainty. *Academy of Management Journal*, *51*(4), p.p. 768-784.

Carmeli, A., & Tishler, A. (2004). The Relationships between Intangible Organizational Elements and Organizational Performance. *Strategic Management Journal*, *25*(13), p.p. 1257-1278.

Carpenter, M. A. (2002). The Implications of Strategy and Social Context for the Relationship between Top Management Team Heterogeneity and Firm Performance. *Strategic Management Journal*, *23*(3), p.p. 275-284.

Carpenter, M. A., & Fredrickson, J. W. (2001). Top Management Teams, Global Strategic Posture, and the Moderating Role of Uncertainty. *The Academy of Management Journal*, *44*(3), p.p. 533-545.

Carpenter, M. A., Geletkanycz, M. A., & Sanders, W. G. (2004). Upper Echelon Research Revisited: Antecedents, Elements, and Consequences of Top Management Team Composition. *Journal of Management*, *30*(6), p.p. 749-778.

Caves, R. E. (1981). Diversification and Seller Concentration: Evidence From Changes, 1963-72. *The Review of Economics and Statistics*, *63*(2), p.p. 289-293.

Certo, S. T., Lester, R. H., Dalton, C. M., & Dalton, D. R. (2006). Top Management Teams, Strategy and Financial Performance: A Meta-Analytic Examination. *Journal of Management Studies*, *43*(4), p.p. 813-839.

Chang, B. R., & Tsai, H. F. (2009). Quantum minimization for adapting ANFIS outputs to its nonlinear generalized autoregressive conditional heteroscedasticity. *Applied Intelligence*, *31*(1), p.p. 31-46.

Chang, F. J., & Chang, Y. T. (2006). Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Advances in Water Resources*, *29*(1), p.p. 1-10.

Cheah, C. Y. J., Garvin, M. J., & Miller, J. B. (2004). Empirical Study of Strategic Performance of Global Construction Firms. *Journal of Construction and Engineering and Management*, *130*(6), p.p. 808-818.

Chen, B. (2014). *Automated On-line Fault Prognosis for Wind Turbine Monitoring using SCADA data*. Durham University.

Chen, H. L. (2011). Does Board Independence Influence the Top Management Team? Evidence from Strategic Decisions toward Internationalization. *Corporate Governance*, *19*(4), p.p. 334-350.

Chen, H. L. (2010). Using Financial and Macroeconomic Indicators to Forecast Sales of Large Development and Construction Firms. *Journal of Real Estate Finance and Economics*, *40*, p.p. 310-331.

Chen, M. Y. (2013). A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering. *Information Sciences*, *220*, p.p. 180-195.

Chen, M. S., Ying, L. C., & Pan, M. C. (2010). Forecasting tourist arrivals by using the adaptive network-based fuzzy inference system. *Expert Systems with Applications*, *37*(2), p.p. 1185-1191.

Cheng, P., Quek, C., & Mah, M. L. (2007). Predicting the Impact of Anticipatory Action on U.S. Stock Market—an Event Study Using Anfis (A Neural Fuzzy Model). *Computational Intelligence*, *23*(2), p.p. 117-141.

Chiang, H. T., & He, L. J. (2010). Board Supervision Capability and Information Transparency. *Corporate Governance*, *18*(1), p.p. 18-31.

Cho, Y. (2003). The organizational boundaries of housebuilding firms in Korea. *Construction Management and Economics*, *21*(7), p.p. 671-680.

Choi, J. (2014). Effects of Contract Announcements on the Value of Construction Firms. *Journal of Management in Engineering*, *30*(1), p.p. 86-96.

Choi, J., & Russell, J. S. (2005). Long-Term Entropy and Profitability Change of United States Public Construction Firms. *Journal of Management in Engineering*, *21*(1), p.p. 17-26.

Clark, E., & Soulsby, A. (2007). Understanding Top Management and Organizational Change Through Demographic and Processual Analysis. *Journal of Management Studies*, *44*(6), p.p. 932-954.

Daellenbach, U. S., McCarthy, A. M., & Schoenecker, T. S. (1999). Commitment to innovation: The impact of top management team characteristics. *R&D Management*, *29*(3), p.p. 199-208.

Dahlin, K. B., Weingart, L. R., & Hinds, P. J. (2005). Team Diversity and Information Use. *Academy of Management Journal*, *48*(6), p.p. 1107-1123.

Dahya, J., McConnell, J. J., & Travlos, N. G. (2002). The Cadbury Committee, Corporate Performance and Top Management Turnover. *The Journal of Finance*, *57*(1), p.p. 461-483.

Daily, C. M., Certo, S. T., & Dalton, D. R. (2000). International Experience in the Executive Suite: The path to Prosperity? *Strategic Management Journal*, *21*, p.p. 515-523.

Daily, C. M., Johnson, J. L., & Dalton, D. R. (1999). On the Measurements of Board Composition: Poor Consistency and a Serious Mismatch of Theory and Operationalization. *Decision Sciences*, *30*(1), p.p. 83-106.

Darmadi, S. (2013). Do women in top management affect firm performance? Evidence from Indonesia. *Corporate Governance: The international journal of business in societ, Emrland*, *13*(3), p.p. 288-304.

Deng, F., & Smyth, H. (2013). Contingency-Based Approach to Firm Performance in Construction : Critical Review of Empirical Research. *Journal of Construction Engineering and Management*, *139*(10), p.p. 1-14.

Deng, F., & Smyth, H. (2014). Nature of Firm Performance in Construction. *Journal of construction engineering and management*, *140*(March), p.p. 1-14.

Dess, G. G., & Beard, D. W. (1984). Dimensions of Organizational Task Environments. *Administrative Science Quarterly*, *29*(1), p.p. 52-73.

Devinney, T. M., Yip, G. S., & Johnson, G. (2010). Using Frontier Analysis to Evaluate Company Performance. *British Journal of Management*, *21*(4), p.p. 921-938.

Díaz-Fernández, M. C., González-Rodríguez, M. R., & Pawlak, M. (2014). Top management demographic characteristics and company performance. *Industrial Management & Data Systems*, *114*(3), p.p. 365-386.

Domowitz, I. (1988). Review: Elements of Econometrics. by Jan Kmenta. *Journal of the American Statistical Association*, *83*(401), p.p. 280-281.

Dote, Y., & Ovaska, S. J. (2001). Industrial Applications of Soft Computing: A Review. *Proceedings of the IEEE*, *89*(9), p.p. 1243-1264.

Dyson, B., & Chang, N. Bin. (2005). Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. *Waste Management*, *25*(7), p.p. 669-679.

Echanobe, J., Campo, I. del, & Bosque, G. (2008). An adaptive neuro-fuzzy system for efficient implementations. *Information Sciences*, *178*(9), p.p. 2150-2162.

Eisenhardt, K. M. (2013). Top management teams and the performance of entrepreneurial firms. *Small Business Economics*, *40*(4), p.p. 805-816.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic Capabilities: What are They? *Strategic Management Journal*, *21*, p.p. 1105-1121.

El-Mashaleh, M. S., Minchin, E. J., & O'Brien, W. J. (2007). Management of Construction Firm Performance Using Benchmarking. *Journal of Management in Engineering*, *23*(1), p.p. 10-17.

Fang, H. (2012). Adaptive Neurofuzzy Inference System in the Application of the Financial Crisis Forecast. *International Journal of Innovation, Management and Technology*, *3*(3), p.p. 250-254.

Finkelstein, S., Hambrick, D., & C. (1990). Top-Management-Team Tenure and Organizational Outcomes: The Moderating Role of Managerial Discretion. *Administrative Science Quarterly*, *35*(3), p.p. 484-503.

Finkelstein, S., & Hambrick, D. C. (1996). *Strategic Leadership: Top Executives and Their Effects on Organizations* (1st Editio). (S.l.) : South-Western College Pub.

Finkelstein, S., Hambrick, D. C., & Cannella, A. A. (2009). *Strategic Leadership: Theory and Research on Executives, Top Management Teams, and Boards (Strategic Management)* (1st Editio). (S.l.) : Oxford University Press Inc.

Frangouli, Z. (2002). Capital Structure, Product Differentiation and Monopoly Power: A Panel Method Approach. *Managerial Finance*, *28*(5), p.p. 59-65.

Funsten, B. T. (2015). *ECG Classification with an Adaptive Neuro-Fuzzy Inference System*. California Polytechnic State University.

Giovanis, E. (2010). A Study of Panel Logit Model and Adaptive Neuro-Fuzzy Inference System in the Prediction of Financial Distress Periods. *International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*, *4*(4), p.p. 423-429.

Gladstein, D. L. (1984). Groups in Context: A Model of Task Group Effectiveness. *Administrative Science Quarterly*, *29*(4), p.p. 499-517.

Glunk, U., Heijltjes, M. G., & Olie, R. (2001). Design Characteristics and Functioning of Top Management Teams in Europe. *European Management Journal*, *19*(3), p.p. 291-300.

Gunz, H. P., & Jalland, R. M. (1996). Managerial Careers and Business Strategies. *The Academy of Management Review*, *21*(3), p.p. 718-756.

Hagan, M. T., Demuth, H. B., Beale, M. H., & Jesus, O. De. (1995). *Neural Network Design*. *Boston Massachusetts PWS* (2nd Editio). (S.l.) : OVERHEADS and DEMONSTRATION PROGRAMS (eBook).

Haleblian, J., & Finkelstein, S. (1993). Top Management Team Size, CEO Dominance, and Firm Performance: The Moderating Roles of Environmental Turbulence and Discretion. *The Academy of Management Journal*, *36*(4), p.p. 844-863.

Hambrick, D. C. . (2007). Upper Echelons Theory: An Update. *Academy of Management Review*, *32*(2), p.p. 334-343.

Hambrick, D. C., Cho, T. S., & Chen, M. (1996). The Influence of Top Management Team Heterogeneity on Firms' Competitive Moves. *Administrative Science Quarterly*, *41*(4), p.p. 659-684.

Hambrick, D. C., & Finkelstein, S. (1987). Managerial discretion: A bridge between polar views of organizational outcomes. *Research in Organizational Behavior*, *9*, p.p. 369-406.

Hambrick, D. C., Finkelstein, S., & Mooney, A. C. (2005). Executive Job Demands: New Insights for Explaining Strategic Decisions and Leader Behaviors. *The Academy of Management Review*, *30*(3), p.p. 472-491.

Hambrick, D. C., & Mason, P. A. (1984). Upper Echelons: The Organization as a Reflection of Its Top Managers. *Academy of Management Review*, *9*(2), p.p. 193-206.

Harrison, D. A., & Klein, K. J. (2007). What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organiztions. *Academy of Management Review*, *32*(4), p.p. 1199-1228.

Haykin, S. (1999). *Neural networks: A Comprehensive Foundation* (2nd Editio). (S.l.) : Pearson Education (Singapore) Pte. Ltd.

Herrmann, P., & Datta, D. K. (2005). Relationships between Top Management Team Characteristics and International Diversification: an Empirical Investigation. *British Journal of Management*, *16*(1), p.p. 69-78.

Hill, C. W. L., Hitt, M. A., & Hoskisson, R. E. (1992). Cooperative versus Competitive Structures in Related and Unrelated Diversified Firms. *Organization Science*, *3*(4), p.p. 501-521.

Hill, C. W. L., & Hoskisson, R. E. (1987). Strategy and Structure in the Multiproduct Firm. *The Academy of Management Review*, *12*(2), p.p. 331-341.

Hillier, D., Grinblatt, M., & Titman, S. (2011). *Financial Markets and Corporate Strategy* (European e). (S.l.) : McGraw Hill Higher Education.

Ho, D. C. W., Chan, E. H. W., Wong, N. Y., & Chan, M. (2000). Significant metrics for facilities management benchmarking in the Asia Pacific region. *Facilities*, *18*(13/14), p.p. 545-556.

Huang, C. N., & Yu, C.-C. (2016). Integration of Taguchi's method and multiple-input, multiple-output ANFIS inverse model for the optimal design of a water-cooled condenser. *Applied Thermal Engineering*, *98*, p.p. 605-609.

Hutzschenreuter, T., & Horstkotte, J. (2013). Performance Effects of Top Management Team Demographic Faultlines in the Process of Prodcut Diversification. *Strategic Management Journal*, *34*, p.p. 704-726.

Ibrahim, Y. M., & Kaka, A. P. (2007). The impact of diversification on the performance of UK construction firms. *Journal of Financial Management of Property and Construction*, *12*(2), p.p. 73-86.

Imandoust, S. B., & Bolandraftar, M. (2013). Application of K-Nearest Neighbor (KNN) Approach for Predicting Economic Events: Theoretical Background. *International Journal of Engineering Research and Applications*, *3*(5), p.p. 605-610.

Jackson, S. E. (1992). Consequences of Group Composition for the Interpersonal Dynamics of Strategic Issue Processing. *Advances in Strategic Management*, *8*, p.p. 345-382.

Jackson, S. E., & Ruderman, M. N. (1995). Introduction: Perspectives for understanding diverse work teams. American Psychological Association.

James, G. (1998). *Majority Vote Classifiers: Theory and Applications*. Stanford University.

Jang, J. S. R. (1993). ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man and Cybernetics*, *23*(3), p.p. 665-685.

Jin, Z., Deng, F., Li, H., & Skitmore, M. (2013). Practical Framework for Measuring Performance of International Construction Firms. *Journal of Construction Engineering and Management*, *139*(9), p.p. 1154-1167.

Joshi, A., & Roh, H. (2009). The Role of Context in Work Team Diversity Research: A Meta-Analytic Review. *Academy of Management Journal*, *52*(3), p.p. 599-627.

Joyce, W. F., & Slocum, J. W. (2012). Top management talent, strategic capabilities, and firm performance. *Organizational Dynamics*, *41*(3), p.p. 183-193.

Kaka, A., & Lewis, J. (2003). Development of a company-level dynamic cash flow forecasting model (DYCAFF). *Construction Management and Economics*, *21*, p.p. 693-705.

Kale, S., & Arditi, D. (1999). Age-dependent business failures in the US construction industry. *Construction Management and Economics*, *17*, p.p. 493-503.

Kale, S., & Arditi, D. (2002). Competitive Positioning in United States Construction Industry. *Journal of Construction Engineering and Management*, *128*(3), p.p. 238-247.

Kale, S., & Arditi, D. (2003). Differentiation, Conformity, and Construction Firm Performance. *Journal of Management in Engineering*, *19*(2), p.p. 52-59.

Kangari, R. (1988). Business Failure in Construction Industry. *Journal of Construction Engineering and Management*, *114*(2), p.p. 172-190.

Kaplan, R. S., & Norton, D. P. (1992). The Balanced Scorecard Measures That Drive Performance. *Harvard Business Review*, *70*(1), p.p. 71-79.

Katsanis, C. J. (1998). *An Empirical Examination of the Relationships Between Strategy, Structure and Performance in Building Industry Organizations*. University of Montreal.

Katzenbach, J. R. (1997). The Myth of the Top Management Team. *Harvard business review*, *75*(6), p.p. 82-91.

Kennerley, M., & Neely, A. (2002). A framework of the factors affecting the evolution of performance measurement systems. *International Journal of Operations & Production Management*, *22*(11), p.p. 1222-1245.

Khan, S. A., Lederer, A. L., & Mirchandani, D. A. (2013). Top Management Support, Collective Mindfulness, and Information Systems Performance. *Journal of International Technology & Information Management*, *22*, p.p. 95-123.

Kharb, R. K., Ansari, F., & Shimi, S. L. (2014). Design and Implementation of ANFIS based MPPT Scheme with Open Loop Boost Converter for Solar PV Module. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, *3*(1), p.p. 6517-6524.

Khoshnevisan, B., Rafiee, S., Omid, M., & Mousazadeh, H. (2014). Development of an intelligent system based on ANFIS for predicting wheat grain yield on the basis of energy inputs. *Information Processing in Agriculture*, *1*, p.p. 14-22.

Kim, A., & Arditi, D. (2010). Performance of MBE/DBE/WBE Construction Firms in Transportation Projects. *Journal of Construction Engineering and Management*, *136*(7), p.p. 768-777.

Knight, D., Pearce, C. L., Smith, K. G., Olian, J. D., Sims, H. P., Smith, K. A., & Flood, P. (1999). Top Management Team Diversity, Group Process, and Strategic Consensus. *Strategic Management Journal*, *20*(5), p.p. 445-465.

Kor, Y. Y. (2003). Experience-Based Top Management Team Competence and Sustained Growth. *Organization Science*, *14*(6), p.p. 707-719.

Kuo, R. J., Hong, S. Y., & Huang, Y. C. (2010). Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection. *Applied Mathematical Modelling*, *34*, p.p. 3976-3990.

Lam, L., & Suen, C. Y. (1997). Application of Majority Voting to Pattern Recognition: An Analysis of Its Behavior and Performance. *IEEE Transactions on Systems Man and Cybernetics Part A Systems and Humans*, *27*(5), p.p. 553-568.

Langford, D., Iyagba, R., & Komba, D. M. (1993). Prediction of solvency in construction companies. *Construction Management and Economics*, *11*, p.p. 317-325.

Langford, D., & Male, S. (2001). *Strategic Management in Construction* (2nd Editio). (S.l.) : Blackwell Science Ltd.

Lau, D. C., & Murnighan, J. K. (1998). Demographic Diversity and Faultlines : The Compositional Dynamics of Organizational Groups. *The Academy of Management Review*, *23*(2), p.p. 325-340.

Lawrence, B. S. (1997). The Black Box of Organizational Demography. *Organization Science*, *8*(1), p.p. 1-22.

Lee, H.., & Park, J. H. (2006). Top Team Diversity, Internationalization and the Mediating Effect of International Alliances. *British Journal of Management*, *17*, p.p. 195-213.

Levy, O. (2005). The influence of top management team attention patterns on global strategic posture of firms. *Journal of Organizational Behavior*, *26*(7), p.p. 797-819.

Lin, G., & Shen, Q. (2007). Measuring the Performance of Value Management Studies in Construction: Critical Review. *Journal of Management in Engineering*, *23*(1), p.p. 2-9.

Lin, Y. H., & Ho, S. P. (2013). Impacts of Governance Structure Strategies on the Performance of Construction Joint Ventures. *Journal of Construction Engineering and Management*, *139*(3), p.p. 304-311.

Loden, M., & Rosener, J. (1990). *Workforce America!: Managing Employee Diversity as a Vital Resource* (1st Editio). (S.l.) : McGraw-Hill Education.

Lutfy, O. F., Noor, S. M., & Marhaban, M. H. (2011). A simplified adaptive neuro-fuzzy inference system (ANFIS) controller trained by genetic algorithm to control nonlinear multi-input multi-output systems. *Scientific Research and Essays*, *6*(31), p.p. 6475-6486.

Markides, C. C., & Williamson, P. J. (1994). Related Diversification, Core Competencies and Corporate Performance. *Strategic Management Journal*, *15*, p.p. 149-165.

Marlin, D., Lamont, B. T., & Geiger, S. W. (2004). Diversification Strategy and Top Management Team Fit. *Journal of Managerial Issues*, *16*(3), p.p. 361-381.

Miller, T., & Triana, M. del C. (2009). Demographic Diversity in the Boardroom: Mediators of the Board Diversity–Firm Performance Relationship. *Journal of Management Studies*, *46*(5), p.p. 755-786.

Milliken, F. J., & Martins, L. L. (1996). Searching for Common Threads: Understanding the Multiple Effects of Diversity in Organizational Groups. *The Academy of Management Review*, *21*(2), p.p. 402-433.

Mombeini, H., & Yazdani-Chamzini, A. (2014). Developing a new approach for forecasting the trends of oil price. *The Business & Management Review*, *4*(3), p.p. 120-132.

Muscettola, M. (2014). Probability of Default Estimation for Construction Firms. *International Business Research*, *7*(11), p.p. 153-164.

Najah, A., El-Shafie, A., Karim, O. A., & El-Shafie, A. H. (2014). Performance of ANFIS versus MLP-NN dissolved oxygen prediction models in water quality monitoring. *Environmental Science and Pollution Research*, *21*, p.p. 1658-1670.

Naranjo-Gil, D., Hartmann, F., & Maas, V. S. (2008). Top Management Team Heterogeneity, Strategic Change and Operational Performance. *British Journal of Management*, *19*, p.p. 222-234.

Negnevitsky, M. (2005). *Artificial Intelligence: A Guide to Intelligent Systems* (2nd Edition). (S.l.) : Pearson Education Limited. Repéré à www.pearsoned.co.uk

Newnan, D. G., Eschenbach, T. G., & Lavelle, J. P. (2004). *Engineering Economics Analysis* (Ninth Edit). (S.l.) : Oxford University Press Inc.

Nielsen, B. B., & Nielsen, S. (2013). Top Management Team Nationality Diversity and Firm Performance: A Multilevel Study. *Strategic Management Journal*, *34*, p.p. 373-382.

Nielsen, K. R. (2006). Risk Management: Lessons from Six Continents. *Journal of Management in Engineering*, *22*(2), p.p. 61-67.

Nielsen, S. (2009). Why do top management teams look the way they do? A multilevel exploration of the antecedents of TMT heterogeneity. *Strategic Organization*, *7*(3), p.p. 277-305.

Nielsen, S. (2010). Top Management Team Internationalization and Firm Performance: The Mediating Role of Foreign Market Entry. *Management International Review*, *50*, p.p. 185-206.

Norburn, D. (1986). Gogos, yoyos and dodos: Company directors and industry performance. *Strategic Management Journal*, *7*(2), p.p. 101-117.

Norburn, D. (1989). The Chief Executive Officer: A Breed Apart. *Strategic Management Journal*, *10*(1), p.p. 1-15.

Norburn, D., & Birley, S. (1988). The Top Management Team and Corporate Performance. *Strategic Management Journal*, *9*(3), p.p. 225-237.

O'Reilly, C. A., Caldwell, D. F., & Barnett, W. P. (1989). Work Group Demography, Social Integration, and Turnover. *Administrative Science Quarterly*, *34*(1), p.p. 21-37.

Özkan, G., & İnal, M. (2014). Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. *Applied Soft Computing*, *24*, p.p. 232-238.

Palich, L. E., Cardinal, L. B., & Miller, C. C. (2000). Curvilinearity in the Diversification-Performance Linkage: An Examination of over Three Decades of Research. *Strategic Management Journal*, *21*(2), p.p. 155-174.

Pegels, C. C., & Yang, B. (2000). The impact of managerial characteristics on strategic assets management capabilities. *Team Performance Management: An International Journal*, *6*(5/6), p.p. 97-107.

Pelled, L. H. (1996). Demographic Diversity, Conflict, and Work Group Outcomes: An Intervening Process Theory. *Organization Science*, *7*(6), p.p. 615-631.

Pereira, J. (2014). Survival Analysis Employed in Predicting Corporate Failure: A Forecasting Model Proposal. *International Business Research*, *7*(5), p.p. 9-20.

Petković, D., Ab Hamid, S. H., Ćojbašić, Ž., & Pavlović, N. T. (2014). Adapting project management method and ANFIS strategy for variables selection and analyzing wind turbine wake effect. *Natural Hazards*, *74*, p.p. 463-475.

Pfeffer, J. (1983). Organizational demography. *Research in Organizational Behavior*, *5*, p.p. 299-357.

Phua, F. T. T. (2007). Does senior executives' perception of environmental uncertainty affect the strategic functions of construction firms? *International Journal of Project Management*, *25*, p.p. 753-761.

Piramuthu, S. (1999). Theory and Methodology: Financial credit-risk evaluation with neural and neurofuzzy systems. *European Journal of Operational Research*, *112*, p.p. 310-321.

Pitcher, P., & Smith, A. D. (2001). Top Management Team Heterogeneity: Personality, Power, and Proxies. *Organization Science*, *12*(1), p.p. 1-18.

Prahalad, C. K., & Bettis, R. A. (1986). The Dominant Logic: a New Linkage Between Diversity and Performance. *Strategic Management Journal*, *7*(6), p.p. 485-501.

Rajagopalan, N., & Rajagopalan, N. (2004). When the Known Devil Is Better Than an Unknown God: An Empirical Study of the Antecedents and Consequences of Relay CEO Successions. *Academy of Management Journal*, *47*(4), p.p. 483-500.

Rebeiz, K. S., & Salameh, Z. S. (2006). Relationship between Governance Structure and Financial Performance in Construction. *Journal of Management in Engineering*, *22*(1), p.p. 20-26.

Reeb, D., Kwok, C. C. Y., & Baek, H. Y. (1998). Systematic Risk of the Multinational Corporation. *Journal of International Business Studies*, *29*(2), p.p. 263-279.

Richard, P. J., Devinney, T. M., Yip, G. S., & Johnson, G. (2009). Measuring Organizational Performance: Towards Methodological Best Practice. *Journal of Management*, *35*(3), p.p. 718-804.

Rivas, J. L. (2012). Diversity & internationalization: The case of boards and TMT's. *International Business Review*, *21*, p.p. 1-12.

Ruigrok, W., Georgakakis, D., & Greve, P. (2013). Regionalization strategy and performance: The moderating role of industry dynamism and top management team diversity. *Multinational Business Review*, *21*(1), p.p. 6-24.

Rustum, R. (2009). *Modelling Activated Sludge Wastewater Treatment Plants Using Artificial Intelligence Techniques (Fuzzy Logic and Neural Networks)*. Heriot-Watt University School.

Saghaei, A., & Didehkhani, H. (2011). Developing an integrated model for the evaluation and selection of six sigma projects based on ANFIS and fuzzy goal programming. *Expert Systems with Applications*, *38*, p.p. 721-728.

Sanders, N. R. (1995). Managing the forecasting function. *Industrial Management & Data Systems*, *95*(4), p.p. 12-18.

Scherer, F. M., & Ross, D. (1980). *Industrial Market Structure and Economic Performance* (2nd Revise). (S.l.) : Houghton Mifflin.

Seaden, G., Guolla, M., Doutriaux, J., & Nash, J. (2003). Strategic decisions and innovation in construction firms. *Construction Management and Economics*, *21*, p.p. 603-612.

Sedighi, M., Keyvanloo, K., & Towfighi, J. (2011). Modeling of Thermal Cracking of Heavy Liquid Hydrocarbon: Application of Kinetic Modeling, Artificial Neural Network, and Neuro-Fuzzy Models. *Industrial & Engineering Chemistry Research*, *50*, p.p. 1536-1547.

Simons, T., Pelled, L. H., & Smith, K. A. (1999). Making Use of Difference: Diversity, Debate, and Decision Comprehensiveness in Top Management Teams. *The Academy of Management Journal*, *42*(6), p.p. 662-673.

Simsek, Z., Veiga, J. F., Lubatkin, M. H., & Dino, R. N. (2005). Modeling the Multilevel Determinants of Top Management Team Behavioral Integration. *The Academy of Management Journal*, *48*(1), p.p. 69-84.

Solanas, A., Selvam, R. M., Navarro, J., & Leiva, D. (2012). Some Common Indices of Group Diversity: Upper Boundaries. Dans *Proceedings of Measuring Behavior 2012 (Utrecht, The Netherlands, August 28-31, 2012)*, p.p. 412-413.

Srijariya, W., Riewpaiboon, A., & Chaikledkaew, U. (2008). System Dynamic Modeling: An Alternative Method for Budgeting. *International Society for Pharmacoeconomics and Outcome Research*, *11*(1), p.p. 115-123.

Srivastava, A., & Lee, H. (2008). Firm performance and top management team age, tenure, and education: a research synthesis. *International Journal of Business Research*, *8*(2), p.p. 1-8.

Stalk, G., Evans, P., & Shulman, L. E. (1992). Connpeting on Capabilities: The New Rules of Corporate Strategy. *Harvard Business Review*, *70*(2), p.p. 57-69.

Stovall, J. F. (2005). *Not-for-Profit Top Management Team Dynamics: Understanding the Top Management Team Potency-Performance Relationship*. Claremont Graduate University.

Swart, E. De. (2010). *Variety, Separation, and Disparity: three typologies to understand employee diversity-An empirical study on employees' perceived diversity and the effects of diversity in the Leisure industry*. Tilburg University.

Teece, D. J. (1980). Economies of Scope and the Scope of the Enterprise. *Journal of Economic Behavior and Organization*, *1*, p.p. 223-247.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), p.p. 509-533.

Terzi, Ö., Keskin, M. E., & Taylan, E. D. (2006). Estimating Evaporation Using ANFIS. *Journal of Irrigation and Drainage Engineering*, *132*(5), p.p. 503-507.

Tihanyi, L., Ellstrand, A., Daily, C., & Dalton, D. (2000). Composition of the Top Management Team and Firm International Diversification. *Journal of Management*, *26*(6), p.p. 1157-1177.

Vahdani, B., Iranmanesh, S. H., Mousavi, S. M., & Abdollahzade, M. (2012). A locally linear neuro-fuzzy model for supplier selection in cosmetics industry. *Applied Mathematical Modelling*, *36*, p.p. 4714-4727.

Valizadeh, N., & El-Shafie, A. (2013). Forecasting the Level of Reservoirs Using Multiple Input Fuzzification in ANFIS. *Water Resources Management*, *27*, p.p. 3319-3331.

Venkatraman, N., & Ramanujam, V. (1986). Measurement of Business Performance in Strategy Research: A Comparison of Approaches. *The Academy of Management Review*, *11*(4), p.p. 801-814.

Venkatraman, N., & Ramanujam, V. (1987). Measurement of Business Economic Performance: An Examination of Method Convergence. *Journal of Management*, *13*(1), p.p. 109-122.

Vorasubin, P., & Chareonngam, C. (2007). Strategic assets driving financial capability of Thai construction firms. *Journal of Financial Management of Property and Construction*, *12*(2), p.p. 87-94.

Wally, S., & Becerra, M. (2001). Top Management Team Characteristics and Strategic Changes in International Diversification: The Case of U.S. Multinationals in the European Community. *Group & Organization Management*, *26*(2), p.p. 165-188.

Wang, F. K., Chang, K. K., & Tzeng, C. W. (2011). Using adaptive network-based fuzzy inference system to forecast automobile sales. *Expert Systems with Applications*, *38*(8), p.p. 10587-10593.

Wethyavivorn, P., Charoenngam, C., & Teerajetgul, W. (2009). Strategic Assets Driving Organizational Capabilities of Thai Construction Firms. *Journal of Construction Engineering and Management*, *135*(11), p.p. 1222-1231.

Wiersema, M. F., & Bird, A. (1993). Organizational Demography in Japanese Firms: Group Heterogeneity, Individual Dissimilarity, and Top Management Team Turnover. *The Academy of Management Journal*, *36*(5), p.p. 996-1025.

Williams, K. Y., & O'Reilly, C. A. (1998). Demography and Diversity in Organizations: A Review of 40 Years off Research. *Research in Organizational Behavior*, *20*, p.p. 77-140.

Wu, H. L. (2008). How do Board-CEO Relationships Influence the Performance of New Product Introduction? Moving from Single to Interdependent Explanations. *Corporate Governance*, *16*(2), p.p. 77-89.

Yang, J. (2010). *Intelligent Data Mining using Artificial Neural Networks and Genetic Algorithms: Techniques and Applications*. University of Warwick.

Yee, C. Y., & Cheah, C. Y. J. (2006). Interactions between Business and Financial Strategies of Large Engineering and Construction Firms. *Journal of Management in Engineering*, *22*(3), p.p. 148-156.

Yip, G. S., Devinney, T. M., & Johnson, G. (2009). Measuring Long Term Superior Performance: The UK's Long-Term Superior Performers 1984-2003. *Long Range Planning*, *42*(3), p.p. 390-413.

Zadeh, L. A. (1965). Fuzzy Sets. *Information and Control*, *8*, p.p. 338-353.

Zadeh, L. A. (1994). Fuzzy logic, neural networks, and soft computing. *Communications of the ACM*, *37*(3), p.p. 77-84.

Zanganeh, T., Rabiee, M., & Zarei, M. (2011). Applying Adaptive Neuro-Fuzzy Model for Bankruptcy Prediction. *International Journal of Computer Applications*, *20*(3), p.p. 15-21.

Zhang, Y., Chai, T., & Wang, H. (2011). A Nonlinear Control Method Based on ANFIS and Multiple Models for a Class of SISO Nonlinear Systems and Its Application. *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council*, *22*(11), p.p. 1783-1795.

Zhang, Y., Chai, T., Wang, H., Fu, J., Zhang, L., & Wang, Y. (2010). An Adaptive Generalized Predictive Control Method for Nonlinear Systems Based on ANFIS and Multiple Models. *IEEE Transactions on Fuzzy Systems*, *18*(6), p.p. 1070-1082.