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This thesis consists of three original articles, as well as the introduction, literature review, discussion and conclusion chapters. The articles are listed below with a brief description of each article and the author's contribution with publication details. In this research, a framework created for estimating the construction project duration with respect to the weather risk and the problems of estimation tools for construction projects are reviewed. In the following papers, a Navigational Support System (NSS) is introduced to help decision makers to monitor and control the performance of projects as a generic engine. Finally, it is applied to the field of construction projects for validating the proposed artefact (NSS).

Paper I

> Marzoughi, F., Arthanari, T.S, & Askarani, D (2017). 'A decision support framework to estimate project duration under impact of weather'- Accepted in the Journal of Automation in Construction (A* according to ABDC Journal ranking)

In this paper, we proposed a decision support (DS) framework that incorporates weather related factors for the purpose of estimating the duration of projects. Inclement weather can have a serious effect on construction projects, particularly with regard to duration and costs. The weather has an impact on human resource productivity, supplier effectiveness and material damage, which can, in turn, affect the duration of a construction project. The proposed five-module framework integrates weather variables, project performance variables and project activity duration. This framework uses expert knowledge about the importance of weather variables: pairwise comparisons of weather variables with respect to different performance criteria, and, similarly, pairwise comparisons of performance variables with respect to project activities. A model based on this framework using multivariate statistical techniques and an analytical network process (ANP) is developed to estimate the duration of project activity, taking into account the impact of weather. The proposed model is illustrated with data from a construction project in Iran. Validation of the model is provided by comparing the actual duration of an activity from similar construction projects with the estimated duration using the proposed framework.

As the first author, Foad Marzoughi has done the literature review, created the framework data collection and written this article, with contributions coming from the co-author, Associate Professor Tiru Arthanari, who is the main supervisor for the doctoral project, and who clarified the framework, editorial matters and expository writings on the tools and concepts used.

Paper II

> Marzoughi, F., & Arthanari, T. (2017). 'Designing a navigational support system – a generic engine for monitoring and controlling project performance' – Extended version of 'Architecture of navigational support system' presented at AMCIS 2016 (Marzoughi & Arthanari, 2016)

In this paper, we propose a decision support system (DSS) as a generic engine called Navigational Support System (NSS) for monitoring and controlling project performance. The NSS aims to help project managers to realise where the project performance is, at any given time by considering the correlation between key performance indicators (KPIs) in a multidimensional space. Moreover, it supports the decision maker's choices to achieve their targets by taking sound actions during the execution phase. An effective monitoring and controlling system can improve project progress to achieve its benchmark targets. Conversely, inadequate performance measurement systems can diminish project progress and can cause delays and cost overruns which are common among all projects around the globe. The proposed 4-module framework uses expert knowledge about the importance of project performance variables, a historical database related to levels of project performance, a historical database related to the level of best practice performance, and expert knowledge regarding different actions taken in various situations. We assume that all of these data are available. To create the NSS, we integrated multivariate measurement systems and a dynamic decision-making tool. Finally, the NSS was tested and evaluated in the construction project field, in the follow-up research: Paper III.

As the first author, Foad Marzoughi has taken the lead in writing this article and implemented the generic engine for the navigational support system. The second author, Associate Professor Tiru Arthanari, proposed a paper based on the idea of navigating in benchmark space; he helped in the conceptual integration of modules and in editing at different stages.

Paper III

Marzoughi, F., & Arthanari, T. S. (2017). 'Application of navigational support system to monitor and control project performance in the construction industry'- Extended version of 'A conceptual framework for a navigational support system for construction projects' presented at ProjMAN 2016 (Marzoughi & Arthanari, 2016)

In this paper, the navigational support system is applied to the field of construction projects. Paper II illustrates the modular design of the NSS, and in Paper III all modules were tested with a real case from construction projects. By applying the NSS in the construction field [1], the most important key performance indicators (KPIs) of the construction project are identified, [2] the benchmark space is created based on the selected KPIs, [3] the project performance is measured in relation to benchmark targets taking into consideration the correlation between KPIs, and [4] finally, it handles the decision-making process by the use of a dynamic model of project performance to support project managers and to choose corrective actions due to uncertainty in projects.

The first author, Foad Marzoughi, applied the generic engine developed in paper II to the construction project navigation in the benchmark space of the project performance. The second author, Associate Professor Tiru Arthanari, contributed to the conceptual development of the relevant benchmark space and ensured the artefact is validated adequately, apart from helping in editorial matters.

Abbreviations

AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BPP	Benchmark Project Performance
BS	Behind Schedule
BSC	Balanced Scorecard
CBA	Cost Benefit Analysis
CCS	Critical Chain Scheduling
CII	Construction Industry Institute
CPM	Critical Path Method
CRAN	Comprehensive R Archive Network
CV	Charge Customers Extra for Any Type of Variations
DBSC	Dynamic Balanced Scorecard
DDMM	Dynamic Decision-Making Module
DEM	Duration Estimation Module
DS	Decision Support
DSR	Design Science Research
DSS	Decision Support System

ED	Euclidean Distance
EKM	Expert Knowledge Module
ES	Exponential Smoothing
EVA	Earned Value Analysis
EVMS	Earn Value Management System
FM	Filtration Module
GPS	Global Positioning System
HNL	Hire New Labour
HQ	High Quality
HS	High Safety
IM	Inject Money
KPIs	Key Performance Indicators
LQ	Low Quality
LS	Low Safety
LWT	Labour Worked Over Time
MA	Moving Average
MCDM	Multi-Criteria Decision Module
MD	Mahalanobis Distance
MD-DSSs	Model Driven Decision Support Systems
MDP	Markov Decision Process
NSS	Navigational Support System
OC	Over Cost
OLAP	Online Analytical Processing

OPP	Ongoing Project Performance
PCA	Principal Component Analysis
PERT	Programme Evaluation and Review Technique
PNET	Probabilistic Network Evaluation Technique
SPCA	Sparse Principal Component Analysis
SS	Stochastic S-curves
WB	Within Budget
WFM	Weather Filtration Module
WS	Within Schedule

1. Introduction

This thesis focuses on research to create a decision support framework to estimate project duration, taking into account the effect of weather on project performance and creating a Navigational Support System (NSS) as a generic engine, aiming to monitor and control project performance. The main contributions of this research are it [1] introduces an approach for estimating weather impact on the duration of construction activities as a decision support framework, [2] creates a novel decision support system to control and monitor project/organization performance and support the decision-making process for improving the performance of the project/organization, and [3] evaluates and tests the NSS in a real case from the construction industry.

The remainder of this chapter is organised as follows: the background problem that has motivated this research is provided in Section 1.1. Then Section 1.2-1.4 provide the nature of the construction projects, causes of delay in construction projects and the deficiencies of current performance measurement systems. Section 1.5 states the aims and objectives of doing this research. Section 1.6 provides a description of the navigational paradigm. Section 2 provides the research methodology adopted in this research. In section 3 all techniques applied in this research to create frameworks is discussed. Then, a graphical overview of papers positioned in this thesis is given. Sections of 4, 5 and 6 present Paper I, II, and III respectively. Section 7 is related to discussion and conclusion. Finally, in Section 8 the future work is recommended.

1.1 Background Problem

In the construction industry, most projects do not finish on time or within budget. For example, according to property brokers and financial institutions in India, 40% of new homes could not be delivered to the buyers in the first quarter of 2013 because of massive construction delays. In addition, around 450,000 residential units under construction in India are likely to be delivered 18 months late (Khan & Teja Sharma, 2013).

Similarly, more than 90% of construction projects by MARA (the biggest company undertaking construction projects in Malaysia) were not delivered on time (Memon et al., 2012). Research in 2012 in Malaysia found that 92% of construction projects did not meet their goals. The delays in delivering construction projects were between 5% and 10% over the duration. Similarly, in Malaysia, in terms of cost, only around 11% of construction projects were completed on budget, with 89% over-running by 5 to 10% of the agreed price (Memon et al., 2012).

In many countries, such as Ghana, the United Arab Emirates and Iran, construction delay is a major problem in the construction industry (Agyakwah-Baah & Fugar, 2010; Asnaashari, Knight, & Farahani, 2009; Makkah, 2013; Motaleb & Kishk, 2010). According to Pires, Teixeira, and Moura (2007), most construction projects with a value of more than 10 million Euros had a 40% delay in expected delivery times, a 14% budget overrun and important non-compliance issues related to quality. In construction projects, there are risk factors that affect project performance and cause delays (Ghosh & Jintanapakanont, 2004). According to, the top three most important factors that cause time overruns in public construction projects are government delay (around 32%), inclement weather (23%), and design changes (18%).

In many construction activities, weather is responsible for adverse effects such as stoppages, productivity loss, cost overruns and delays (S. A. Assaf & Al-Hejji, 2006; Aziz, 2013; Doloi, Sawhney, Iyer, & Rentala, 2012; Sambasivan & Soon, 2007). Among various weather conditions, rainfall and hot and cold weather are regarded as the major factors that affect building construction activities (Joseph L, 2005). Many construction activities are highly sensitive to rainfall as this can reduce productivity (during the rainfall) and affect construction activities for several days afterwards. Extreme hot and dry weather can also affect human productivity (for example, due to the significance of thermal discomfort) (Koehn & Brown, 1985), and the time needed to complete other aspects of construction activities which are sensitive to weather (weather sensitive activity), such as the delivery of materials, masonry, mortar, paint, seals and sealant, equipment and so on (Joseph L, 2005). While considerable work has been done to find the risk factors that affect the time and cost of construction projects, research that enables us to design a decision support framework to forecast the duration of construction activities due to severe weather is scant. Hence, developing a decision support framework for construction projects to estimate the duration of each activity (with respect to weather risk) is vital for project scheduling to overcome time delays in construction projects and increase the project performance.

Inaccurate estimating of project duration affects project performance; however, poor controlling and monitoring of a project is another factor that causes poor performance. Accordingly, one of the main challenges for project managers is to diagnose the performance of projects with respect to agreed Key Performance Indicators (KPI) (benchmark targets) (Acebes et al., 2014; Al-Tmeemy, Hassen, Abdul-Rahman, & Harun, 2011; Y. Chen et al., 2012). The dynamic and complex nature of projects, especially construction projects (Ford, Lyneis, & Taylor, 2007), makes it difficult for project managers to understand where project performance is, with respect to benchmark targets (Acebes et al., 2014). Although some performance measurement systems are used to measure the performance of projects, most of the time they are not implemented successfully (Franceschini et al., 2007) due to inflexibility, their static nature and lack of dynamic decision making. The statistics of project management failure in different industries in New Zealand are illustrated in Figure 1-1:

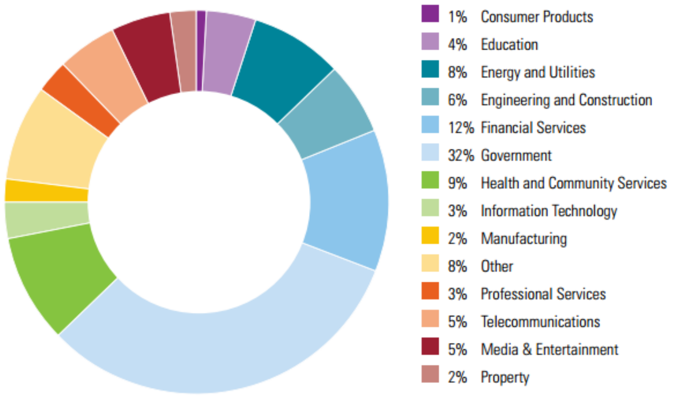

Figure 1-1 Statistics of project management failure in New Zealand (KPMG, 2010)

Due to the problems mentioned above, it is necessary for project managers to have a reliable computer system to monitor and control project performance so they know where project performance is, and where it will be. We will continue our discussion on the current nature of construction projects, the factors that cause project delay and problems of performance measurement systems.

1.2 Construction Project Behaviour

1.2.1 Nature of Construction Projects

Construction projects and the industry itself by nature are complex due to dynamic and indeterminate factors (João, Paulo, & Elísio, 2013), such as technology, budgets and development processes. This aspect of construction projects creates difficulties for even the best project managers in meeting project objectives (Duy Nguyen, Ogunlana, & Xuan, 2004). The dynamic environment of projects includes moving targets and high rates of technology changes daily or weekly. According to Collyer and Warren (2009), dynamism in projects decreases both speed and flexibility by increasing the amount of re-work required. Thus, project managers should reconsider demand for speed and flexibility in order to compensate for dynamism. Decision making should be rapid to take corrective action in time to exploit fleeting opportunities (Collyer & Warren, 2009). The long duration of projects means that there are changes in the scope, project targets, and specifications by the owner, work schedules, and other things. Adjustment or cancellation of construction projects after initiating construction is very costly, and such projects may not lend themselves to the same levels of experimentation or change.

A successful project will finish without delay, within budget and in accordance with stakeholders' expectations. A construction project has multiple stakeholders, like contractors, client/owner, consultants and designers. Thus, project success depends on their perspectives and objectives related to a variety of elements including technical, financial, educational, social and professional issues (Sanvido, Grobler, Parfitt, Guvenis, & Coyle, 1992). Moreover, satisfying all parties of a construction project is a very difficult task. Project success is very subjective (Al-Tmeemy et al., 2011; Cooke Davies, 2002; Ika, 2009; Molenaar, Javernick-Will, Bastias, Wardwell, & Saller, 2013). For example, a project at the time of execution may be regarded as a failure if it exceeds time and cost or if a fatal accident occurs. However, a project may be regarded as successful in the longer term if it brings development to the area, better employment and prosperity in terms of an increase in property values and better living conditions. Nevertheless, a project deemed successful at the time of execution may be seen as a failure at the time of production/occupation (Jha Kumar, 2013). It has been argued (Cooke Davies, 2002) that project success can be measured only when a project finishes. However, project performance can be measured during the progress of the project. C. Chua and Lim (2009) argued that "even though the levels of several critical success factors were weak, the project nevertheless succeeded". There is a distinction between project success and project management success. Project success is measured against the overall objective of the project, while project management success is measured against measures of performance like cost, time and quality (De Wit, 1988).

Enshassi, Mohamed, and Abushaban (2009) observed that many construction projects fail in terms of performance because of a lack of monitoring, controlling and decision-making systems, which would enable project managers to make reliable decisions based on the current performance.

Of course, success has different meanings to different stakeholders in construction projects. For example, "an architect may consider success in terms of aesthetic appearance, an engineer in terms of technical competence, an accountant in terms of dollars spent under budget, and a human resources manager in terms of employee satisfaction" (Koelmans, 2004). Achieving project success is a highly critical issue for companies surviving in a competitive environment (Neringa, Laima, & Audrius, 2013).

1.2.2 Causes of Delays in Construction Projects

Much research has been done since 1980 to identify the factors that cause delays in construction projects (Jyh-Bin, Mei-Yi, & Huang, 2013). From previous studies, factors that cause delays in construction projects can be categorized into various groups. Some of the most important factors that cause delay in construction projects are: improper interruptions, lack of resources caused by contractors during the drawing phase, financial difficulties and changes to orders (Le-Hoai, Lee, & Lee, 2008).

On the other hand, uncertainties, such as earthquakes and ongoing seismic activity (Anne, 2011), floods, hurricanes, wind damage and fires cause delays in construction projects. These kinds of uncertainties are called “Acts of God” or environmental factors (Jyh-Bin et al., 2013).

After the earthquake in Christchurch, New Zealand in 2011, most of the construction projects were cancelled or suspended (Anne, 2011). Moreover, earthquakes can cause delays in construction projects of neighbouring countries. For instance, after several earthquakes happened in Iran in 2013, a majority of construction projects in Dubai faced delays because the government made project managers consider the safety of buildings against earthquakes (Lucy, 2013).

From 41 studies of construction projects around the world published between 1995 and 2012, the factors that cause delay in construction projects are classified into 18 groups (Table 1-1).

Table 1-1 Factors that cause delays in construction projects

Category No.	Category name	References
1	Finance related	(S. Assaf, Al-Khalil, & Al-Hazmi, 1995; Ramanathan, Narayanan, & Idrus, 2012)
2	Project related	(S. A. Assaf & Al-Hejji, 2006; Ramanathan et al., 2012)
3	Project attributes	(Duy Nguyen et al., 2004)
4	Owner/client-related	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002)
5	Contractor related	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002)
6	Consultant related	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002; Ramanathan et al., 2012)
7	Design related	(S. A. Assaf & Al-Hejji, 2006)
8	Coordination	(Duy Nguyen et al., 2004)
9	Materials	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002)
10	Plant/equipment	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002)
11	Labour	(S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002)
12	Environment	(S. Assaf et al., 1995; S. A. Assaf & Al-Hejji, 2006; Odeh & Battaineh, 2002; Sambasivan & Soon, 2007)
13	Contract	(Odeh & Battaineh, 2002)
14	Contractual relationship	(S. Assaf et al., 1995)
15	External	(S. A. Assaf & Al-Hejji, 2006)
16	Changes	(S. A. Assaf & Al-Hejji, 2006; Sambasivan & Soon, 2007)
17	Scheduling and control	(S. Assaf et al., 1995)
18	Government relationship	(S. Assaf et al., 1995)

1.2.3 Effects of Delays

According to previous studies, a delay in a construction project is defined as exceeding the completion time of the construction project with respect to the agreed time in the contract (S. A. Assaf & Al-Hejji, 2006). Moreover, the causes of construction project delays vary from faults and weakness of contractors, owner/clients, consultants and designers (internal causes), to environmental problems, government, and others (external causes) (Haseeb, Xinhai, Aneesa, Maloof, & Wahab, 2011). Delays caused by any of the four stakeholders may affect project success in terms of cost, time, quality and safety. For example, they can cause late completion, lost productivity, increased cost and contract cancellation (Arditi & Pattanakitchamroon, 2006).

From international studies, the most important effects of delay in construction projects can be divided into seven groups (Haseeb et al., 2011; Sambasivan & Soon, 2007) as shown in Figure 1-2.

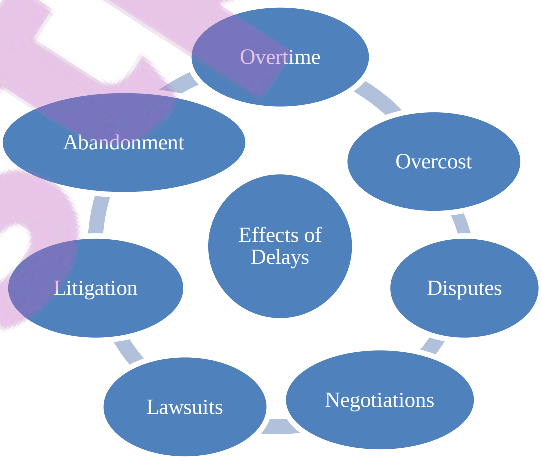

Figure 1-2 Effects of delays in construction projects (Haseeb et al., 2011)

All seven factors in Figure 1-2, frequently happen in building projects (Aibinu & Jagboro, 2002). In other words, delays in construction projects have a significant effect on increasing the duration of projects. Moreover, extra expenses are incurred during the delay period caused by overruns.

A lot of research has been done to discover the main factors that cause cost and time overruns in construction projects. The factors that cause cost and time overruns are financial factors, parties' lack of experience, lack of quality project managers, incomplete design at time of tender, changes, lack of cost planning/monitoring during pre- and post-contract stages, poor condition of the site, adjustment of prime costs and provisional sums, and so on (Kaming, 1997).

For example, faults in the design phase make design teams spend extra time correcting the errors, which cause cost overruns (Ambituuni, 2011). Similarly, design without comprehensive investigation of the site can lead to errors in design. Another factor that causes time and cost overruns is scope change (Singh, 2009). Scope changes significantly impact the budget, schedule and quality of work. An additional factor is inappropriate and inadequate procurement and faulty contractual management systems (Ambituuni, 2011; Singh, 2009). Lack of experienced contractors with the technical capability to handle the project also lead to cost overruns, time overruns and poor quality. The fourth important factor is the complexity of the project. The last factor that causes cost and time overrun is slow termination, such as late changes in orders, poor close-out of final account, poor documentation of project success and slow client acceptance (Ambituuni, 2011).

Cost overruns in construction projects are a very common problem. In many developing countries, the actual construction project cost exceeds 100% of the planned cost (Serdar, Syuhaida, & Nooh, 2012). Serdar et al. (2012) and (Ambituuni, 2011) presented the sub-factors that cause cost overruns in construction projects, which are listed in Table 1-2:

Table 1-2 Prioritized sub-factors that cause cost overruns in construction projects (Serdar et al., 2012)

Sub-factors of Financial Factors	Sub-factors of Project management factors	Sub-factors of External factors
High cost of needed resources; **High land prices;** **Cost of the Reworks;** **Inadequate Project Finance;** **Improper use and waste of materials on site;** **Inappropriate Government Policies;** **Litigation costs.**	Improper planning; inaccurate project cost estimation; Lack of coordination between parties; Inadequate duration of contract period; Lack of communication between parties; Poor on-site management; Cost overruns arising from design changes; inadequate site investigations; inadequate construction method; Wrong method of cost estimation.	Soil conditions; Site location and environment; Inclement weather; On-site accidents.

1.3 Criteria to Measure Construction Project Success

Construction project success is an abstract term; it is problematic to say if a project was a success or failure (A. Chan, Scott, & Lam, 2002). A previous study in the late 1990s found the most important factors to evaluate the success of project management are time, cost, and quality, which are called the iron triangle (Figure 1-3) (Atkinson, 1999).

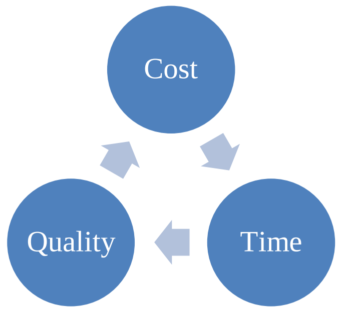

Figure 1-3 The iron triangle (Atkinson, 1999)

Time, quality and cost are the principal feasible objectives of the client that should be monitored and controlled in the life cycle of a construction project. The objectives of a construction project are not independent, but intricately related to each other (Rezaian, 2011). Project managers are responsible to balance these three most important targets (time, cost and quality).

1.3.1 Cost

Cost traditionally means the price of making goods or performing services (Rezaian, 2011). Cost has a direct effect on efficiency. Efficiency in a construction project means transforming input to output at the lowest cost. All construction companies try to reduce the cost of projects to benefit their shareholders. Total investments, costs of operations (services) and costs of maintenance are some cost factors in construction projects that should be monitored and controlled during the project's life (W. Yu, Baoyin, & Wang, 2008).

1.3.2 Time

Time management is a key factor to project success in the construction industry. Construction companies need to reduce the time to completion of projects and response to customers. According to Rezaian (2011), a time target includes three dimensions in any organization: time of new product and service development, time of response to the customer, and time of product delivery. In other words, there is a high correlation between customer satisfaction, and time of response to customers and delivery time of products.

1.3.3 Quality

The quality aim in construction projects consists of unity of work quality, project quality and the final quality of project functions, products or services (W. Yu et al., 2008). Quality involves safety and technological standards. Construction quality consists of quality of materials and equipment, quality of each part of the construction, and quality of the entire construction. Operation quality consists of quality of functions, products, services, reliability of operations and services, safety of operations and maintenance. The quality target in construction projects is to increase customer satisfaction and productivity, and decrease the cost of construction (Rezaian, 2011).

Performance measurement criteria change over time in the construction industry. According to a framework developed by Toor and Ogunlana (2010), there are other important performance indicators, such as safety, efficient use of resources, effectiveness, satisfaction of stakeholders, and reduced conflicts and disputes, as illustrated in Figure 2-3. Moreover, some have argued that the iron triangle may be too simplistic to measure the performance of construction projects in today's construction industry (Pheng & Chuan, 2006). These authors highlighted customer satisfaction as an important criterion for project evaluation, time, cost, quality, team member relations, function and aesthetics. In other words, the success of project management cannot be restricted to the three principal factors of the iron triangle. According to Table 1-3, the components of project success can be project management success or product success, or both.

Project success is divided into three main groups: project characteristic-related factors, organizational variables, and job-condition related variables.

Table 1-3 Important working environment factors (Pheng & Chuan, 2006)

Ranking	Working Environment variable	Group of factors affecting Project success
1	Team relationship	(Project characteristic-related factors)
2	Availability of information	(Job-condition related variables)
3	Type of client	(Organizational variables)
4	Time availability	(Project characteristic-related factors)
5	Salary	(Job-condition related variables)
6	Complexity of project	(Project characteristic-related factors)
7	Project size	(Project characteristic-related factors)
8	Job satisfaction	(Job-condition related variables)
9	Project environment	(Job condition-related variables)
10	Level of authority	(Organizational variables)
11	Materials and supplies	(Project characteristic-related factors)
12	Duration of project	(Project characteristic-related factors)
13	Working hours	(Job-condition related variables)
14	Company size	(Organizational variables)
15	Job security	(Job-condition related variables)

Project success models can be grouped into two viewpoints: macro level and micro level (Long, Ogunlana, Quang, & Lam, 2004; Toor & Ogunlana, 2010). On the macro level, the project should be on time and on budget, with efficient use of resources. On the other hand, the micro view point is concerned with the satisfaction of construction stakeholders, such as consultants and contractors.

Figure 1-4 shows how the model for performance measurement of construction projects has changed from the iron triangle (time, cost, quality) measures towards a mix of quantitative and qualitative measures, such as safety, minimization of disputes, stakeholders' expectations, sustainability, operational flexibility, maintainability and energy efficiency (Toor & Ogunlana, 2010).

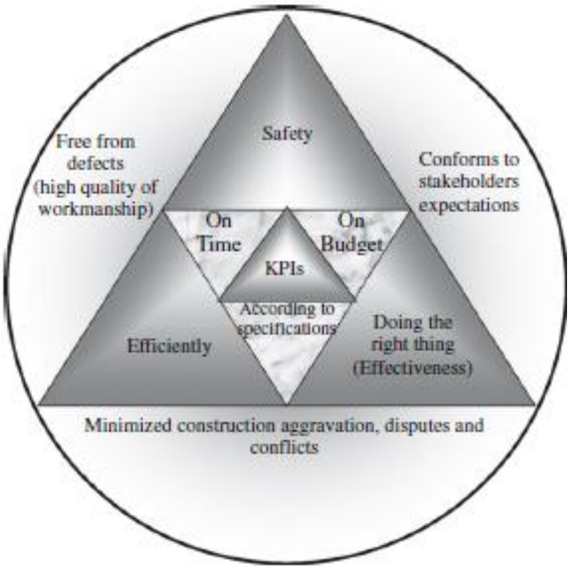

Figure 1-4 Performance measurement criteria for construction projects (Toor & Ogunlana, 2010)

According to Al-Tmeemy et al. (2011), project success is a strategic management concept achieved when both the short- and long-term goals of companies align with project efforts. Project success depends on several factors and comes from several categories: project related, manager related, contractor related, project management team/team related, external, institutional and client related. Furthermore, each of these factors consists of several sub-factors. As such, construction projects can vary greatly as they are influenced by unpredictable factors. Figure 1-5 shows the most recent critical success factors for construction projects.

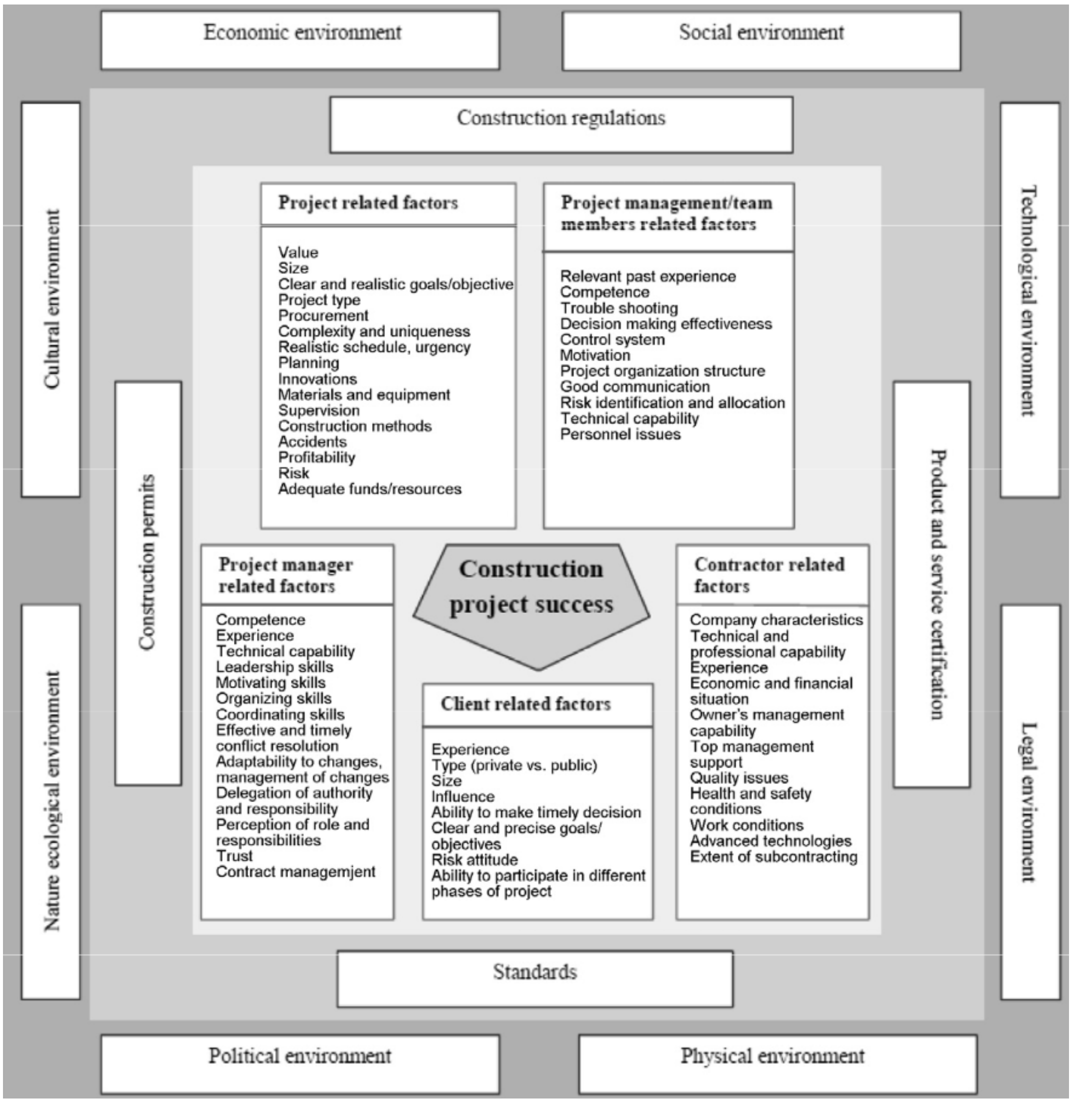

Figure 1-5 Critical success factors for construction projects (Neringa et al., 2013)

Project success factors are not independent, but are correlated with each other (Lehtiranta, Kärnä, Junnonen, & Julin, 2012). For example, if a project manager wants a project to be delivered with high quality and fast, then the cost will be increased. If a project is to be fast and cheap, then the quality will be compromised, and if a project is to be delivered with high quality and cheaply, then it will take more time to complete (Karen Young, 2010; Ko & Cheng, 2007). Neringa et al. (2013) suggested that there is a correlation between the sub-factors so the underlying relationship between them should be considered for identifying the effects on benchmark space (project success). Finding the interrelationships among critical success factors helps project managers to control the key factors and lets them make rational resource allocations (Y. Chen et al., 2012).

1.3.4 Dynamic Behaviour of Construction Projects

Due to the dynamic nature of construction projects (Collyer & Warren, 2009), a system dynamic approach is used for strategic decision making by construction management executives (Chritamara, Ogunlana, & Bach, 2002). System dynamics is a methodology for understanding the behaviour of complex systems over time through multiple feedback loops. A causality (cause and effect) link between variables is considered as positive and negative, represented by plus and minus signs. A plus sign between two factors represents a tendency to move in the same direction of change, and a negative sign depicts that they tend to move in the opposite direction. Similarly, there are two types of feedback loop: negative and positive. A negative feedback loop processes a stabilized system or describes goal-seeking processes that generate actions aimed to move a system to a desired state. The positive feedback loop processes a destabilized system and moves the system to a growth or decline state (Forrester, 1961). Dynamic modelling is widely practised in construction management (Chritamara et al., 2002). From beginning to completion, project management in construction involves different processes, parties and variables that interact and affect each other in varying degrees. Some of these critical success factors are controllable during the construction process, such as delays in design phase, significant changes in design, and lack of owner information. On the other hand, some of the variables are uncontrollable, such as economic conditions, environmental factors and unforeseen factors (Chritamara et al., 2002).

For example, if a project is behind schedule, management can take some combination of actions, such as applying pressure on project staff to work quicker, having staff work overtime, or hiring more staff; these measures aim to get the project back on track. However, while these actions improve the time performance, they may negatively affect the cost and quality performance. For example, having overtime work leads to increased fatigue, working faster increases the rate of errors, and having additional staff can reduce short- and long-term productivity due to the time needed for training new staff.

Moreover, by adjusting targets like extending a deadline or reducing the scope of the project, performance can be brought back on track (Ford et al., 2007). There are five important variables that control the dynamics of a construction project: scope of the employer's requirement, procurement progress, financial inflow, design progress and construction progress (Chritamara et al., 2002). These factors are connected to each other and have impacts on each other. From the system dynamic models of construction projects, some policies emerge that increase the performance of construction projects in terms of time and cost reduction. The dynamic behaviour of the factors mentioned can be seen in Figure 1-6.

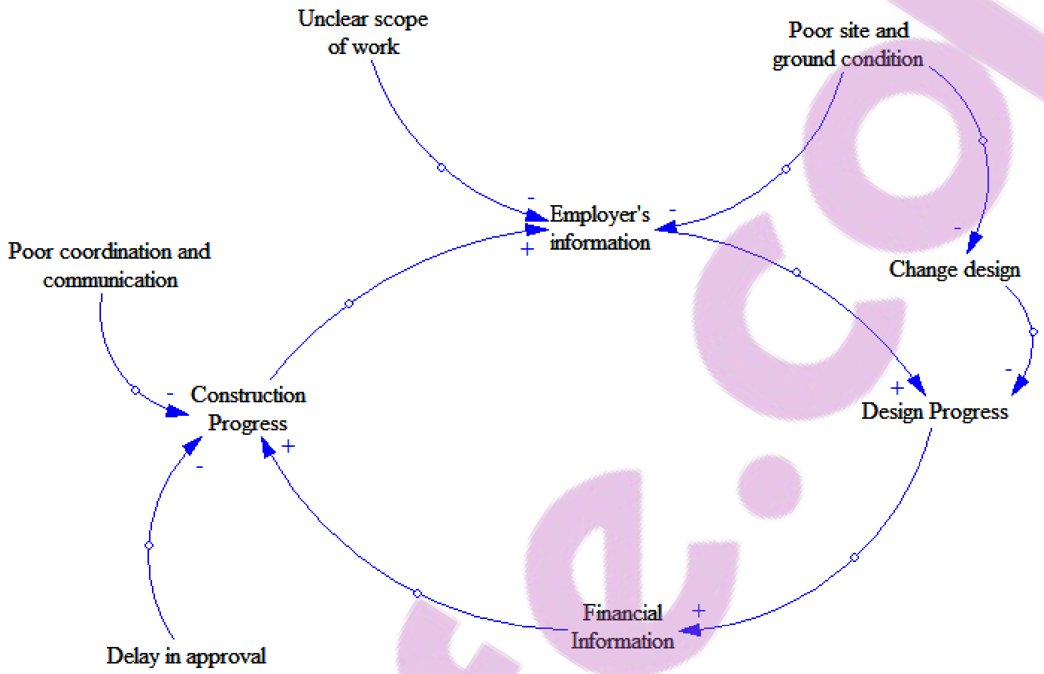

Figure 1-6 Feedback structure of work in progress in a construction project (Chritamara et al., 2002)

For example, in the material management system, the amount of materials in storage depends on the required material usage and the desirable inventory level. Material adjustment is made based on design information, financial information and the adjustment of materials on site. Sometimes materials do not arrive on time when they are required. They are delayed due to the long lead time required to produce and transport them (Chritamara et al., 2002). In the field of material handling policies, (Chritamara et al., 2002)found that material ordering based on average use is the most appropriate for improving project performance. This is because it can help to smooth the construction process while reducing both acquisition and inventory costs. To be more effective, however, the value of the average material use needs to be carefully estimated.

1.4 Current Tools for Monitoring and Controlling Project Performance

1.4.1 Defining Performance Measurement

In the previous section, the difficulties in defining success and failure of a project were discussed. The process of assessing performance with respect to a defined goal is called performance measurement. This identifies where the project is and where it is going (Kenneth, 1995). Measuring performance can show the status and direction of a project (T. Hillman & William, 1996)**.** In other words, a business tool for assessing management performance, managing human resources, and formulating corporate strategy is performance measurement (I. Yu, Kim, Jung, & Chin, 2007).

It is also true that without a measurement and evaluation tool, improvement in performance cannot be achieved. According to Cooke Davies (2002), criteria for managing performance are called success factors which lead to project success. A lot of research has been done in the construction industry to identify the success factors that lead to the success of a construction project. Performance measurement is a critical issue for project success in a competitive environment. However, though there are some similarities in activities and stages in construction projects, every project is considered unique because there are differences in the design and size of each project (Wegelius-Lehtonen, 2001).

Another issue which is very important is that all the stakeholders in construction projects, such as architects, structural and mechanical engineers, contractors and sub-contractors, assess the construction process from their own point of view (Wegelius-Lehtonen, 2001). According to Wegelius-Lehtonen (2001) performance measures consist of two different groups. The first one is improvement measures and the second one is monitoring measures. The goal of improvement measures is to find out the current level of performance and the improvement potential.

1.4.2 Dimensions of Performance

Project success in construction depends on several different factors, such as project complexity, contractual agreements, relationship between project participants, the ability of project managers, and the ability of key project team members: architects, quantity surveyors, and engineers. (Baker, Murphy, & Fisher, 2008; S. O. Cheung, Suen, & Cheung, 2004; D. Chua, Kog, & Loh, 1999; Mohsini & Colin, 1992). In total, eight categories of project performance measure were identified in construction projects: cost, time, quality, safety, health, environment, client satisfaction and communication (S. O. Cheung et al., 2004). In addition, it is suggested that by making a system that can be adopted as an industry platform, benchmarking can be achieved (S. O. Cheung et al., 2004) and a measurement system should be dynamic to identify what should be measured tomorrow (Kennerley & Neely, 2002).

According to Beatham, Anumba, Thorpe, and Hedges (2004), there are several criteria for measuring performance: meeting budget, schedule, the quality of workmanship, stakeholder satisfaction, transfer of technology, and health and safety. A. Chan and Tam (2000) found some more components that should be considered: environmental performance, user expectation/satisfaction, actor satisfaction and commercial value (A. Chan & Tam, 2000).

1.4.3 Key Performance Indicators (KPIs) in Construction Projects

The purpose of key performance indicators (KPIs) in the construction project is to assess the performance of construction operations (Cox, Issa, & Ahrens, 2003). These measures are used for benchmarking and navigating projects to achieve benchmark targets (Raynsford, 2000). KPIs are tools to monitor and control organizational performance, to increase quality and conduct benchmarking (Radujković, Vukomanović, & Dunović, 2010).

The KPI framework is divided into two levels: project level, and organization or company level. KPIs at the project level include construction cost, construction time, predictability cost, predictability time, defects, client satisfaction with product, and client satisfaction with service. The organization level KPIs are safety, profitability and productivity.

Table 1-4 Construction key performance indicators

Construction Key Performance Indicators (KPIs)	**(Keith et al., 2012)**	**(Radujković et al., 2010)**	**(Egan, 1998)**
1	Economic indicators	Quality	Construction cost
2	Client satisfaction	Cost (material, labour, equipment, waste)	Construction time
3	Defects	Number of investors' interference	Defects
4	Predictability cost – project	Changes in project support	Client satisfaction (product)
5	Predictability cost – design	Time increase	Client satisfaction (service)
6	Predictability of time – design	Client satisfaction	Profitability
7	Predictability of time – project	Employees' satisfaction	Productivity
8	Profitability	Innovation and learning	Safety
9	Productivity	Time (on time milestone completion)	Time predictability
10	People indicator	Identifications of client interest	Cost predictability (design)
11	Environmental indicators		Time predictability (design)
12			Cost predictability

Performance indicators are measures to assess the progress of the project during its implementation (Gayatri & Saurabh, 2013). Key performance indicators in construction (Table 1-4) are shown key performance indicators for the construction projects such as economic indicators, defects, productivity, material cost, labour cost and safety.

According to Cox et al. (2003) Key performance indicators in construction projects are divided into quantitative indicators, such as units/labour hour, $/units, resource management, cost, on-time completion, quality control/rework, percentage complete, earned labour hour, lost time accounting, punch list reporting, and qualitative indicators like worker behaviour on the job, safety, absenteeism, motivation and turnover

Another classification of KPIs in construction projects is between results-oriented and process-oriented. Results-oriented indicators are construction costs, construction time, defects, client satisfaction, profitability and productivity. Process-oriented KPIs are the predictability of the design cost and time, and predictability of construction costs and time, and safety (Roshana & Akintola, 2002).

1.4.4 Balanced Scorecard

Balanced Scorecard (BSC) was introduced as a performance measurement framework by R. S. Kaplan and Norton (1992) with four different perspectives: financial, customer, internal processes and innovation (see Figure 1-7). A good BSC consists of leading (performance drivers) and lagging (outcomes) measures, and indicators. Lagging measures tell what has happened and leading measures forecast what will happen in the future. BSC is a performance measurement tool for describing, implementing and managing strategies at all levels in any organization. It also helps the construction company to have a more comprehensive performance measurement system by looking at four different perspectives, compared to a measurement system which only looks at financial measures (Striteska & Spickova, 2012).

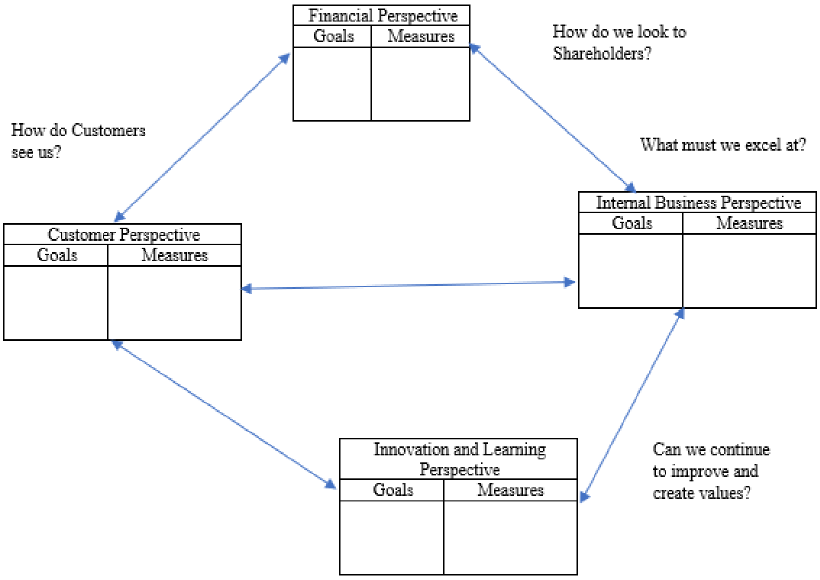

Figure 1-7 "The balanced scorecard measures that drive performance" (R. S. Kaplan & Norton, 1992)

Methods used in construction projects to measure performance via BSC are:

1. Financial perspective, such as risk assessment, cash flow and cost benefit analysis (CBA).
2. Internal business processes, for instance, critical path analysis.
3. Customer viewpoint.
4. Innovation and learning.

The goal of BSC is to give senior project managers a fast and comprehensive information model by establishing a balance between the four interrelated perspectives. Balance in BSC means the balance between the short-term and the long-term goals, required inputs and outputs, internal and external performance factors, and financial and non-financial indicators (Michail Kagioglou, Cooper, & Aouad, 2001; Tennant & Langford, 2008).

1.4.1.1 Financial Perspective

Financial information looks at past and previous performance without predicting future achievements (Tennant & Langford, 2008). It identifies the financial performance of a company and the critical success factors to show the financial performance of the company. The other three perspectives of BSC look at the future of construction performance by evaluating customer perspectives, internal business perspectives, and innovation and learning perspectives (Tennant & Langford, 2008).

1.4.1.2 Customer Perspective

The customer perspective emphasizes customer needs and how to satisfy customers in any organization. Most of the time, it measures the factors that are important for customers, such as time to provide service, quality, and customer perceptions on meeting their goals. These factors are known as leading indicators (D. R. Kaplan, 1992).

1.4.1.3 Internal Business Process

This perspective refers to internal business processes. Metrics based on this perspective let the managers know how well their business is running, and whether its products and services adapt to customer requirements and achieve their mission. These measures should be identified by experts (D. R. Kaplan, 1992).

1.4.1.4 Innovation and Learning

This perspective includes human resource measures. Human resources can be employee well-being, training and development, and corporate cultural attitudes related to both individual and corporate self-improvement and effectiveness (Evans, 2005; D. R. Kaplan, 1992). The importance of learning and growth has to be considered to achieve the quality and performance objectives. Some examples of success factors of the four interrelated perspectives of BSC are given in Table 1-5.

Table 1-5 Success factors of the four perspectives of BSC for construction projects (Evans, 2005; LIU, 2007)

Example of success factors	Financial perspective	Customer perspective	Internal business process	Innovation and learning
1	Total assets / employee ($)	Number of customers (no.)	Processing time (no.)	R&D expense ($)
2	Revenues / employee ($)	Market share (%)	On-time delivery (%)	Investment in training ($)
3	Profits / employee ($)	Customers lost (no.)	Average lead time (no.)	Patents pending (no.)
4	Market value ($)	Satisfied-customer index (%)	Inventory turnover (no.)	Satisfied-employee index (no.)
5	Return on net assets ($)	Customer-loyalty index (%)	Improvement in productivity (%)	Empowerment index (no.)
6	Return on total assets (%)	No. of visits to customers (no.)	IT capacity / employee (no.)	Ratio of new products (%)
7	Value added / employee ($)	No. of complaints (no.)	Emissions from production (no.)	Leadership index (no.)
8	Profit margin (%)	Marketing expenses	Environmental impact (no.)	Motivation index (no.)
9	Contribution margin (%)	Brand-image index (%)	Industrial accidents (no.)	Employee turnover (%)
10	Cash flow ($)	Average customer size ($)	Cost of administrative errors (%)	Average absenteeism (no.)
11	Solvency (%)	Customer rating (%)	Administrative expense ($)	University degree holders (no.)
12	Return on investment (%)		Contracts field without error (no.)	CPD training hours (no.)
13	Total costs		Time for decision making (no.)	

1.4.5 Dynamic Balanced Scorecards

Dynamic Balanced Scorecards (Sloper, Linard, & Paterson, 1999a) resolves the complex causal relations in the implementation process of BSC. In the other words, a dynamic balanced scorecard is a useful tool to analyse cause-and-effect relationships between key variables of a company. To overcome some weaknesses of BSC, the dynamic balanced scorecard (DBSC) was developed by (Akkermans & Oorschot, 2002). DBSC overcomes four limitations of BSC: unidirectional causality, ignoring the time delay, static evaluation, and lack of validation capabilities. Some of the pros and cons of BSC and DBSC are given in Table 1-6.

Table 1-6 Pros and cons of BSC and DBSC (Marcela, Michaela, & Ondrej, 2011)

Balanced Scorecard	**Dynamic Balanced Scorecard**
Positive aspects	
- easier implementation - faster application - positive experience - well-known method	- complex conception of indicators and relationships - weighted evaluation - more precise results - flexible to company´s vision and strategy
Negative aspects	
- causal relationships "action - reaction" - effect uncertainty - time delay - no relationships´ quantification - possible mistakes in results	- new method (not tested) - high implementation requirements (knowledge,etc.) - more abstract - correct selection of goals and indicators - correct evaluation of relationships

In this section we have reviewed the existing performance measurement system and in the next sub section we will discuss the aims and objectives of this research.

1.5 Aims and Objectives

Estimating project duration accurately is crucial in a project management life cycle for project stakeholders. According to (Vellanki & Reddy, 2005), reliable forecasting of the duration of activities is one of the major issues faced by construction engineers. This reliability relates to the factors that affect project duration, such as the uncertainty of events in the project environment, like inclement weather and productivity levels (Vellanki & Reddy, 2005). Thus, there is a need for a decision support (DS) framework to take into consideration the correlations between activities and risk factors, to be able to estimate the duration of construction activities. Therefore, we created a framework in Paper I aiming to estimate project duration, taking into account the effect of weather on project performance. As mentioned earlier, the project nature is dynamic and complex, so it is important to monitor and control the project along with the execution of the project. Otherwise, projects cannot meet their targets even if estimated perfectly. There are some tools available to monitor and control project performance to make sure that they are aligned with targets, but most of the time they are not implemented successfully (Franceschini et al., 2007) due to inflexibility, static type and lack of dynamic decision making. For example, dashboards can only give static information regarding the performance of a system and cannot support the decision-making process dynamically. To overcome this problem, this research aims to make a decision support system called the Navigational Support system (NSS) for construction projects to support project managers by identifying the position of a current project with respect to best projects and find the best action that they can take to reach the targets. The architecture of the NSS is presented in Paper II as a generic engine for projects/organizations' performance followed by validation of the proposed system in a construction project in Paper III.

1.6 Navigational Paradigm

From Christopher Columbus to the space shuttle, navigation has long been an important and vital concern for exploring the world (Darken & Sibert, 1996). Generally, navigation focuses on monitoring and controlling the movement of a vehicle or craft from one position to another. For example, a boat guided toward the finish line in the America's Cup yacht race or sending a rocket to Mars, is being navigated. In other words, navigation is a process of finding a way from one place or position to another place in their respective spaces (sea, galaxy). For any navigation system, we need a measurement tool to identify where we are, with respect to the destination (benchmark target). By improving technology such as global positioning system (GPS) it is much easier for sailors to identify their position in relation to the goals. One of the most important goals of navigation at sea is to move a ship efficiently and safely along an assumed trajectory (Pietrzykowski, Borkowski, & Wołejsza, 2012). Navigators in the sea space have to carry out two important tasks:

1. The ship should move through a present trajectory without any collision (correctly position the ship).
2. Effective decision making to avoid any collisions depends on the ship's movement data with respect to the constraints resulting from the shape of the area (make effective decisions to avoid any collision).

A navigational decision support system for controlling a ship at sea is a real-time system that is used by a navigator to observe and record information in a navigational situation. There are several tools used at sea to control and monitor ships, such as electronic charts (Electronic Chart Display and Information System), and NAVDEC (navigation decision support system).

A recommendation system enables the ship to move safely without fear of collision. An example of NAVDEC is shown in Figure 1-8.

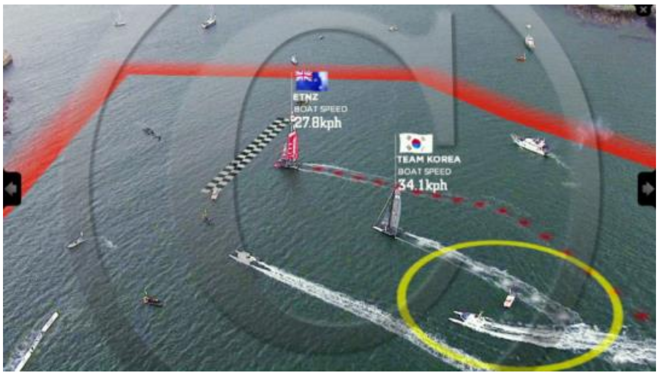

Figure 1-8 Navigation in the America's Cup (Sparkart, 2013)

According to Allmendinger et al. (2017) navigation means going through a set of points within an objective space, as part of an interactive procedure. This procedure is facilitated by a decision maker.

Another example of navigation is the progress of treatment of a patient. Typically, a patient visits a doctor because they are ill and the doctor does some tests. Then the doctor compares the test results with healthy groups (benchmark space) and measures how far the patient is from being a healthy person. Based on the results, the doctor decides to prescribe some medication (take actions). In a medical check-up, diagnoses are made with the experience of a doctor along with the results of testing. The patient takes the medicines and visits the doctor later to monitor his/her progress. The doctor monitors and controls the progress of medication to help the patient reach the benchmark space (healthy group). For this kind of navigation, GPS is not an appropriate tool to identify the position of unhealthy people in respect to a healthy group. Thus, there is a need for a measurement tool to measure the distance of an unhealthy individual from healthy ones.

In business, a company’s performance can be considered as an object that should move from its current state to the desired state that involves best practice.

The manager should take actions based on the company’s current performance to improve the performance of the company and bring it to the standard level, which can be considered benchmark space.

Similarly, the idea of finding a way to reach the target in a construction project in the benchmark space is like the navigational decision support system for ships at sea in different spaces. Figuratively, we can assume a project is like a ship, a project manager a sailor, and moving a project performance toward the benchmark target, a navigation situation. Paper II discusses the architecture of the navigation support system and Paper III addresses how it can be applied to the construction project area.

1.6.1 Benchmark Space

According to Arthanari (2010), benchmark space is defined as a space which consists of best practice. In other words, benchmark space consists of all the important KPIs from each area of a study’s best practices. For example, in the field of construction projects, the value of the most important KPIs, such as time, cost, safety and so forth from the best projects around the world are considered as benchmark space.

In healthcare, the benchmark space consists of the level of important health KPIs that people’s health can be measured from a healthy group of people. Benchmark space for a company’s performance can be considered as the value of the most important KPIs from best practice all around the world from companies in similar industries which are from top organizations.

1.6.2 What is a Navigational Support System?

A Navigational Support System (NSS) is a kind of decision support system that helps decision makers take better action to achieve the target. NSS tries to find nearly the best action in a dynamic environment by taking into account the relationship between the factors that affect decision making. In NSS, two important features should be considered:

1- The position of the current object performance which is intangible space, such as project performance, patient’s health status, and company’s performance.
2- The actions that are nearly the best actions to take to reach the desired state or benchmark state.

NSS considers the correlations between different KPIs to create benchmark space. Each benchmark space in each field of study is different from the next. For example, the benchmark space of a construction project consists of KPIs related to the construction project, and the benchmark space for a patient’s health status is related to the metrics related to a measure of the health status of the patient, such as levels of cholesterol, and sugar.

The rest of this research is structured as follows: Section 2 discusses different research methodologies for information system research. Then we highlight the strengths and weaknesses of existing approaches. Section 3 reviews the literature of technologies applied to create a decision support framework (Paper I) and a navigational support system framework

(Papers II and III). Section 4 (Paper I) proposed a decision support framework for estimating project duration under the impact of weather which has been validated and tested in a real-case construction project. Section 5 (Paper II) is related to the architecture of the navigational support systems and in section 6 (paper III) this framework is tested and evaluated in a real-case construction project. Section 7 relates to the discussion of the findings and explains the contributions of this research. Finally, in section 8, a future research direction is discussed.

2. Research Methodology

Research methodology is answering unanswered questions or exploring that which currently does not exist (Goddard & Melville, 2004). Research questions are derived from practical problems and designed to address such problems (Booth, Colomb, & Williams, 1995). Research methodology is a way to find out the result of a given problem on a specific matter, which is also referred to as a research problem.

This section aims to discuss the methodology used for creating frameworks and evaluating proposed systems in this research. To accomplish the research methodological requirements for literature review, theory building, system development and artefacts, we have used a multi-methodological approach. According to (Adams & Courtney, 2004; Cao et al., 2006; v. A. Hevner, Salvatore , Jinsoo, & Sudha, 2004; Nunamaker, Chen, & Purdin, 1990), a multi-methodological research approach for guiding information systems research has been recommended for a long time.

There are many forms of multi-methodological research framework available, such as the two dimensional research framework proposed by March and Smith (1995), the information system (IS) research framework proposed by (v. A. Hevner et al., 2004), DAGS (**D**esign science, **A**ction research, **G**round Theory and **S**ystem development) introduced by (Adams & Courtney, 2004) and an integrated multi-methodological research framework introduced by (Bai, White, & Sundaram, 2013). In the following subchapter we have reviewed these frameworks and identified their pros and cons. Finally, we have chosen the appropriate framework for our research.

2.1 Methodological Requirements

This research creates a framework to estimate the duration of construction activities under the impact of weather (Paper I) and creates and evaluates a navigational support system (Papers II and III). It falls under the umbrella of information systems due to the fact we have used a multi-methodological research approach to develop and evaluate the artefacts.

IS research is complex and dynamic in nature, thus a single methodological approach is not appropriate (Galliers & Land, 1987). Information systems research consists of many research areas such as the design, development and delivery of information systems, and the influence of deploying information systems in organizations (Keen, 1987).

Furthermore, in our research for identifying the problems about the decision support framework to estimate the duration of construction activities under weather risk and navigational support systems, there is a need for proper observation methods. Effective concepts, processes, frameworks and architectures need to be developed to address these identified problems and issues. To prove the validity of a proposed framework, a system should implement and deploy through an appropriate system development methodology. Moreover, both the framework and system should be validated and refined in real-case scenarios, which leads to the requirements for an appropriate experimentation methodology.

2.2 A Review of Multi-Methodological Framework

According to Mingers (2001), a multi-methodology approach is a set of research methods which are integrated to support different frameworks. In the following subsection we study some of the existing multi-methodological approaches.

2.2.1 Nunamaker et al. (1990)

Nunamaker et al. (1990) introduced a multi-methodological research framework consisting of four main strategies: observation, theory building, system development and experimentation. By doing observations we understand the research problem in the area of research properly; for example, helping with the formation of new research questions to be tested for the experimentation plan. Theory building helps to design and develop new concepts, frameworks and models. When the new theory such as a framework is developed or created, a system development methodology should be applied to make the framework applicable in the real world. Finally, the system should be examined and validated to refine the theory. In this framework, the system development strategy plays a main role to interact with observation, theory building and experimentation.

For applying this research methodology in IS research, Nunamaker et al. (1990) introduced a five-step system development approach. The first step is dealing with identifying and understanding the research problem. The second step is to identify the goal of the systems development and the architecture of the proposed system. The third step is related to analyzing the requirements for implementing the architecture; for example, selecting proper techniques and technologies. The fourth step is related to developing a system and validating the proposed framework and the fifth step is considering the evaluation of the developed system, which can pledge a new iteration of the system development approach.

2.2.2 March and Smith (1995)

According to March and Smith (1995), IS research is a combination of design science and natural science due to the fact that the relevance and effectiveness of IS research can be identified by how well the research activities involved in design and natural sciences are performed (March & Smith, 1995).

March and Smith (1995) proposed a two dimensional IS research framework, which identifies the four general research activities of build, evaluate, theorize and justify, and four types of research outputs: constructs, models, methods and instantiation. They joined these two categories together and made a 16 block table with different objectives, efforts, methods and evaluation strategies.

2.2.3 v. A. Hevner et al. (2004)

According to the conceptual framework proposed by v. A. Hevner et al. (2004), design science and behavioural science are combined. This framework consists of three main categories: research environment, IS research and knowledge base. The research environment summarizes how the business requirements should be defined to address a particular problem; the IS research category relates to the way design science and behavioural science combine to satisfy business requirements through developing theories and building/evaluating artefacts; those theories, frameworks and artefacts should be developed based on the available knowledge in the field of study (knowledge base) (v. A. Hevner et al., 2004). By using this framework, researchers can figure out IS research, and the fundamental rules that need to apply in IS research, and they can do IS research rigorously and effectively (v. A. Hevner et al., 2004).

2.2.4 Adams and Courtney (2004)

Based on the framework introduced by Nunamaker et al. (1990), another framework called DAGS was introduced by Adams and Courtney (2004) which consists of four different methodologies: design science, action research, grounded theory and system development. In this framework, the theory building will develop through design science methodology and grounded theory, then testing and refining theories will develop through systems development and action research.

In the following subsection we will discuss the strengths and weaknesses of each framework.

2.3 Strengths and Deficiencies of Mentioned Frameworks

According to Bai et al. (2013), the main strength of the framework proposed by Nunamaker et al. (1990) is that the four strategies used in this framework can lead to complementary research outcomes if used appropriately. For instance, developing a prototype using a system development strategy can contribute to the validation of a proposed framework by applying a theory building strategy. Furthermore, the centre point of Nunamaker et al.'s (1990) framework is a system development strategy and the research process involving research development will be more comprehensive and dynamic (Burstein & Gregor, 1999).

One of the strengths of Hevner et al.'s (2004) framework compared to March and Smith's (1995) framework is that it contributes to the environmental factors of people, organization, and technology (Bai et al., 2013). According to Bai et al. (2013), the DAGS framework is quite confusing because the design science, which is involved as one of the methodologies in this framework, consists of all four strategies of Nunamakers et al.'s (1990) framework, so it is incorrect to claim that the DAGS framework is only used for theory building.

In the subsequent section, we discuss the methodologies applied in each paper in this research.

2.4 Methodology Adopted in This Research

The research methodology adopted in this thesis is a mixed methodology for Paper I and a design science research (DSR) approach for Papers II and III. DSR is a pragmatic methodology that creates artefacts to solve real-life problems (v. A. Hevner et al., 2004). Design science methods try to solve problems through the creation of artefacts that address an unsolved problem in a unique or innovative way (v. A. Hevner et al., 2004).

In Paper I we reviewed the literature to identify the research problems (observation strategy), then we developed a framework to estimate the project duration based on the weather risk, and we addressed the effect of weather factors on project performance and project duration. This framework uses expert knowledge about the importance of weather variables, pairwise comparisons of weather variables with respect to different performance criteria, and, similarly, pairwise comparisons of performance variables with respect to project activities (theory building strategy). A model based on this framework using multivariate statistical techniques and an analytical network process (ANP) was developed to estimate the duration of project activity, taking into account the impact of weather. The proposed model was illustrated with data from a construction project. Validation of the model was provided by comparing the actual duration of an activity from similar construction projects with the estimated duration using the proposed framework (experimentation strategy).

According to Nunamaker et al. (1990), in the framework in Paper I we used only three strategies and we did not develop any system in this paper.

In Paper II we reviewed the problem of current performance measurement systems and described the architecture of the NSS as a generic tool for monitoring and controlling the project performance in multidimensional space [observation strategy]. This system uses expert knowledge to find the most important KPIs and performance levels from best practice to create a benchmark space. The multivariate statistical tools, such as spars principal component analysis (SPCA), Mahalanobis distance metric, and dynamic decision-making techniques such as Markov decision process (MDP) are integrated for developing the NSS [theory building and system development strategy]. In Paper III the NSS is applied to a construction project for further validation [experimentation strategy]. In the following, we have selected several multivariate statistical techniques and dynamic decision-making tools which are used in this research. We start with a description of each technique and the usage of each one in related papers.

In the next section, we review the techniques which can be used to create each framework.

3. Literature Review on the Techniques Applied in Each Frameworks

A review of the existing literature was performed on journal articles, conference proceedings, technical reports and online forums related to the area of study.

The goal was to understand what has been done in the field of study and identify gaps to be filled. This research is about creating a decision support framework for construction projects and a navigational support system as a generic engine applied to the construction industry.

In this research, for creating a framework to estimate project duration, multiple statistical and analytical tools, and, for NSS, multivariate statistical tools and dynamic decision-making tools, are used. A description of the methods and their applicability are given in the following section.

3.1 Decision Support System and Models

Decision support systems (DSS) were introduced by Gorry and Morton (1971) into the information system literature as “a computerised system that supports managers’ decisions in semi-structured decision situations”.

According to D. Power (2002), decision support systems are categorised into five different types ranging from communication-driven, data-driven, document-driven, knowledge-driven and model-driven decision support systems. Communication-driven systems emphasise network and communication technologies, such as collaboration systems to support group decision-making tasks (D. Power, 2002). Data-driven DSSs use and manipulate external and internal time series data, real time data and online analytical processing (OLAP) (Codd, Codd, & Salley, 1993) to help decision makers at the operational or strategic level (D. Power, 2002).

Document-driven DSSs emphasise different types of documents, such as oral, written and video by integrating a variety of storage and processing technologies to provide document analysis and retrieval. Model-driven DSSs (MD-DSSs) (Alter, 1982) emphasize access to and manipulation of financial, statistical and/or simulation models. Complex techniques are being used to create model-driven DSSs, such as decision analysis, mathematical programming and simulation (D. J. Power & Sharda, 2007). The majority of model-driven DSSs aim to find the desired decision criteria. In some MD-DSSs, forecasting techniques, such as time series analysis, are applied to bring accuracy to managerial decisions (Bermúdez, Segura, & Vercher, 2006). We will explain the usage of time series models in DSS in the next sub section.

Knowledge-driven DSSs use artificial intelligence and statistical inference technologies to extract knowledge from databases and recommend actions to managers (Holsapple, Whinston, Benamati, & Kearns, 1996). Due to the development of tools which are available to support decision making, the need for a decision support system is vital in a decision making process (D. J. Power, Sharda, & Burstein, 2015).

3.2 Multiple-Criteria Decision-Making

Multiple-Criteria Decision-Making is responsible for structuring and solving decision and planning problems containing multiple criteria (Zionts, 1979). According to Majumder (2015), there are six steps in the decision-making process:

1. Identifying the goal of the decision-making process.
2. Selecting factors.
3. Selecting available alternatives.

4. Selecting weighting methods to identify the importance, such as analytical hierarchy (T. Saaty, 2008), analytical network process (Thomas L Saaty, 2001), and fuzzy multi-criteria decision-making process.
5. Methods of aggregation, including product, average or a function.
6. Decision making based on aggregation results.

The multiple-criteria decision-making methods are categorised into two groups: compensatory methods and outranking methods (Billings & Marcus, 1983; Vincke, 1992). Compensatory decision making is systematic decision making that takes into account the importance of different attributes in decision making such as a linear model, AHP, Fuzzy logic decision-making (Billings & Marcus, 1983; Majumder, 2015).

A noncompensatory model, such as elimination by aspects (EBA) (Tversky, 1972), is a model of a decision-making technique when decision makers are faced with several options. First of all a single attribute will be identified as the most important attribute for the decision maker. When the option does not meet the criteria for an attribute then it will be eliminated from being the most important and different attributes are applied until the best option is left. There are a variety of techniques available in noncompensatory models such as log-linear regression, non-linear regression and ANOVA (Billings & Marcus, 1983).

3.2.1 Analytical Hierarchy Process and Analytical Network Process

The analytical hierarchy process (AHP) is a structured technique for organising and analysing complex decisions; it was developed by T.L. Saaty (1990). It is based on mathematical and psychological concepts and is widely used around the world in a variety of decision-making situations. According to T. Saaty (2008), the AHP provides a comprehensive and rational framework (in a hierarchy) for structuring a decision problem, which is able to quantify its elements, relates those elements to the overall goals, and helps decision makers to evaluate alternative solutions. After framing the hierarchy, the AHP helps decision makers to evaluate the impact of each element by comparing them one at a time.

AHP has been applied in different branches of construction, such as [a] selection of final constructor (S.-O. Cheung, Lam, Leung, & Wan, 2001), [b] evaluation of advanced construction technology (Skibniewski & Chao, 1992), [c] selection of critical success factors in construction management (D. Chua et al., 1999), [d] cost estimation of construction projects (An, Kim, & Kang, 2007) and procurement risk management (Hong & Lee, 2013). AHP is systematically adopted to determine the relative importance of elements to the goals of projects through a pairwise comparison of the elements. Generally, AHP modelling first breaks down a complex problem in the form of simple hierarchies, and then performs a pairwise comparison of the decision elements by computing their relative weights (F. K. Cheung, Kuen, & Skitmore, 2002). Although AHP is widely used in different parts of construction projects for decision making, this method suffers some deficiencies in practice due to its underlying assumptions. For example, AHP assumes that there are unidirectional relationships between criteria and sub-criteria across the hierarchy level of elements. Also, it does not consider the correlation of different elements within each cluster. Hence, it fails to consider the interrelationships in each cluster of a component in a decision-making process (Thomas. Saaty, 2006). This is the reason which motivated development of the ANP model in a generic form which is known as the Analytical Network Process to overcome AHP limitations. The ANP technique is a suitable tool for decision-making when there are interrelationships between different elements (Thomas

L Saaty, 2001). ANP allows all decision elements within each cluster to be compared pairwise in relation to the overall goal.

If there are interdependencies among components of each cluster then the components should be compared pairwise. In the ANP method, a super matrix should be formed to show the priorities of all clusters and components. After forming the super matrix, the next step is ranking and prioritizing the alternatives by summing up the values of each column in the normalized super matrix and selecting the alternative which has the highest overall priority. We have used this tool in the module of multi-criteria decision-making to prioritise weather variables which effect project performance and project activities in Paper I.

3.3 Time Series Analysis

Time Series analysis is a statistical tool used to forecast data by monitoring essential variables over time. This tool is suitable when data are collected over time too, such as stock prices, sales volume, interest rates, weather and quality measurements. In time series analysis, there are several models that use the raw data to make a final model for forecasting. Auto regressive (AR), moving average (MA), auto regressive moving average (ARMA), exponential smoothing (ES), and autoregressive integrated moving average (ARIMA) are some of the models used.

In theory, ARIMA modelling is the most general class of models for forecasting a time series which can be standardised by transformations (such as differencing and lagging) (G. E. P. Box, Jenkins, Gregory, & Greta, 2016). ARIMA modelling can take into account the trends, seasonality, cycles, errors and non-stationary aspects of a data set whilst creating or designing forecasts. In the ARIMA (p, d, and q) model, p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors in the prediction equation. For more details, readers are directed to Peter J. Brockwell and Davis (2002). Due to the dynamic nature of construction projects, the information should be analysed dynamically. The main objective of time series is understanding the dynamic or time-dependent structure of the observations of a single series (univariate) or multivariate series. The attributes of the dynamic structure are expected to contribute to an accurate forecast of future observations and to the design of optimal control schemes where it is required, such as process quality assurance (Peña, Tiao, & Tsay, 2001). The details of a times series model which is used to create a model-driven decision support system is explained in Paper I.

3.4 Regression Analysis

Regression analysis is a statistical technique to explore the relationships between variables. Usually this investigation reveals the causal relationship between a dependent variable and a set of independent variables (Sykes, 1993). There are different types of regression models, such as simple linear regression models, non-linear or polynomial regression, stepwise or multiple regression, logistic regression (Freedman, 2009), ridge regression, lasso regression (Tibshirani, 1996), and elastic net regression (Hui. Zou & Hastie, 2005).

Simple linear regressions deal with only two variables, a single dependent variable and an independent variable, to find a linear function to predict the dependent variable values based on historical values of the independent variable. In data-driven decision support systems, regression models are used to predict the value of dependent variables (Pardoe, 2012). Multiple regression analysis considers the relationship between a dependent (criterion) variable with several independent variables (Hair, Black, & Babin, 2010).

According to Montgomery (2006), a general Multiple Linear Regression (MLR) model can be formulated as shown in Equation 3-1.

$$\boldsymbol{y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon} \qquad \textbf{Equation 3-1}$$

where: y = independent variable (response),

β_0 = intercept,

$\beta_1 \ldots \beta_k$ = model parameters (coefficients),

$x_1 \ldots x_k$ = independent (regressor),

ε = error.

The multiple linear regression model can be explained in the format of matrix as shown in Equation 3-2:

$y = \boldsymbol{X\beta} + \varepsilon$, the least square principle is used to estimate $\boldsymbol{\beta}$ and minimise the error of estimation (ε).

$$\boldsymbol{b = argmin_\beta}[(\boldsymbol{y - X\beta})'(\boldsymbol{y - X\beta})] \qquad \textbf{Equation 3-2}$$

When there is a non-linear relationship between the factors, non-linear regression analysis is useful to predict the dependent variable. The non-linear regression models are nonlinear in the regression coefficients (Montgomery, 2006).

One of the common problem in development of non-linear models is related to overfitting problem. Overfit regression models happen when too many parameters will be estimated from the sample. one way of understanding overfitting is by decomposing generalization error into bias and variance (Domingos, 2012). To avoid overfitting there are several methods such as cross-validation and regularization. Cross-validation is a standard way to find out of sample prediction error using k-fold cross validation (Domingos, 2012).

3.5 Multidimensionality and Dimension Reduction Techniques

3.5.1 Principal Component Analysis (PCA) and Sparse Principal Component Analysis

Principal component analysis (PCA) is a statistical technique to reduce the dimensionality of datasets with *p* variables and *n* observations (I. T. Jolliffe, 2002). The main goal of PCA is to find a sequence of orthogonal factors (uncorrelated factors) from linear combinations of all variables. One of the main problems of PCA is, however, it finds a fewer number of important factors, and each factor is a combination of all variables, not only important variables. It is very difficult for a decision maker to understand which variables are important for one factor. Hui Zou, Hastie, and Tibshirani (2006) introduced a new method called sparse principal component analysis to solve this problem (Hui Zou et al., 2006). The lasso (Tibshirani, 1996) is a technique to reduce the dimensionality of datasets by considering possible zero loading factors. However, there are some shortcomings with lasso as stated by Hui. Zou and Hastie (2005). The number of variables selected by lasso depends on the sample size or number of observations. In other words, if the number of variables is more than the number of observations, the maximum number of variables that can be selected would be same as the number of observations. Hui. Zou and Hastie (2005) generalised lasso to solve the problem and called it elastic net where lasso is a special case of elastic net when the L_2 penalty is 0. SCotLASS is another technique to find sparse loadings of factors (Ian T. Jolliffe, Trendafilov, & Uddin, 2003). The high computational cost is one of the shortcomings of SCotLASS (Hui. Zou & Hastie, 2005). PCA can be written in regression type (Cadima & Jolliffe, 1995). As mentioned earlier, each principal component is a linear combination of all variables, hence the loadings can be estimated from a simple linear regression model.

Definition 1. "For each i, denoted by $Z_i = U_i\ D_{ii}$ the ith principal component. Consider a positive λ and the ridge estimates $\hat{\beta}_{ridge}$ given by Equation 3-3

$$\hat{\boldsymbol{\beta}}_{ridge} = \mathbf{arg\,min}\ ||\boldsymbol{Z}_i - \boldsymbol{X\beta}||^2 + \boldsymbol{\lambda}||\boldsymbol{\beta}||^2 \qquad \textbf{Equation 3-3}$$

Z are considered as principal components

U is called Eigen-vector

D is the diagonal matrix of singular value of D_i, where D_i is the square root of eigenvalues of Z^TZ".

Sparse principal component analysis (SPCA) (Hui Zou et al., 2006) is a method to find the most important factors, like PCA, by considering sparse vectors. The SPCA algorithm is suitable for both situations where the number of observations (n) is very huge as long as the number of dimensions (p) is small and also it is efficient when the number of dimensions is really bigger than the number of observations P>>n. Hui Zou et al. (2006) stated that it was easier for learners to interpret the outcome of SPCA than using ordinary PCA.

The SPCA method is available in the comprehensive R archive network known as CRAN in the package of elastic net (Hui Zou et al., 2006). In Paper I, PCA is used in the filtration module of the proposed framework to find a subset of important variables from a large number of weather-related variables and project performance variables, and in Paper II, SPCA is used in the filtration module of the proposed NSS to find the most important key performance indicators to create benchmark space.

3.5.2 Distance Measurement

The most commonly used distance measures are Euclidean distance (ED) and Mahalanobis distance (MD) (Mahalanobis, 1936). MD was created by Mahalanobis (1936) as a general form of distance (see Equation 3-4), and Euclidian distance is a special form of MD when variables are uncorrelated. Mahalanobis distance can be used in original variables and considers the correlation between the variables.

$$\boldsymbol{MD_i^2} = (\boldsymbol{x_i} - \boldsymbol{\mu})\boldsymbol{\Sigma^{-1}}\,(\boldsymbol{x_i} - \boldsymbol{\mu})^{\boldsymbol{T}} = \boldsymbol{a}(\boldsymbol{constant}) \qquad \textbf{Equation 3-4}$$

where $\sum$ is a variance-covariance matrix to consider the correlation between the variables of dataset X, μ is mean of a set of observations, x represents observations and the MD_i^2 shows the distance of observation from the mean of a set of observations with consideration of the correlation between observations. In Paper II, MD is used in the positioning module to find the distance of current project performance from benchmark targets.

3.5.3 Dynamic Decision-Making Techniques

Dynamic decision making is a kind of decision making in the situation where there is a series of decisions, which are related to each other (dependent) and the states of the world or situations change over time (Brehmer, 1992). One of the decision-making techniques which can be used in dynamic environments and under uncertainty is the Markov Decision Process (Leong, 1998). Dynamic decision-making modelling is widely used in real world applications, such as fighting fires, navigational control, battlefield decisions, medical emergencies, and so on.

3.5.3.1 Markov Decision Process

There is a limitation with standard decision trees regarding the situation which is very complex, particularly when events occur over time (Alagoz, Hsu, Schaefer, & Roberts, 2009). The decision process is based on a standard Markov based model, and it is computationally impractical when the number of nodes is very large. In other words, if the number of decisions is really large then it will be very difficult to simulate the model over time (Alagoz et al., 2009). When the situation is uncertain and dynamic, one of the tools that can solve these complex problems is the Markov Decision Process (MDP) (Bellman, 1957). The MDP model is a quintuple consisting of the following elements, as shown in Equation 3-5.

$$(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{P_a}(\boldsymbol{s}, \boldsymbol{s'}), \boldsymbol{R_a}(\boldsymbol{s}, \boldsymbol{s'}), \boldsymbol{\gamma}) \qquad \textbf{Equation 3-5}$$

Where

S: is a set of states which is finite

A: is a finite set of actions

$P_a(s, s')$: The probability of transiting from state ***s*** at time ***t*** to state $\boldsymbol{s'}$ at time ***t+1*** by taking action ***a***

$R_a(s, s')$: The immediate reward received from transition from state ***s*** at time ***t*** to state $\boldsymbol{s'}$ at time ***t+1,*** by taking action ***a***

γ: Discount Factor $(0 \leq \gamma \leq 1)$. It helps to get the present value of the rewards received in future.

The aim of using MDP is to find the optimal policy or determine the best action that can be taken in state ***s*** known as policy iteration (Howard, 1960).

$$\boldsymbol{\pi}^*(\boldsymbol{s}) = \boldsymbol{argmax_a}\left(\sum_{\boldsymbol{s'}} \boldsymbol{T}(\boldsymbol{s},\boldsymbol{a},\boldsymbol{s'})\ \boldsymbol{U}^*(\boldsymbol{s'})\right) \qquad \textbf{Equation 3-6}$$

$$\boldsymbol{U}^*(\boldsymbol{S}) = \boldsymbol{R}(\boldsymbol{S}) + \boldsymbol{\gamma}\ \boldsymbol{max_a}\left(\sum_{\boldsymbol{s'}} \boldsymbol{T}(\boldsymbol{s},\boldsymbol{a},\boldsymbol{s'})\ \boldsymbol{U}^*(\boldsymbol{s'})\right) \qquad \textbf{Equation 3-7}$$

where $\pi^*(s)$ is the optimal policy (Equation 3-6) that maximizes rewards $U^*(S)$ (Equation 3-7).

The MDP is applied in many fields of study to find the best policy when the situation is uncertain with some probability ranging from healthcare (Alagoz et al., 2009), construction project site management (Manjia, Abanda, & Pettang, 2014), artificial intelligence (Bertsekas & Tsitsiklis, 1995) and so forth. We have used MDP in Paper II in a decision-making module of the proposed NSS to support project managers’ decisions to take appropriate action to reach their goals.

3.6 Overview of Three Papers

An illustrative overview of the papers included in this thesis is shown in Figure 3-1. In Figure 3-1 each paper is located in a two-dimensional chart, where the x-axis is the tools which are created and the y-axis is the phases of the project life cycle. A standard project life cycle in construction projects, in general, has five major phases: [1] initiation, [2] planning, [3] execution, [4] performance and monitoring, and [5] closure.

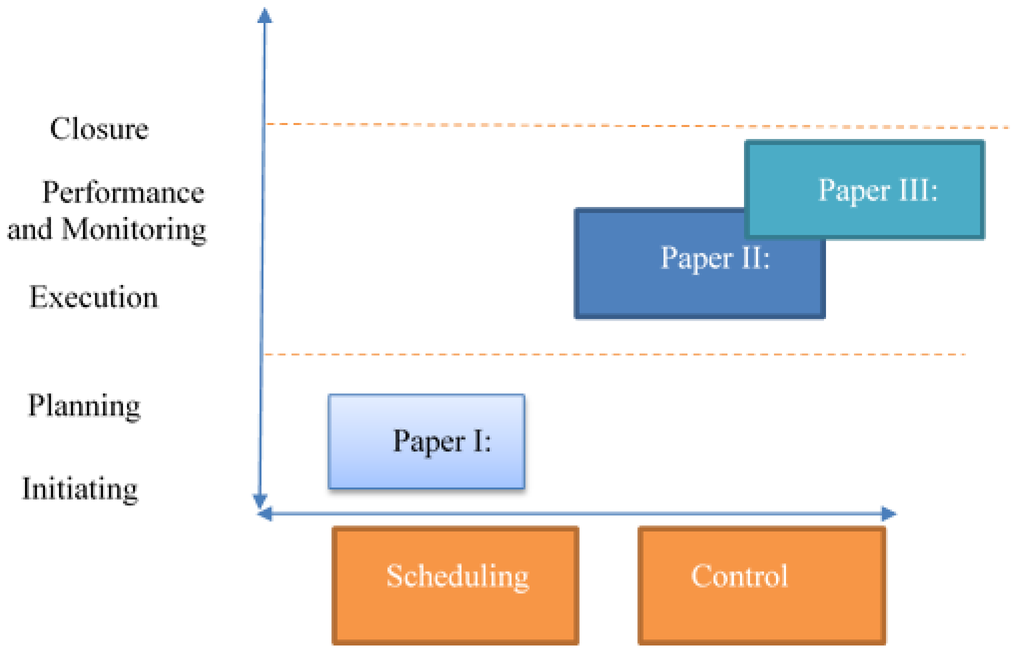

Figure 3-1 Overview of papers' position and the project life cycle

In Paper I a decision support framework was developed to estimate the duration of project activity under the effect of weather. The estimated performance can be used in Paper II. In Paper II, NSS is introduced as a generic engine to help the project manager to monitor and control the project performance. Paper III considers how to apply NSS in construction projects to validate it, discusses the limitations of applying it in construction projects, and how it can be improved as a future work.

4 Paper I

A Decision Support Framework for Estimating Project Duration under the Impact of Weather

Foad Marzoughi and Tiru Arthanari

■ Accepted in the Journal of Automation in Construction (2017)

Abstract

This paper proposes a decision support (DS) framework that incorporates weather-related factors for the purpose of estimating the duration of projects. Inclement weather can have a serious effect on construction projects, particularly with regard to duration and costs. The weather has an impact on human resource productivity, supplier effectiveness and material damage, which can, in turn, affect the duration of a construction project. The proposed five-module framework integrates weather variables, project performance variables and duration of project activities. This framework uses expert knowledge about the importance of weather variables, pairwise comparisons of weather variables with respect to different performance criteria, and, similarly, pairwise comparisons of performance variables with respect to project activities. A model based on this framework, using multivariate statistical techniques and an analytical network process (ANP), is developed to estimate the duration of project activities, taking into account the impact of weather. The proposed model is illustrated with data from a construction project in Iran. Validation of the model is provided by comparing the actual duration of an activity with the estimated duration, using the proposed framework.

Keywords: construction project management, weather risk, analytical network process (ANP), time series model, nonlinear regression, and principal component analysis

4.1 Introduction

Construction projects are commonly affected by multiple risk factors. According to Ghosh (2004), risks can jeopardise the successful completion of a project by causing cost and time overruns. Risks in construction projects are divided into two main categories. These are defined as project risks (which are internal) and external risks (Aziz, 2013; Sigmund & Radujković, 2014). Project risks relate to managerial factors, design documentation, human factors, delivery and logistics, and contractual elements (Sigmund & Radujković, 2014). External risks consist of legal, political (Li & Liao, 2007; Sambasivan & Soon, 2007), economic, social, natural (O. Moselhi, Gong, & El-Rayes, 1997; Sambasivan & Soon, 2007; Shahin, AbouRizk, Mohamed, & Fernando, 2007; Wasiu, Adekunle, & Ogunsanmi, 2012) and technical risks. According to Sweis (2013), the top three most important factors that cause time overrun in public construction projects are government delay (around 32%), inclement weather (23%), and design changes (18%). Moreover, severe weather can cause financial risks for construction projects (Wasiu et al., 2012).

Inclement weather has a direct effect on the health and safety of site labourers and can affect human resource productivity, supplier effectiveness and material damage (E. H. W. Chan & Au, 2008; Huang & W. Halpin, 1995; Koehn & Brown, 1985; O. Moselhi et al., 1997). Human resource productivity and the efficiency of construction activities are directly related (O. Moselhi et al., 1997). According to Wiguna, Scott, and Khosrowshahi (2005), inclement weather, such as heavy rain affects sandy rivers and results in the sand mixing with mud. It also decreases the quality of the sand, causing a shortage in local market stock which leads to construction delays. While considerable work has been done to find the risk factors that affect the time and cost of construction projects, research that enables us to create or design an automated system to forecast and visualize the impact of weather risk on construction sites is scant. Hence, developing a decision support system for construction projects to estimate the duration of each activity (with respect to weather risk) is vital for project scheduling.

Moselhi et al. (1997) have developed an automated decision support system (WEATHER) to predict the combined effects of reduced labour productivity and work-stoppage (caused by adverse weather conditions) on construction sites. However, even though WEATHER can provide an estimate of construction productivity as well as the duration of construction activities and weather patterns that facilitate the application of risk analysis in planning, it fails to consider the relationship between the effect of weather on construction resources and construction activities (O. Moselhi et al., 1997).

The objective of this study is to develop a framework to estimate project duration, taking into account the effect of weather on project performance. The proposed framework in this paper uses three databases or information sources: [a] a database of weather-related variables, [b] a knowledge base available to project managers (based on the interrelationship and relative importance of project activities), and [c] a historical project performance database. This framework integrates various multivariate statistical tools and multicriteria decision-making approaches to achieve its objective.

The rest of the paper is organised as follows: Section 4.2 reviews the literature on construction project performance monitoring tools and the impact of weather on project delays and costs. Section 4.3 briefly outlines the multiple methods used in this study. Section 4.4 presents the proposed conceptual framework. A model implementing this framework is illustrated with data from a real case in Section 4.5-4.6. These sections also provide a statistical comparison of the actual and predicted duration of activities, thereby validating the model. Finally, the concluding section (4.7) summarises the results and discusses future research directions.

4.2 Literature Review

According to several previous studies, the possible causes of construction project delays vary from the faults and weaknesses of contractors, owners/clients, consultants and designers (internal causes), to environmental or governmental problems (external causes) (Alaghbari, Mohd, Kadir, & Azizah, 2007; Haseeb et al., 2011; Hegazy, Said, & Kassab, 2011; L-P. Kerkhove & Mario Vanhoucke, 2017; Omar, 2009).

Some of the main factors that cause cost and time overruns can be listed as follows: financial factors, lack of experience of the various parties, lack of qualified project managers, incomplete design at the time of tender, changes, lack of cost planning/monitoring during pre- and post-contract stages, poor condition of the site, adjustment of prime cost and provisional sums (Hegazy et al., 2011; Kaming, 1997; Kasimu, 2012). There are a number of other factors which can cause delay in construction projects, such as interruptions, lack of resources caused by contractors during the drawing phase, financial difficulties and changes to orders (Le-Hoai et al., 2008; Palaneeswaran & Kumaraswamy, 2008). According to Kumar and Reddy (2005), reliable forecasting of the duration of activities is one of the major issues faced by construction engineers. This relates to the factors that affect project duration, such as the uncertainty of events in the project environment, such as weather, and productivity levels (Vellanki & Reddy, 2005).

However, given the limited resources to examine all possible influencing factors in a single study, on the one hand, and the impact of weather factors as the most influential factor, on the other (S. A. Assaf & Al-Hejji, 2006; Aziz, 2013; Doloi et al., 2012; Sambasivan & Soon, 2007), in this study we focus solely on the impact of weather on the duration of construction projects.

In many construction activities, the weather is responsible for adverse effects such as stoppages, productivity loss, cost overruns and delays (S. A. Assaf & Al-Hejji, 2006; Aziz, 2013; Doloi et al., 2012; Sambasivan & Soon, 2007). Among various weather conditions, rainfall and hot and cold weather are regarded as the major factors that affect building construction (Joseph L, 2005).

Many construction activities are highly sensitive to rainfall as this can reduce productivity (during the rainfall) and affect construction activities for several days afterward. Extremes of hot and dry weather can also affect human productivity (for example, due to the significance of thermal comfort) (Koehn & Brown, 1985), and the time needed to complete other aspects of construction activities which are sensitive to weather (weather sensitive activities), such as the delivery of materials like masonry, mortar, paint, seals and sealant, and equipment (Joseph L, 2005). According to the literature, different weather factors can affect cost and productivity, and cause delay in construction projects (Jyh-Bin et al., 2013; Shahin, AbouRizk, Mohamed, & Fernando, 2013). El-Rayes and Moselhi (2001) confirm that rainfall can cause a complete stoppage in highway construction. Koehn and Brown’s (1985) investigation suggests a clear relationship between overall construction performance and weather-related factors such as temperature and humidity. For example, labour-dependent activities are generally affected by temperature and humidity, whereas crane operations are sensitive to wind speed (H. Randolph & Iacovos, 1987; Koehn & Brown, 1985). According to Shahin et al. (2013), inclement weather such as cold spells can have an impact on tunnelling projects and high-speed winds of more than 50 km/h, or low temperatures (e.g. below zero Celsius) can cause stoppages in building projects (Shahin et al., 2013). According to Haseeb et al. (2011), a delay in a construction project is defined as exceeding the completion time with respect to the contractually agreed time.

Hence, weather can play an important role in estimating the duration of construction projects (which is an important factor in the preparation of a construction plan), as well as in the application of formal project scheduling methods, such as the critical path method (CPM) or the programme evaluation research task (Moder, Phillips, & Davis, 1983). Uncertainties in relation to weather factors, design, labour efficiency, equipment, site condition and so forth may directly or indirectly affect construction scheduling and planning during project implementation (Jun-yan, 2012). Estimating project duration at the project planning and scheduling stage is somehow subjective and depends on engineering judgment (Hendrickson, Martinelli, & Rehak, 1987). CPM and bar charts are the most popular techniques for project scheduling; however, these techniques cannot handle uncertainty. Building on CPM and in order to handle the uncertainty (by taking risk factors into consideration), several techniques have been developed as follows: Programme evaluation and review technique (PERT) (Diaz & Hadipriono, 1993), the probabilistic network evaluation technique (PNET) (Ang, Chaker, &

Abdelnour, 1975), and critical chain scheduling (CCS) (McKay & Morton, 1998). Although these techniques consider uncertainties, they ignore the correlational impact between activities and risk factors (Hendrickson & Au, 1989; L-P. Kerkhove & Mario Vanhoucke, 2017; Omar, 2009; W. Wang & Demsetz, 2000). They assume that there is no dependency upon the relationship between activities and risk factors (Jun-yan, 2012).

Thus, there is a need for a more comprehensive decision support (DS) framework to take into consideration the correlations between activities and risk factors, in order to be able to estimate the duration of construction activities. The rest of this paper is devoted to developing such a framework with an illustration of a model based on that framework, and discussion.

4.3 Research Methodology

This research uses multiple methodologies to integrate weather-related variables in the process of estimating the duration of activities affected by weather. For this purpose, multivariate data analysis methods, such as principal component analysis, time series model building approaches, multi-criteria decision-making tools, non-linear multiple regression and qualitative and quantitative data collection methods, are used and integrated into a framework. To validate the model developed from the framework, a real-life case is used. Validation is done by statistically analysing the difference between the duration predicted by the model with that of an actual case. Weather-related data that is collected from official meteorological sources from the region where the project is undertaken are used. Expert opinions on the importance of weather variables on the duration of project activities and performance are essential, so methods to elicit this information become important. Also, the relative weighting of the different factors and their interaction is found using multi-criteria decision-making tools, together with the input from experts. In addition, a prediction of weather factors becomes necessary at the time of planning the project. This forecasting is done using time series models for different weather factors. Non-linear multiple regression is used to predict activity duration that is based on predicted weather and levels of performance. For data collection, both quantitative and qualitative methods are used in different stages. Brief accounts of some of these methods are given.

4.3.1 Principal Component Analysis

Principal component analysis (PCA) is a multivariate statistical tool used to reduce the dimensionality of the data set on several variables and observations, by identifying a smaller number of underlying dimensions that explain most of the variability in the data (I. Jolliffe, 2005). PCA finds a sequence of uncorrelated (orthogonal) factors. These factors are different linear combinations of all variables in the dataset. We use this tool in the filtration module of the proposed framework to find a subset of important variables from a large number of weather-related variables and project performance variables.

4.3.2 Analytical Network Process

When a decision-making process involves many criteria and there are several alternatives available to choose from, the problem of finding a 'best' alternative is complex. Multi-criteria decision-making literature contains many different approaches to this problem (Alter, 1980; Billings & Marcus, 1983; Thomas Saaty, 1980; Vincke, 1992). T.L. Saaty (1990) proposes an analytical hierarchical process (AHP) to arrive at weightings for the different criteria based on the importance of the different criteria to the decision maker. These weights are used in evaluating the alternatives and selecting the one that is best. When we have a criterion which is made up of several sub-criteria, then we have a hierarchy among criteria and we face problems with AHP in some situations, such as when there are interrelationships among the different criteria at one or different levels (Thomas L Saaty, 2004). This is the main reason for Saaty (Thomas L Saaty, 2004; T. L. Saaty, 2008) proposing a more comprehensive approach called Analytical Network Process (ANP) to handle such situations.

ANP has been utilized in various multi-criteria decision-making problems in the construction industry, such as in project selection decisions (Diaz & Hadipriono, 1993; Le-Hoai et al., 2008) and risk assessment (Bu-Qammaz, Dikmen, & Birgonul, 2009). We use ANP in the multi-criteria decision-making module of the framework to obtain weightings for the different project performance factors and project activities, depending on weather factors and based on their importance. This is suggested by expert knowledge. In this module, the elements of each factor are compared pairwise with respect to the criterion under consideration. For example, the components of weather-related factors such as wind, temperature and humidity can be compared pairwise with respect to construction project resources, such as manpower, material damage and supplier effectiveness.

4.3.3 Time Series ARIMA Modelling

Time series analysis follows a standard procedure in the following sequence (G. Box & Jenkins, 1970; Peter J Brockwell & Davis, 2016; Chatfield, 2016; Hamilton, 1994): recognition of the data model; and checking the dependency of data, model fitting, recognition of model correctness, forecasting and updating. In time series analysis, there are several approaches to finding a model for forecasting, such as exponential smoothing (ES), autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA). ARIMA models are the most general models for forecasting with time series data. We use the ARIMA approach in the forecasting module of the proposed framework.

4.3.4 Non-linear Multiple Regression Model

Non-linear multiple regression models describe the non-linear relationship between dependent and several independent variables. Given that previous studies have shown that adverse weather has a non-linear effect on project performance (Cachon, Gallino, & Olivares, 2012; Koehn & Brown, 1985; Sachuk, 1988), the estimation module of the proposed framework uses non-linear regression models.

Further details of these methods will be given in Section 5 (applying to a real case of a decision support model derived from the proposed framework). The next section details a conceptual framework and description of how these methods are relevant in different modules of the framework.

4.4 Conceptual Decision Support Framework

The proposed framework to estimate the duration of activities, including the effect of weather variables, has five main modules (Figure 4-1): [1] Expert Knowledge Module (EKM), [2] Filtration Module (FM), [3] Multi-Criteria Decision Module (MCDM), [4] Weather Forecasting Module (WFM), and [5] Duration Estimation Module (DEM). The Expert Knowledge Module (EKM) consists of knowledge elicited from experts and the literature on the importance of different weather variables depending on the extent to which they affect a construction project’s performance and the duration of a project. For example, in earlier sections we mentioned a few instances of how weather affects different project performance norms. Necessary information for this module can be prepared through interviews with experts in the field or through questionnaires. Experts may be asked to rank the importance of a particular weather variable on a project activity or project performance indicator. This information is used in preparing the necessary input for the Filtration Module (FM) and also in the Multi-Criteria Decision Module (MCDM) to arrive at the pairwise preference matrices that are used as required input in the ANP tool. The FM processes data on the importance of weather variables, activities and performance variables, and using PCA, it produces a smaller set of the most important weather factors, performance factors and important activities. The output from FM is used in the MCDM along with the relevant output from the EKM to arrive at weightings for combining the different project performance criteria values in evaluating the importance of different project activities.

We assume we have two other databases containing information on [1] historical weather data relevant to the region where the construction project is carried out, and [2] historical project performance. We obtain the values for the most important weather variables from the weather database and feed it to the weather forecasting module. The forecasting module, WFM, uses an ARIMA process to identify the best forecasting model for each of the important weather factors. Finally, the estimation module (EM) uses the output from the MCDM and WFM together with the values for the most important project performance factors from the database containing historical performance, to give estimates of activity duration as output. Consequently, project duration impacted by weather can be estimated.

Based on this conceptual framework, we develop a model which implements the different modules using a particular tool or choice among available approaches. We then validate the model with the following case study.

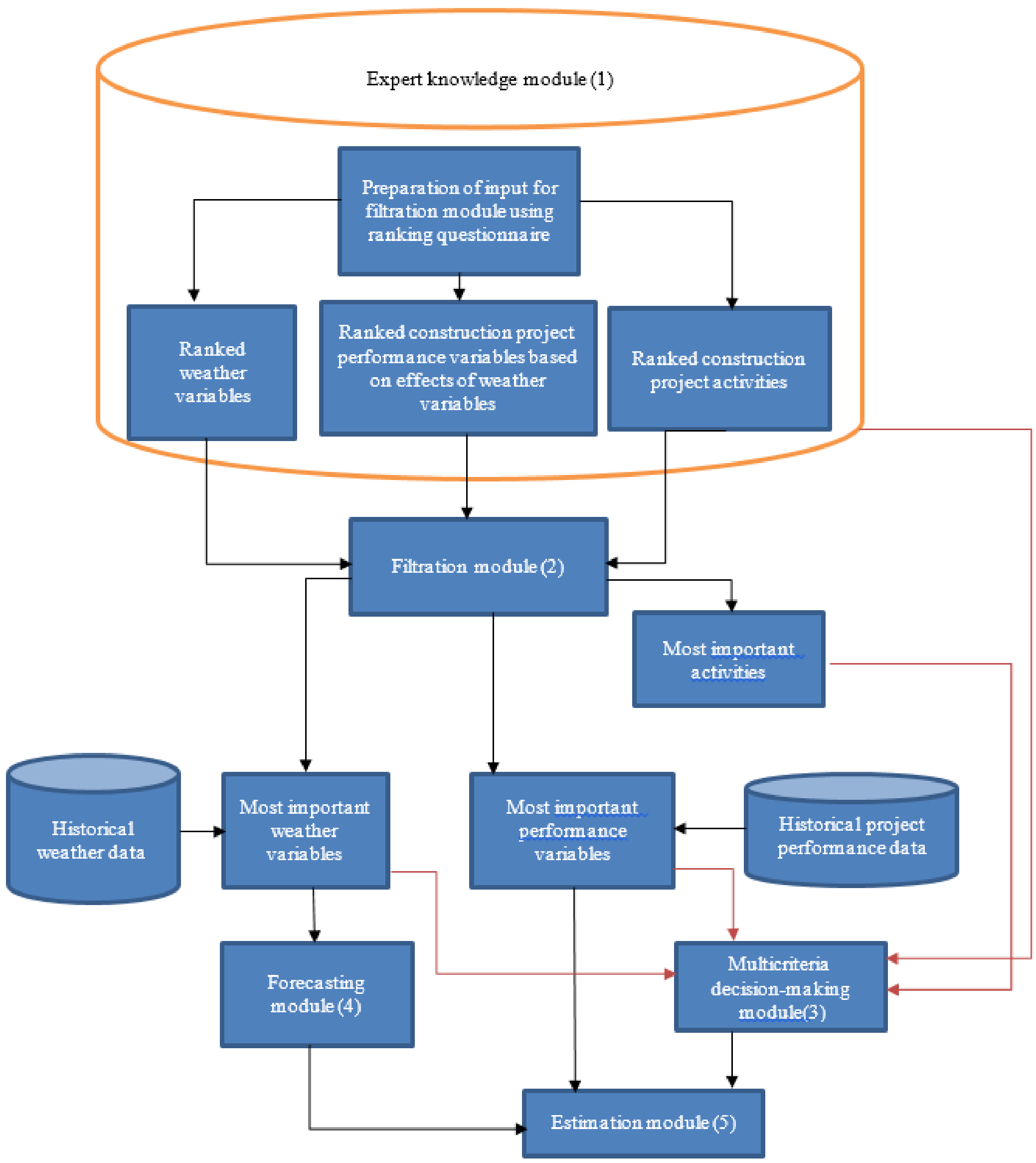

Figure 4-1 A framework for estimating project duration with the impact of weather

4.5 Case Study

In order to prove the efficacy of the proposed framework, we consider a model which implements and validates it, using case study data from a residential construction project on Kish Island in Iran. Table 4-1 gives details of the construction project.

Table 4-1 Case construction projects-some details

Name of the Company	Fadak
Name of the project	Bahonar
Area	14000 m2
Number of houses	100
Time performance	Behind schedule by 0.28 %
Cost Performance	On budget
Duration	42 month
Type of project	House Building Project

4.5.1 Developing the Expert Knowledge Module

Initially, semi-structured interviews were carried out with five experts to obtain necessary information, such as the role of weather on their projects, the types of variables affected by weather and the impact of these variables on the duration of each activity, human resources, material wastage and the effectiveness of suppliers. A typical set of questions used in the interviews is given in Appendix 1, along with a sample response to a question with the extracted information.

After gathering the responses, we used a coding method to analyse them. We categorised the information into different segments and labelled each segment with a code. For example, our codes for weather include rainy, snowy, windy, sunny, humid, hot, cold, foggy, blizzard, sand-storm and hail. We used this information to design a questionnaire to gather relevant information on the impact of weather on three different parameters: construction projects in general, construction project performance, and specific construction project activities.

The questionnaire was distributed to 110 construction project managers who had on average more than five years' experience. Analysis of the questionnaire identified the most important weather factors affecting the duration of construction projects, as well as the most important project performance factors that are impacted upon by weather. This became the input for the filtration module (FM). Appendix 2 gives a list of weather variables, construction performance variables and construction project activities. We enter the data according to the ratings given by the 110 respondents on the variables mentioned above.

Another questionnaire that was based on the output of the first questionnaire was designed to consider the effect of selected weather conditions on construction delays to prioritise the activities that are affected by weather.

Subsequently, we asked five construction engineers who had an average of seven years' work experience and who worked for major construction companies in Iran, to fill out the above-mentioned questionnaire and identify the pair importance of relevant variables in the model. This became the input for the MCDM. Table 4-2 gives an example of a pairwise comparison of weather variables with respect to the criterion of human resource productivity. Here the values reflect the relative importance of the variables. For example, 7 in cell row 2, column 1 means humidity is seven times more important than temperature when it comes to human resource productivity. The weightings in a sense rank the weather variables based on their effects on any performance variable. Similarly, the weightings of the project performance variables with respect to any activity duration, help rank them. The inclusion of variables in the non-linear regression models to predict any performance variable makes use of these importance rankings. In a sense MCDM output cross-validates the short-listed important variables from the filtration module.

Table 4-2 Weather components priority with respect to human resource productivity

Human Resource productivity	Temperature	Humidity	Wind	Priority
Temperature	1	1/7	1/5	0.064
Humidity	7	1	6	0.736
Wind	5	1/6	1	0.2

4.5.2 Filtration Module

In this module, we use a dimension reduction technique like Principle Component Analysis to identify a subset of important variables from the input matrix of respondents' ratings on all variables. We used SPSS version 16.0 software for the application of PCA and identified two dimensions from the seven weather variables. Table 4-3 gives the loadings on the dimensions for the different variables. Usually in factor analysis, these dimensions are given suitable names depending on the magnitude of loadings. Here we have not followed this convention. However, the loadings are important in the subsequent steps. Similarly, we identified the first two principal components for each activity and performance variable, respectively. We can observe from Table 4-4 (from PCA for project activities), that the variables with higher loadings on the first principle component are: construction and installation of steel structures (W6), installing ceilings (W7), installing walls (W8), installing channels and ceilings (W10), initial installation and installation of rails (W13), installing stone stairs (W17), installing flooring (W19), installing valves and accessories (W22), and eliminating defects and cleaning (W28). These activities are considered important with respect to weather risk.

Table 4-3 Loadings on the components for weather variables

	Principal component	
Variable	1	2
Wind	0.258	**0.738**
Dry	0.083	-0.162
Sun	0.045	-0.037
Dew point	0.085	-0.031
Temperature	**0.908**	-0.032
Wet	0.023	-0.062
Humidity	0.281	**0.657**

Table 4-4 Loadings on the components of construction activities

Variable	**Code**	**Principal component**	
		1	**2**
Construction and installation of steel structures	W6	**0.577**	0.041
Run Ceiling	W7	**0.654**	0.153
Run Wall	W8	**0.474**	0.053
Run Channels and ceiling	W10	**0.874**	0.133
Initial installation and installation of rails	W13	**0.830**	0.386
Run the stone stairs	W17	**0.850**	0.346
Implementation of the final installation and elevators	W19	**0.697**	0.208
Install valves and accessories	W22	-0.425	**0.878**
Eliminate defects and cleaning	W28	-0.359	**0.762**

4.5.3 Weather Forecasting Module

After a formal request to the meteorological organization of Iran (http://www.weather.ir/), with their permission the database of weather variables was created. Data on the most important weather variables, over a period of 30 years, in the Kish region of Iran, were collected from Iran's meteorological organisation. This information shows that the weather on Kish Island varies from very hot to moderately hot with high humidity.

To forecast the value of important weather factors, Time Series Analysis is applied. Time Series Modelling is widely used in forecasting weather conditions by examining the past behaviour of weather factors, like rainfall, humidity, temperature, streamflow and many other environmental parameters (Cheema, Rasul, Ali, & Kazmi, 2011; Chung, Park, & Lee, 2011; Machiwal & Jha, 2009; Nury, Koch, & Alam, 2013; Radzuan, Othman, & Bakar, 2013; S. Wang, Fend, & Liu, 2013). Daily weather parameter values from Kish station were collected from the Iran Meteorological Organization and stored in a database which covers the last 30 years. Time Series Modelling is generally used as a data-driven forecasting method for weather variables based on historical data (Hans, 2014).

We considered using the ARIMA process for finding adequate forecasting models for important weather variables, because ARIMA models are the most general class of models for forecasting a Time Series which can be standardised by transformations (such as differencing and lagging) (G. E. P. Box & Jenkins, 1976). ARIMA modelling can take into account the trends, seasons, cycles, errors and non-stationary aspects of a dataset whilst creating or designing forecasts. In the ARIMA (p, d, and q) model, p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors in the prediction equation. For more details, see Anderson (1976) and Brockwell (2016). Due to the dynamic nature of construction projects, information should be analysed over time. The main objective of a time series is understanding the dynamic or time dependent structure of the observations of a single series (univariate) or multivariate series. The attributes of the dynamic structure are expected to contribute to an accurate forecast of future observations and to the design of optimal control schemes where required, such as process quality assurance (Peña et al., 2001). We analysed the weather data using ARIMA, AR and MA models and selected the best model for each of the weather variables: temperature, humidity and wind. Table 4-5 summarises the selected forecasting models for the different weather variables.

Table 4-5 Summary of the selected forecasting models for different weather variables

Weather Variables	Model building parameters	Coefficient	P value	Final Time series Model
Temperature	AR(1)	0.726	0.003	ARIMA(1,1,1)
	MA(1)	-0.423	0.009	
	Constant	8.694	0.000	
Humidity	AR(1)	0.3405	0.000	AR(1)
	Constant	44.835	0.000	
Wind	MA (2)	0.592	0.000	IMA(2,2)
	constant	-0.144	0.000	

For instance, to predict the temperature we found the following model:

$$z_t = 8.695 + 0.7261 z_{t-1} + a_t - (-0.4231) a_{t-1}, \qquad \textbf{Equation 4-1}$$

where z_t is the forecasted temperature for period *t*, and a_t is the parameter of the moving average for period *t*.

Similarly, we obtained equations for predicting other important weather variables. These forecast weather values are used as one of the required inputs for the estimation module to estimate project performance based on forecast weather data in the scheduling phase.

4.5.4 Multi-criteria Decision-Making Module

Necessary data needed for the multicriteria decision-making module are provided by the FM and EKM for the ANP computations. From the filtration module, we obtain three weather variables, three project performance variables and eight project activities, as necessary information for this module. From the KM, we have the pairwise comparison matrices for the relevant variables and performance criteria. Figure 4-2 gives the analytical network process structure in this project.

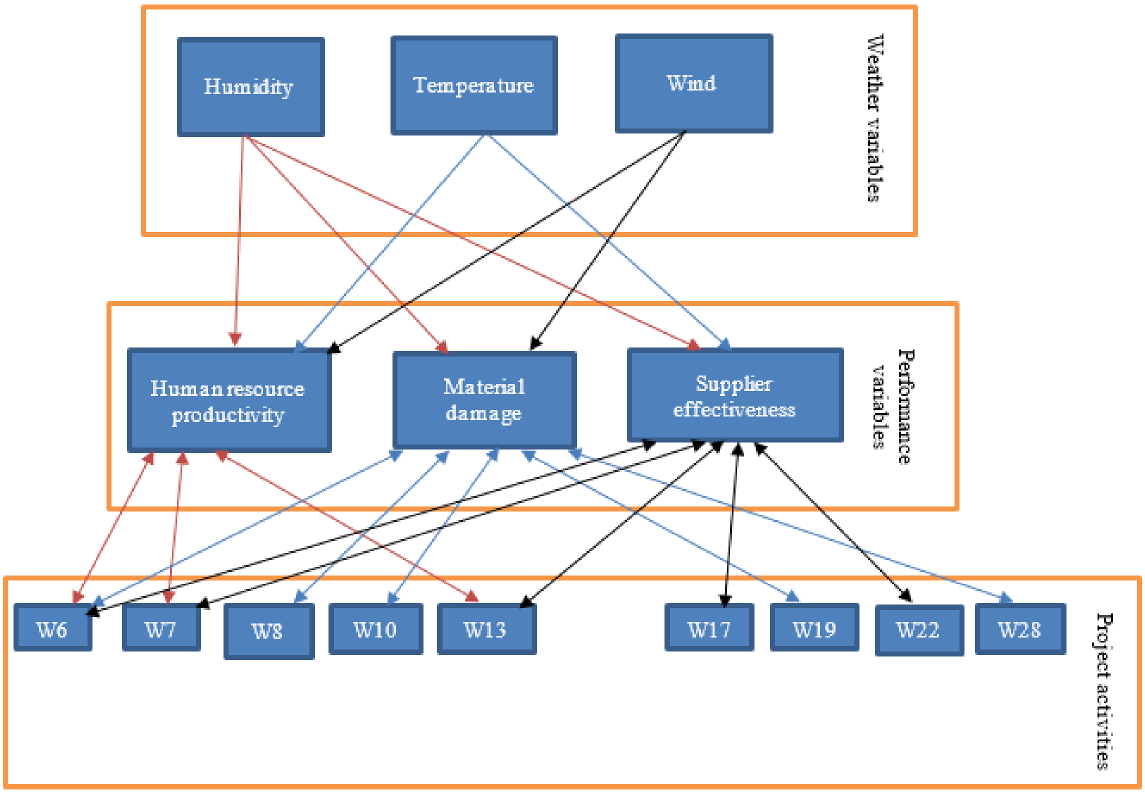

Figure 4-2 The analytical network process structure to illustrate the dependency between weather variables, performance variables and project activities

The ANP outputs relevant weightings for the criteria. For instance, according to Table 4-6 the weightings for weather variables, temperature, humidity and wind, with respect to human resource productivity are 0.064, 0.736 and 0.2 respectively. This means humidity has the highest impact on human resource productivity.

Similarly, the weightings for project performance variables with respect to duration of installation of steel are 0.62, 0.09 and 0.28 respectively. This implies human resource productivity has the highest impact on this activity.

In a similar vein, pairwise comparison of different activities affected by supplier effectiveness yields weightings for activities, W5, W7, W13, W17, and W22 which are 0.27, 0.45, 0.12, 0.11 and 0.036 respectively. Here W22 is least affected by supplier effectiveness.

Table 4-6 Weather components' priority with respect to human resource productivity

Human Resource productivity	Temperature	Humidity	Wind	Priority
Temperature	1	1/7	1/5	0.064
Humidity	7	1	6	0.736
Wind	5	1/6	1	0.2

ANP also outputs a super matrix that provides weightings for all the variables and activities taken together, so as to bring out their interdependence across different groups (weather, performance and activities). Appendix 3 gives the super matrix obtained in our analysis.

4.5.5 Estimation Module

The historical database of project performance variables from the construction company, along with the corresponding data on weather conditions during those periods were used to build non-linear multiple regression models for predicting activity duration based on performance variables. However, performance variables themselves are dependent on weather variables, therefore first we built non-linear multiple regression models for predicting each of the performance variables using weather variables as independent variables.

Table 4-7 gives the models obtained for the different performance variables based on the weather variables.

Table 4-7 Selected models for predicting different performance variables

Model for estimating	Description	Coefficient	Adjust R^2
Human Resource Productivity (P)	Constant	187.875	$R^2 = 0.974$
	Temperature (T)	-5.245	
	Humidity (H)	-0.722	
	T^2	0.046	
	H^2	0.002	
	$(Wind)^2$	0.001	
Material damage(M)	Constant	319.295	$R^2 = 0.986$
	Temperature	1.701	
	T^2	0.023	
Supplier efficiency (S)	Constant	92.841	$R^2 = 0.978$
	Temperature	20.156	
	T^2	-0.347	
	Humidity	-3.145	

Table 4-8 gives an activity duration prediction model based on performance variables for the construction and installation of steel structures.

Table 4-8 Selected model for predicting activity duration based on performance variables

Model for estimating	Description	Coefficient	Adjust R^2
Duration of construction and installation of steel structure	Constant	19.977	$R^2= 0.94$
	Productivity (P)	0.523	
	Supplier efficiency (S)	0.120	
	Material (M)	-0.702	
	M^2	0.001	
	S^2	-0.002	
	P^2	-0.005	

For all activities, duration estimation models can be developed in a similar way. By inserting the activity durations in CPM software, one can estimate project duration.

4.6 Validation of the proposed Model

According to Gonzalez and Sol (2012) validation within design science research in an information system is not clear. In design science research in the information system (DSRIS), the theoretical contribution can be validated using a formative or summative perspective including process oriented or product oriented respectively. Validation of DSRIS cab be formative (process oriented) or it can be summative (product oriented) (Gonzalez & Sol, 2012). Formative evaluations focus more on the results and support the kinds of decisions that intend to improve the system (William & Black, 1996). On the other hand summative evaluation focuses more on the meanings support those kind of decisions that affect to the selection of system for an application (William & Black, 1996).

Moreover evaluation of DSRIS can be based on a case study or an action research, means that shows applicability in practice by arranging an expert survey (shows general interest) or by laboratory experiments (simulations) (Offermann et al., 2009).

In this paper we have validated the decision support framework that incorporates weather-related factors to estimate the duration of projects using an empirical evaluation (Siau & Tan, 2008).

The construction company, Fadak, ran several similar construction projects. We collected data on the activity duration of the construction and installation of steel structures from a sample of 10 sites. Column one of Table 4-9 gives the actual duration for this activity on those sites.

Table 4-9 The duration of construction and installation of steel structure

Actual duration	Estimated duration
41	43.62
55	58.39
64	67.92
70	67.42
75	67.19
77	81.28
78	77
80	80.75
83	83.5
85	80.2

We predicted the weather variables corresponding to the dates of the activity on the different sites from the forecasting module. These predicted values were used in the models for predicting performance variables (Table 4-7). Using the model given in Table 4-8, we predicted corresponding durations for this activity. Column two of Table 4-9 provides these estimated durations. We found the difference between the actual and the estimates were not statistically significant using sign test (p-value 0.344), as our sample size was small. Table 4-10 gives the details of the sign test.

Table 4-10 Sign test for comparing actual data and estimated data

Model Duration-Actual Duration	N
Negative Differences	4
Positive Differences	6
Ties	0
Total	10
P-value computed for 2 tailed test	0.344

Apart from working through the different modules of the proposed framework, this illustration also considers particular tools for integrating weather information into the estimation of project activity duration. In addition, we have validated the model with one activity from the construction project.

4.7 Conclusions

This paper proposes a decision support (DS) framework which can incorporate weather-related factors into estimating the duration of projects. A model is also implemented based on the proposed framework. This framework has five modules which use three databases, weather variables, expert knowledge, and project performance variables. Multiple methods are used, such as multivariate analysis, multicriteria decision-making tools, and quantitative and qualitative research for data collection and analysis. Expert knowledge is acquired in the Expert Knowledge Module and this provides two types of output: [1] ranking of variables according to their importance and activities, and [2] pairwise comparison of relevant variables and criteria. The Filtration Module, using principal component analysis, identifies important weather and performance variables, and activities that are impacted by weather variables. The multicriteria decision-making module uses ANP for obtaining weightings for combining different performance variables, for assessing weightings for weather variables with respect to different performance variables and for finding the relative weightings of performance variables on activity duration. The forecasting module provides predicted weather variable values for the period of interest. Finally, the estimation module predicts activities' duration using non-linear regression models that are developed from a project performance database. The proposed model has been illustrated with data from a real construction project in Iran. We have validated the proposed model using a comparison of predicted and actual activity duration for a particular activity on different project sites.

This study has some limitations as follows: the proposed decision support framework in this paper is generic and the model implemented is based on this framework for illustration purposes only. This is one among many possible alternatives. We are therefore not claiming that this is the best way of implementing the framework. Some other limitations include: [1] the validation of a model that might consider multiple construction projects with different complexities or types; [2] the non-availability of some of the databases required that might prevent the use of this framework; [3] difficulties in finding experts to provide the knowledge base; and [4] one of the common problem in pure analytical models such as non-linear and nonparametric models is related to overfitting problem (Jason, 2016; Tom, 1995).

Further research in this area could create an integrated computer system, following design science principles, which automates the integration of the different modules within the frameworks. Also, such a system might offer different tools to choose from (in each of the modules), which would give users a wider choice. We believe a similar approach is possible to incorporate other risk factors that affect activity duration, such as political instability, economic downturn, corruption and natural disasters. Finally, for creating a more robust prediction models to avoid overfitting a resampling technique to estimate the model accuracy such as K-fold validation can be applied.

4.8 References

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4.9 Appendices

4.9.1 Appendix 1

A List of typical semi-structured interview questions

Question 1): What are the effects of the weather factors on your construction project?

Question 2): Which weather factors mostly affect your current project?

Question 3): Which part/s sections of your project are affected the most by weather factors? Please explain them with examples from your experience. Also, please explain how these factors might affect the duration of activities in the project. Which activities are more sensitive?

Example reply to question 3:

Respondent 1:

Our project is located in the south of Iran, where we are not faced with cold weather and stoppage due to rainfall and snowfall. However, this does not mean that weather has no adverse effect on our project. This area is characterized by extreme humidity and high temperatures. Our observations show that with changing weather, the duration of activities changes dramatically. In periods of higher humidity and higher temperature, the duration of activities can increase (as such, weather conditions impact on labour productivity). Also, weather can have an impact on the performance of suppliers due to its undeniable role in transportation (especially in some projects located in surrounding islands such as Kish).

According to our experience (respondent 1), the main factors which can have an impact on the duration of construction projects in our study are as follows: wind, humidity and temperature (these variables affect the supplier's effectiveness, labour productivity and equipment).

Information Extracted (For instance):

Important weather variables: wind, humidity and temperature.

Affected performance variables: supplier effectiveness, labour productivity, material damage, amount of management time to rearrange work schedule/contractor management time.

4.9.2 Appendix 2

List of weather variables, performance variables, and construction activities

Weather & performance variables/ construction activities	Acronyms
Weather variables	Rainy (R), Snowy (S), Windy (W), Sunny (U), Humidity (H), Hot (T), Cold (C), Foggy (F), Blizzard (B), Sand-Storm (SS) And Hail (L), Wet (WE), Dry (D), Temperature (T), Dew Point (DP)
Project activities	Land purchase (W1) Designing and preparing maps (W2) Discharge property (W3) Equip workshop (W4) Foundation (W5) Construction and steel structure (W6) Run ceiling (W7) Run wall (w8) Isolation roof and slope operation scheme (w9) Run channels and ceiling (W10) Run plaster and installing doors and windows (W11) Construction and installation (W12) Initial installation and installation of rails (W13) Isolation and services classified slope (W14) Run mosaic carpet (W15) Tile and ceramic work (W16) Run the stone stairs (W17) Run the wooden floor (W18) Install floor frame (W19) Install wooden and aluminium doors (W20) Construction and installation of fence entrance (W21) Install valves and accessories (W22) Painting walls and ceilings (W23) Install glass (W24) Floor parking and storage (W25) Installation structure (W26) Temporary delivery (W27) Eliminate defects and cleaning (W28) Landscaping (W29) Permanent delivery (W30)

Performance variables	Human Resource Productivity (H), Equipment (EF), Supplier Effectiveness (SE), Material damage(MD), Stakeholder (SH)

4.9.3 Appendix 3

Supper Matrix												
	W6	W7	W8	W10	W13	W17	W19	W22	W28	Human Resources	Supplier Effectiveness	Material
W6	0	0	0	0	0	0	0	0	0	0.137	0.137	0.137
W7	0	0	0	0	0	0	0	0	0	0.100	0.100	0.100
W8	0	0	0	0	0	0	0	0	0	0.012	0.012	0.012
W10	0	0	0	0	0	0	0	0	0	0.166	0.166	0.166
W13	0	0	0	0	0	0	0	0	0	0.035	0.035	0.035
W17	0	0	0	0	0	0	0	0	0	0.017	0.017	0.017
W19	0	0	0	0	0	0	0	0	0	0.005	0.005	0.005
W22	0	0	0	0	0	0	0	0	0	0.005	0.005	0.005
W28	0	0	0	0	0	0	0	0	0	0.023	0.023	0.023
Human Resources	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0	0	0
Supplier Effectiveness	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0	0	0
Material	0.303	0.303	0.303	0.303	0.303	0.303	0.303	0.303	0.303	0	0	0
Humidity	0	0	0	0	0	0	0	0	0	0.381	0.381	0.381
Temperature	0	0	0	0	0	0	0	0	0	0.036	0.036	0.036
Wind	0	0	0	0	0	0	0	0	0	0.075	0.075	0.075

5 Paper II

Designing a Navigational Support System-A Generic Engine for Monitoring and Controlling Project Performance

Foad Marzoughi and Tiru Arthanari

■ Unpublished- extended version paper presented at AMCIS 2016 (Marzoughi & Arthanari, 2016a)

Abstract

In this paper, we propose a decision support system (DSS) as a generic engine called Navigational Support System (NSS) for monitoring and controlling project performance. NSS aims to help project managers to realise where the project performance is at any given time or over time, by considering the correlation between key performance indicators (KPIs) in a multidimensional space. Moreover, it supports decision-makers' choices to achieve their targets by taking sound actions during the execution phase. An effective monitoring and controlling system can improve project progress to achieve its benchmark targets. Conversely, poor performance measurement systems can diminish project progress and can cause delays and cost overruns which are common among all projects around the globe. The proposed 4-module framework uses expert knowledge about the importance of project performance variables, historical databases related to the level of project performance, historical databases related to levels of best practice performance, and expert knowledge regarding different actions

taken in various situations. We assume that all these data are available. To create NSS, we integrate multivariate measurement systems and a dynamic decision-making tool. We have evaluated NSS by applying it to monitor and control interior design projects and collect the users' (in this case interior designers') feedback from a survey. For more validating NSS we will apply it to another case from construction projects.

Keywords: Navigational support system (NSS), Benchmark space, Decision support systems (DSS), Performance measurement systems, Key performance indicators (KPIs)

5.1 Introduction

The idea of navigation in benchmark space (intangible space) was first introduced by Arthanari (2010), although the idea of physical navigation (tangible space) on land and sea is ancient, and in the air or in space it has become increasingly efficient and viable. In general, the process of monitoring and controlling the movement of a vehicle from one place to another is called navigation (Bowditch, 1802). Similarly in projects, performance is like an object in multidimensional space (which is intangible space), such as cost, time, quality, health and safety, productivity, client satisfaction and the environment (Enshassi et al., 2009) that changes over time. Change of project performance over time is considered as movement of performance from a current position to another position. Based on the current level of project performance with respect to different KPIs, project managers should take corrective actions in appropriate time to align the project with its targets (Hazır, 2015), otherwise projects will face delays and cost overruns. In order to reach the project goals in dynamic environments (João et al., 2013), and under the threat of different uncertainties (Aytug, Lawley, McKay, Mohan, & Uzsoy, 2005; Herroelen & Leus, 2005), creating an effective project monitoring and controlling system is essential in project-based organizations (Hazır, 2015; Shtub, Bard, & Globerson, 2005). Also, Hazır (2015) emphasized that these systems should contain an early warning mechanism, analytical tools to select corrective actions, a user friendly interface and be integrated in a single package. These kinds of systems are Decision Support Systems (DSS). According to Shim et al. (2002), DSS are computer-based systems that support decision making by combining and analysing data, and providing analytical models and tools for the selection of alternatives.

The majority of projects worldwide fail to meet their objectives and only a few of them are successful (KPMG, 2010; Memon et al., 2012). The dynamic and complex nature of projects (Timothy, Ford, & Lyneis, 2007) makes it difficult for project managers to understand where the project performance is with respect to benchmark targets. Although there are some performance measurement systems to measure the performance of projects, most of the time they are not implemented successfully (Fiorenzo, Galetto, & Maisano, 2007) due to inflexibility, static type and lack of dynamic decision making. For example, dashboards can only give static information regarding the performance of a system and cannot support the decision-making process dynamically due to the fact deterministic control methods are not efficient in controlling projects (Barraza, Back, & Mata, 2000). In this research, we have designed a model driven DSS (D. J. Power & Sharda, 2007) called Navigational Support System to answer the following research questions:

[1]: What are the true dimensions of benchmark targets for projects?

[2]: What is the current position of an ongoing project in the multi-dimensional space of benchmark targets?

[3]: What is the best course of action at the time to reach benchmark targets?

Hence, we have created NSS aiming to: [1] diagnose the true dimensions of the benchmark targets of projects to reduce the scope of study and to ease decision making for project managers, [2] identify the position of project performance regarding multiple KPIs from best practice, and [3] based on the current position of project performance and dynamic models of projects, recommend corrective actions to decision makers.

The rest of the paper is structured as follows: Section 5.2 reviews current performance measurement tools and decision support systems for controlling and monitoring project performance. Section 5.3 explains the generic framework of NSS and shows some examples of NSS in different industries. Section 5.4 briefly describes the steps of the design science research (DSR) which is used in this study. Section 5.5 presents the proposed conceptual framework of NSS. In Section 5.6 we develop a prototype of NSS and explain multiple methods which are used for the development in detail. In Section 5.7 we evaluate NSS by applying it to interior design projects. Finally, in Section 5.8 we summarise the results and discuss future research directions.

5.2 Domain Background and Related Work

5.2.1 Current Top Features of Project Management Software

There are several installed and web-based project management software available such as Primavera, Microsoft Project, Atlassian, Podio and Wrike that professionals widely use to manage projects. From previous studies, these packages are mostly used for critical path planning (around 87%) and time-cost trade-off analysis (around 19%) (Liberatore & Pollack-Johnson, 2003). These software are mostly used for planning (Hazır, 2015). The existing software does not have reliable early warning systems (Vanhoucke, 2012) which are required for project managers. Vanhoucke (2012) stated that dynamic scheduling is crucial for bringing projects back on track in case of problems, such as cost and time overruns. According to Vanhoucke (2012), dynamic project control tries to support project managers to take a correct and timely response during project control to bring the project performance close to its targets. There is no feature in the project management software currently available to show the status of project performance by considering the correlation between the project performance variables and support decision making dynamically. In the following section, we discuss the shortcomings of some common performance measurement tools.

5.2.2 Current Performance Measurement Tools

There are numerous performance measurement tools available in the literature to measure project performance (see e.g. Earned Value Analysis, Balanced Scorecard and Dynamic Balanced Scorecard). "Performance measurement systems are made to trigger corrective actions and hence serve as early warning systems to generate signals when the desired performance drops below a certain predefined management threshold" (Vanhoucke, 2012).

5.2.2.1 Earned Value Analysis (EVA)

EVA is a performance measurement tool widely used to measure project progress. It compares the actual amount of work with the planned value to control if the actual time, cost and amount of work are aligned with the planned value (Hazır, 2015; Marshall, 2007). However, while this tool is broadly used by professionals, it does not consider all key performance indicators (KPI). It only takes care of the time, cost and scope of the project (i.e. the 'Iron Triangle'). Moreover, it assumes that there are no correlations between key performance variables, i.e. independency assumption (Lauras, Marques, & Gourc, 2010), and it does not support decision makers in selecting the best course of action to keep a project on track. Moreover, forecasting and project performance are not constant functions of time; however, EVA assumes that they are constant functions of time (Plaza & Turetken, 2009). This tool is static by nature and cannot adapt itself to the dynamic nature of projects (Cândido, Heineck, & Neto, 2014; Hall, 2012; Kim & Ballard, 2000; Narbaev & De Marco, 2014; White & Fortune, 2002).

5.2.2.2 Key Performance Indicators (KPI)

The purpose of KPI in projects is to assess the performance of project operations (Cox et al., 2003). There are many dashboards available to show the overview of KPI to project managers, such as Easy Project, Freedcamp, Scoro, Zoho Projects, Paymo and so forth. According to Leis (2017), they are the top six project management software in the market that show a quick overview of the project, real-time KPI dashboard, Gantt charts and an overview of project progress. However, they do not consider the correlation between different KPI and do not make recommendations to project managers on which action to take to bring the project progress back on track. The other tools to measure project performance are project auditing, project status report and documentation checklist, all of which are static and do not use a decision-making approach to keep projects on track (Huan, 2010; Michail Kagioglou et al., 2001; Lin & Shen, 2007).

5.2.2.3 Balanced Scorecard (BSC) and Dynamic Balanced Scorecard (DBSC)

Balanced scorecard (BSC) was introduced as a performance measurement framework by R. S. Kaplan and Norton (1992) in four different perspectives: financial, customer, internal processes and innovation. The main goal of BSC is to strike a balance between short-term and long-term goals in an organization. Compared to EVA, BSC is a multidimensional tool to monitor and control progress. However, it is more commonly used in organizations as a strategic control tool (Chenhall, 2005; Drew & Kaye, 2007; Malmi, 2001). Some limitations of BSC according to previous studies are as follows: Ahn (2001) stated that it suffers from [1] lack of flexibility, meaning that when companies face problems because of rapid change, then BSC cannot adapt itself, [2] it is a static tool, and [3] only internal comparison is possible between KPIs (Bontis, Dragonetti, Jacobsen, & Roos, 1999), which means the level of performance cannot be compared with best practice (i.e. external benchmarks). To overcome some weaknesses of BSC, dynamic balanced scorecard (DBSC) was developed (Henk & Kim van, 2002). DBSC overcomes four limitations of BSC: unidirectional causality (one way relations), ignoring the time delay, static evaluation and lack of validation capabilities (Marcela et al., 2011). In other words, BSC cannot answer such questions as: "what will happen if a particular action is taken?" (static manner) and in reality it takes time to see the consequences of taking a particular action on project performance, and BSC does not consider that time (ignores the time delay) and it may lead to incorrect conclusions (Rydzak, Magnuszewski, Pietruszewski, Sendzimir, & Chlebus, 2004).

DBSC gives an opportunity for decision makers to conduct thorough analyses of the whole system (Rydzak et al., 2004) by developing a dynamic model of the system using a system dynamic approach (Forrester, 1961). It covers many deficiencies of other performance measurement tools but it only measures the performance of the entire organization (strategic level) and does not calculate the distance of current performance of the organization with respect to best practice, or visualize the position of the organization performance from benchmark targets in a graph by considering the correlation between KPIs.

Current performance measurement tools such as Benchmarking (Associates., 1988), BSC (R. S. Kaplan & Norton, 1992) and EVA (Aliverdi, Moslemi Naeni, & Salehipour, 2013; Blanco, 2003; Lipke, 1999) are used to monitor and control project performance, but these are static, cannot identify project status in a multi-dimensional space by considering the correlation between KPI, and do not consider dynamic decision making. Among these performance measurement systems, only Dynamic Balanced Scorecards (Sloper, Linard, & Paterson, 1999b) considers the dynamism of projects by developing a system dynamic model, but has high implementation requirements, is more abstract, and does not show the distance of current project performance from external benchmarks (Huan, 2010; M. Kagioglou & Cooper, 2001).

5.2.3 Current Decision Support Systems Integrated to Project Management Software

To increase the performance of projects, a DSS can be integrated into project management software in the planning and control phase (Hazır, 2015). DSSs are used to facilitate planning and controlling of projects under uncertain environments. For example, it can be used to solve scheduling problems with Gantt charts or solve resource allocation problems to show resource usage and capacities with bar charts (Kastor & Sirakoulis, 2009; Tavares, 2002; Trautmann & Baumann, 2009; Williams, 2003). On the other hand, some DSS tools are created to analyse risk in project management, such as Crystal Ball (Buehlmann, Ragsdale, & Gfeller, 2000). The majority of DSS tools only support scheduling and risk analysis (Vanhoucke, 2012), while project managers need a reliable multidimensional project control system to measure the project objectives and indicate the project status during the project life cycle (Rozenes, Vitner, & Spraggett, 2006) , whereas most existing software do not do this (Trietsch & Baker, 2012). Hazır (2015) emphasized that it is vital to have analytical project control tools to support project managers to undertake corrective actions at the right time and to intervene efficiently. Analytical project tools control projects in different situations (project is over budget and ahead of schedule, over budget and behind schedule, or under budget and ahead of schedule) to bring project performance back on track (Snyder, 2011). Statistical and analytical tools such as dynamic decision-making approaches, dynamic programming and optimal control can be used to create a decision support system that facilitates an understanding of the complex, stochastic and dynamic behaviour of real projects (Chang & Tong, 2013; Hazır, 2015; Hollocks, 2008; Lauras et al., 2010; Williams, 1999). According to Hazır (2015), in industry, managers face multidimensional, dynamic and open systems; however, in academic studies there are assumptions on closed systems (less complex problems) and availability of information in advance. Then project managers need to have project management software or a comprehensive DSS to control non-determinist and more complex problems. The rest of the paper is devoted to the development of such a framework and a prototype, followed by discussion.

5.3 Navigational Support System, Generic Framework

The generic engine of a navigational system monitors and controls progress of intangible objects, such as project performance, company performance, and patient health status. According to Figure 5-1, if we want to use a navigational support system in any field of study, we need to have available knowledge in the area of study in terms of KPIs so that the progress of an object can be measured over time. Then the system will find the most important KPIs that should be measured and compared with benchmark targets. Then NSS recommends best actions to reach the benchmark targets given the current position. This process continues until the object reaches benchmark targets. We describe the application of NSS in three different industries in Figure 5-1 below:

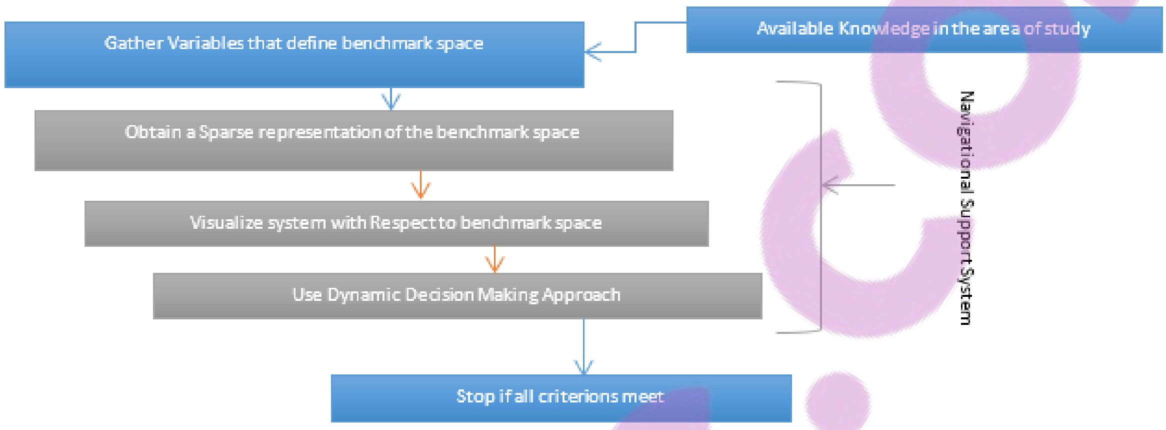

Figure 5-1 Generic framework of navigational support system

5.3.1 Example: Application of NSS in Healthcare

For example, in monitoring a patient's progress, when a patient visits a doctor to check if they are healthy, the doctor performs relevant tests (Strandberg-Larsen & Krasnik, 2009). In the tests, there are some variables that should be measured to assess the patient's current levels of cholesterol, triglyceride, glucose in blood, insulin produced, vitamin D requirements and so on (Wu, Cagney, & John, 1997). The metrics that should be tested to check the patient's health status are available in this area of study (doctors have this knowledge). For each disease, different metrics may be used and the NSS will find the most important metrics for each particular disease, based on the doctor's opinion of the importance of each metric. This intangible space created by relevant metrics to monitor the patient's health status is called the benchmark space. Then the NSS system compares the health status of the patient with a healthy group of people (benchmark targets) and measures how far the patient is from a healthy group.

Based on the results, the doctor decides whether to prescribe some medication (take action). In a medical check-up, diagnoses are made with the experience of the doctor along with the results of the testing.

For example, a specialist doctor checks a patient's health with some KPIs such as weight, blood pressure, cholesterol level, glucose and so on. Based on the range of KPIs, the doctor gives a prescription to a patient consisting of several actions, such as regular exercise, eat small meals, refrain from smoking, and diet according to the food pyramid. By doing each of these actions, an unhealthy person would get closer to the normal group. This case can thus be modelled as a dynamic programming model that a patient at time, t, is at a known state, s, in S, the set of possible states, with respect to the normal range of KPIs. Then by taking a set of actions A which are known, a doctor expects that the status of the patient's health will move to a different known state, s', with a known transition probability. This scenario can be modelled as deterministic dynamic programming when the state and the next stage are completely determined by the state and policy decision at the current stage. The dynamic programming approach assumes we know where the system is and how the transition from this state to another state takes place (Bellman, 1957).

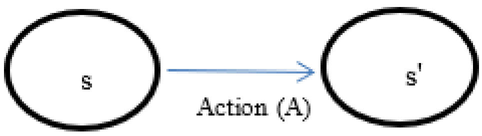

Figure 5-2 Transition from state S to S' based on an action taken

Also in the state of s' (Figure 5-2) the doctor measures the 'healthiness' of a patient with respect to benchmark targets. The new position of the unhealthy person with respect to benchmark targets is known. The doctor then makes decisions based on the level of abnormality of a patient. For instance, if a patient is mildly abnormal then the doctor takes some sort of action like do more exercise and meditate which is different from when a patient’s abnormality is medium. In this case, the knowledge is available within the doctor’s mental model that he/she prescribes some actions to a patient with some probability to make an unhealthy person reach benchmark targets. For example, if a patient suffers from severe anxiety, the possible actions for patients to take as prescribed by doctors can be as follows: deep breathing, meditate instead of self-medicate, change diet, or attend a social gathering (Linda, 2014). In NSS, the new position of the system with respect to benchmark targets will be diagnosed by the first phase. Thus, we use existing knowledge about the dynamics of the system in NSS to recommend best action for the decision maker (in this case the doctor) to choose. Then NSS will show the new status of the patient based on the action taken and this process continues until the patient is treated completely.

Example: Application of NSS in the Education System

For monitoring the progress of a university, there are several KPIs available that should be measured, such as rate of research outcome, student diversity percentage, staff satisfaction, student satisfaction, faculty resources, continuing education services, curriculum planning and so forth (S.-H. Chen, Wang, & Yang, 2009). By using NSS, the most important metrics will be identified and compared with the same metrics from the best universities around the globe.

For example, the University of Auckland is ranked in the top 100 world university rankings: its ranking is 82 among all universities ("Qs world university rankings," 2017). The higher ranked universities can be considered as benchmark universities, such as Massachusetts Institute of Technology (MIT), Stanford University, Harvard University and so forth. NSS can visualize the current performance of a university (in this case the University of Auckland) and show the distance from the top universities' performance (benchmark targets). Then NSS can recommend to decision makers the best actions that they can take to reach benchmark targets. This process continues until the university reaches the target. We assume that the dynamic model of performance of the educational system is available. If the dynamic model is not available then we have to develop it to use in NSS for finding the nearly best action/actions to reach benchmark targets.

Example: Application of NSS in Software Projects

Another example is related to the application of NSS for monitoring and controlling the performance of software projects. The knowledge about KPIs related to software projects is available in the following databases from Q/P Management Group ("Q/P Benchmarking Data," 2011), International Software Benchmarking Standards Group ("International Software Benchmarking Standards Group," 2017) or international function point user's group (IFPUG) (Y. Cheung, Willis, & Milne, 1999). These companies can provide the benchmark values related to software project's KPIs such as effort attributes, defects, schedule details, documentation used, platform details, project size and so forth.

Hence, for applying NSS framework in the area of software development, the benchmark values can be collected from these organizations. The current project performance is available from an ongoing project. Then the dynamics of the software development should be creating or if it is available in the form of system dynamic models or dynamic programming can be applied in the framework.

Example: Application of NSS in Construction Projects

Another example is related to the application of NSS for monitoring and controlling the performance of construction projects. Similarly, the knowledge about KPIs related to construction projects is available and a dynamic model of construction project performance is available too. Similarly, in a construction project the performance of a project is an object that moves toward benchmark targets under constraints, such as time and cost. The performance benchmarking space has multiple dimensions, such as cost, time, quality, safety, customer satisfaction and so forth. Moreover, the critical success factors in construction projects are correlated to each other (Y. Chen et al., 2012; Elizabeth, David, Kioumars, & Naresh, 2007; Sparkart, 2013). NSS will calculate the distance of construction project performance from benchmark targets and then recommend to project managers the best action to close the gap.

The assumptions to utilise NSS are shown as follows:

- The data related to rank KPIs in any type of projects are assumed to be available. If these data are not available, then we have to design a questionnaire to collect them from experts in the area of study. This limitation can also cause the NSS to be inapplicable.
- The data related to benchmark projects needs to be available from historical data. In the case that these data are not available, then the planned values of relevant KPIs can be considered as benchmark targets.
- The dynamic model of the project needs to be available in terms of a dynamic programming model, including a set of states, a set of actions, and the probability of transition of the project performance from one particular state to another state based on the action/actions taken.

Hence, any of these limitations can cause NSS to be inapplicable. NSS can be applied for all mentioned examples in both operational and strategic levels of monitoring and controlling the progress of an object in the benchmark space. In the following section, the methodology of how to create NSS in the project level is explained in detail.

5.4 Research Methodology

This research follows design science research methodology (DSR) (v. A. Hevner et al., 2004; March & Smith, 1995; Nunamaker et al., 1990; Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007). Hevner (2004) stated that DSR should either solve problems through the creation of artefacts that address an unsolved problem in a unique or innovative way, or solve problems in a more effective way. In this research, by using DSR, a Decision Support System is created (called NSS) to show the performance of an ongoing project compared with best practice in a multi-dimensional space and to support project managers to take corrective actions to reach benchmark targets.

We have followed five main activities of DSR (Geerts, 2011) to create NSS as 'an instantiation artefact' (March & Smith, 1995): [1] We have thoroughly reviewed the literature to identify the problems and weaknesses of current performance measurement systems to confirm that there is a need to address those problems. [2] We developed a conceptual framework to address how those problems need to be approached and solved. [3] Afterwards, we designed and developed NSS as a computer based system (instantiations). [4] Then we used sample data from an interior design project to prove that the NSS works properly. [5] Finally, to evaluate the NSS (artefact), we have interviewed interior designers for their feedback on functionality, reliability and performance of the developed system. For creating NSS, an expert's opinion (in this case interior designers) on the importance of specific KPIs relative to one another on finding the most important KPIs (benchmark space) is an essential input. For this purpose, a questionnaire should be designed and distributed to experts (such as project managers/ interior designers) to rate each KPI on a given Likert scale (where 1= not important at all, 2=not necessarily important, 3= important sometimes, 4= important, 5= extremely important). A multivariate statistical method (dimension reduction technique) is used to filter the KPIs to find the most important KPIs. The value of important KPIs from ongoing projects and best practice are another crucial input required to identify the distance of project performance from benchmark targets. An appropriate distance metric such as Mahalanobis Distance (Mahalanobis, 1936) should be used to determine the closeness of the project to the target, taking into account the correlation between different KPIs. Finally, an analytical method should be used to create a dynamic model of current project performance such as a Markov Decision Process (MDP) to support project managers to take corrective actions based on the distance of different KPIs from benchmarks. For this purpose, we have interviewed three experts in the area of study (in this case interior designers) to create a dynamic model of the system based on their experience.

For data collection, both quantitative and qualitative methods are used in different stages of the proposed framework. Brief accounts of some of these methods are given.

5.4.1 Sparse Principal Component Analysis

Principal component analysis (PCA) is a multivariate statistical tool used to reduce the dimensionality of the data set on several variables and observations by identifying a smaller number of underlying dimensions that explain most of the variability in the data (I. Jolliffe, 2005). PCA is widely used in dimensionality reduction (i.e. analyses to reduce the number of variables to those most important) and data processing, with several applications in engineering, biology and social science. However, it suffers from the fact that each principal component is a linear combination of all variables (Hui Zou et al., 2006). In other words, the true dimension reduction will not occur after executing PCA. To overcome this problem, Hui Zou et al. (2006) proposed a new method of dimension reduction called sparse principal component analysis (SPCA). SPCA considers the zero impact of variables on the components (sparsity) and is more efficient when the number of variables is much larger than the number of observations. We use SPCA in the filtration module of NSS to find the true dimension of KPIs.

5.4.2 Mahalanobis Distance (MD)

Mahalanobis distance (MD) was introduced by Professor Mahalanobis (1936). MD is a general form of distance, and Euclidian distance is a special form of MD when variables are uncorrelated. MD considers the correlation between variables. According to Lande (2004), MD is used to distinguish patterns of certain groups from normal groups, and is a useful tool for determining the similarity of a known set of values with that of an unknown set. MD considers the variance and covariance of the measured variables instead of considering only the mean value. We used MD metric to determine the closeness of the ongoing project performance with the performance of best practice in positioning the module of NSS.

5.4.3 Markov Decision Process (MDP)

Dynamic decision making is a kind of decision-making in a situation where there are a series of decisions which are related to each other (i.e. co-dependent) and where situations change over time (Brehmer, 1992). One of the decision-making techniques which can be used in a dynamic environment and under uncertainty is the Markov Decision Process (MDP) (Bellman, 1957; Leong, 1998) Dynamic decision-making modelling is widely used in real world applications, such as management of construction sites, navigational control (Fakoor, Kosari, & Jafarzadeh, 2016), battlefield decisions, medical emergencies (Ni, Wang, & Zhao, 2017) and so on. We used MDP in the decision-making module of NSS to support decision makers for taking the best action to reach benchmark targets. MDP algorithms will find the corrective action based on the available dynamic model of the system (see Appendix 2).

5.5 Conceptual Framework of Navigational Support System

The proposed framework of the navigational support system has four main modules (Figure 5-3): [1] Expert Knowledge Module (EKM), [2] Filtration Module (FM), [3] Positioning Module (PM) and [4] Dynamic Decision-Making Module (DDMM). The Expert Knowledge Module (EKM) consists of knowledge gleaned from experts and literature on the importance of KPIs, by asking experts to rank the importance of KPIs for a particular project. This information is used in preparing the input for the FM. The FM processes the input on the importance of KPIs, and, using SPCA, produces a smaller set of the most important KPIs. The output of FM is used for creating benchmark space.

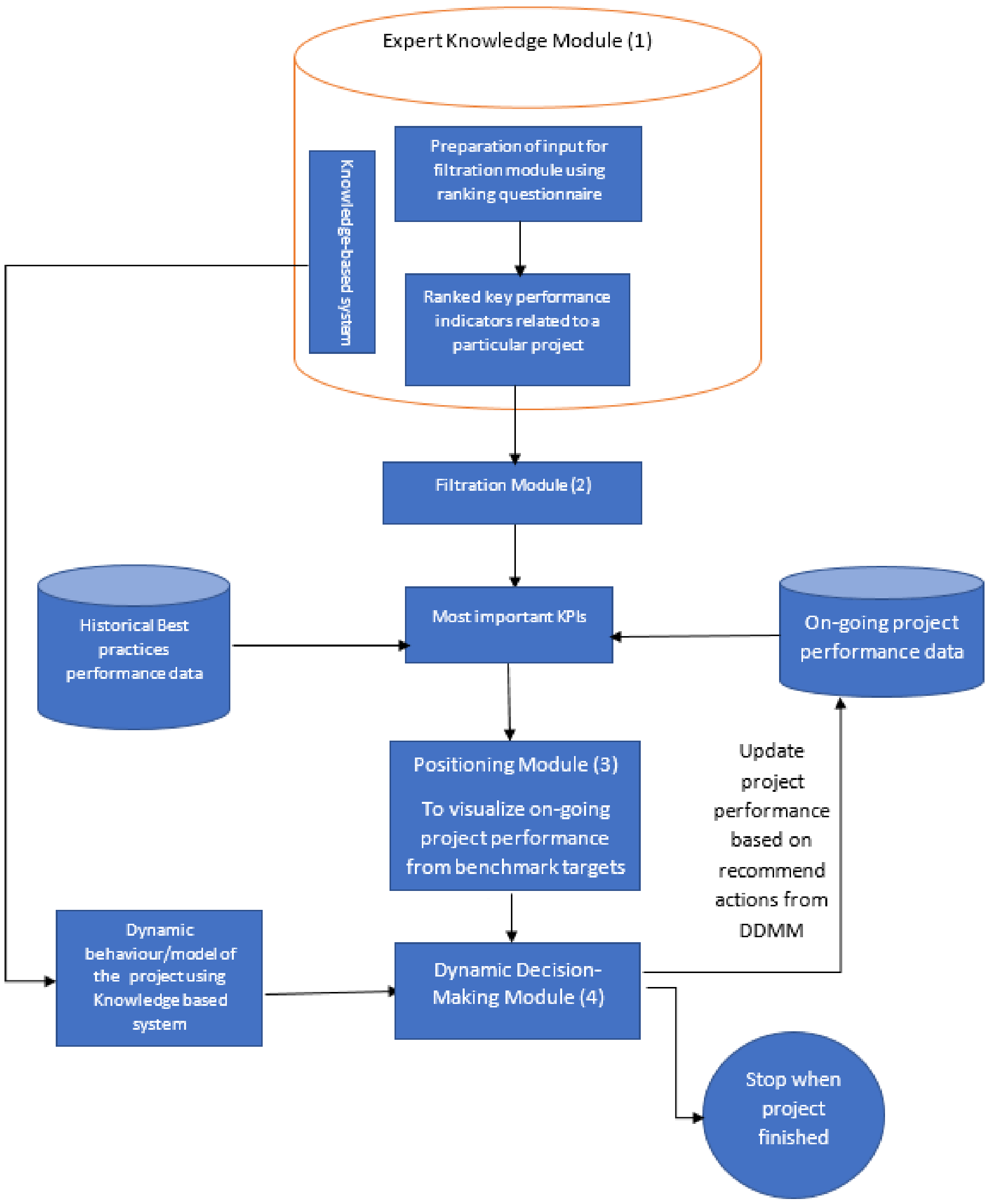

Figure 5-3 Generic framework of navigational support system

We assume we have the following databases: [1] historical database related to the level of performance from best practice, and [2] historical database of an ongoing project performance.

The structure of the databases which have been used in the framework of NSS is shown in Figure 5-4, where the arrows show the cardinality of entities.

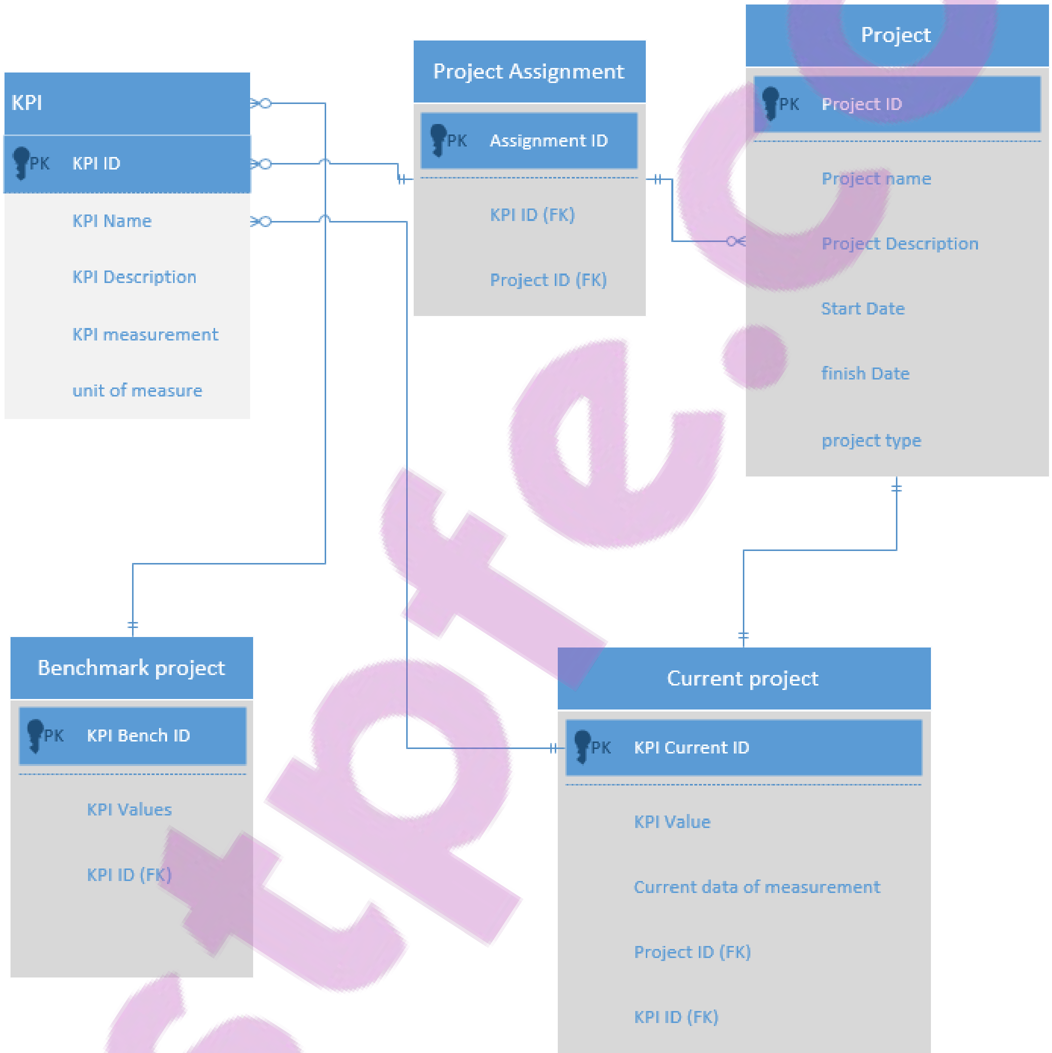

Figure 5-4 Structure of historical and ongoing project performance databases

Then we obtained the value for the most important KPIs (output of FM) from mentioned databases and fed them into the Positioning Module (PM). The Positioning Module (PM) uses a distance metric, like Mahalanobis Distance (MD), to determine the distance of the current project performance from benchmark targets. The Dynamic Decision-Making Module (DDMM) uses the history of actions that project managers have taken in different situations (states) from a project database at a given time to recommend the best action to take among alternatives. This is done based on the assumption of the availability of capturing the dynamic behaviour of a project, then the new values for project performance at time t+1 with respect to the recommended action will be added to the project performance database as the current value of project performance. The updated project performance will be fed to the Positioning Module (PM) to find the new position of project performance from benchmark targets. This process continues until the project reaches its benchmark targets.

In order to provide a proof of concept , we developed a prototype using Shiny R, a web application framework with R language (version 3.2.3) (Gardener, 2012), which implements the different modules of proposed conceptual frameworks using particular tools, and Microsoft Excel macros written in VBA. The application can be used for hosting and deployment in the cloud using shinyapp.io or it can be hosted locally by installing Shiny server (Chris, 2013). We then validated the artefact based on the guideline of design validation with a real case from the interior design project (v. A. Hevner et al., 2004). The criteria of design validation are in terms of functionality, completeness, reliability and performance, and fit with the organization.

5.6 Prototype development using a case from an interior design project

In order to develop a prototype of NSS, we integrated four modules which are explained in detail below. We applied NSS to interior design projects from New Zealand to prove the efficacy of the proposed framework. We used the following steps to collect relevant data for NSS.

5.6.1 Expert Knowledge Module (EKM)

To identify the KPIs of a project in an industry, it is necessary to design a structured questionnaire of the project KPIs. Then the questionnaire is distributed to the experts of each field of study to rank the KPIs. To do this, respondents should be asked to rate each KPI based on their professional judgment on a Likert scale (where 1= not important at all, 2=not necessarily important, 3= important sometimes, 4= important, 5= extremely important). The ranked KPIs should be saved using the format of a Microsoft Excel file (.csv, .xlsx). This external file is used as the input of the FM. We used Visual Basic in Microsoft Excel to manage the EKM. In our case we collected these ranking data from 32 interior designers in New Zealand. They filled in the questionnaire (See Appendix 1) to rank the KPIs of interior design projects. Then this information was fed into the next module (Filtration Module) as an input to identify the most important KPIs rather than working on all KPIs.

5.6.2 Filtration Module (FM)

The Filtration Module is responsible for reducing the number of KPIs collected from experts to rank the importance of KPIs through a designed structured questionnaire (saved as a Microsoft Excel format file). The huge number of these KPIs can overwhelm decision makers trying to understand which factors really affect project performance. To overcome this information overload, the Filtration Module (see Figure 6-1) will reduce the number of variables to find out the true dimensions of project performance. We developed this module by applying SPCA as a dimension reduction technique to identify the most important KPIs for each major component. According to Hui Zou et al. (2006), the SPCA method is suitable in both situations when the number of variables is less or greater than the number of observations.

In our case the number of observations and KPIs are same (32). The external ranked KPIs file (collected from 32 interior designers) should upload to FM. Then the FM module will find the most important KPIs related to a particular project using SPCA and convert them into major components. Figure 5-5 shows all ranked KPIs and the number of principal components. By clicking on “View KPIs”, users can only see the most important KPIs (Figure 6-2). According to Figure 5-6, only 8 KPIs are selected among 37 KPIs in total, and they are loaded on 3 major components. Comp1 consists of ‘time required to amend defects and late delivery of materials’, Comp2 consists of ‘cost related to variation of orders and labour cost of project’ and Comp3 consists of ‘quality control by interior designer, process of decision-making by interior designer, material quality and skills of manpower’. Then the first, second and third components can be labelled as time performance, cost performance and quality performance respectively. The Y-axis in the most important KPIs’ graph shows how much variation is explained by each important KPI. For example, in the third component, quality control by an interior designer explains around 20% of variations and the process of decision-making by the interior designer is around -30% of variations. The negative sign in the process of decision-making by the interior designer shows that this variable has a negative correlation with quality control by the interior designer variable.

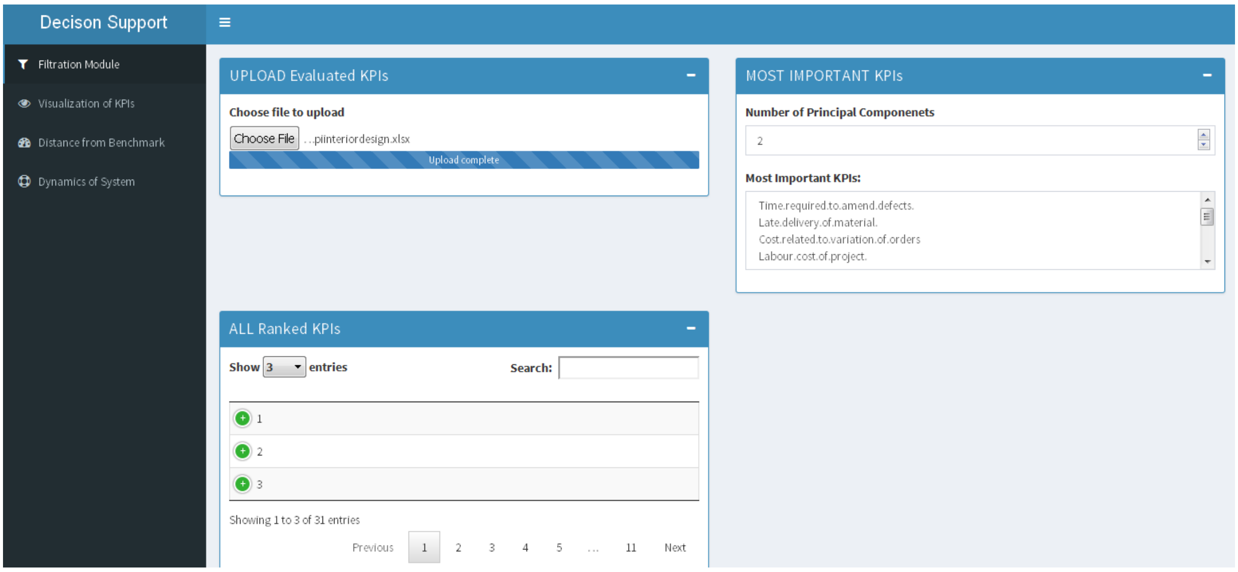

Figure 5-5 Filter all KPIs of a particular project

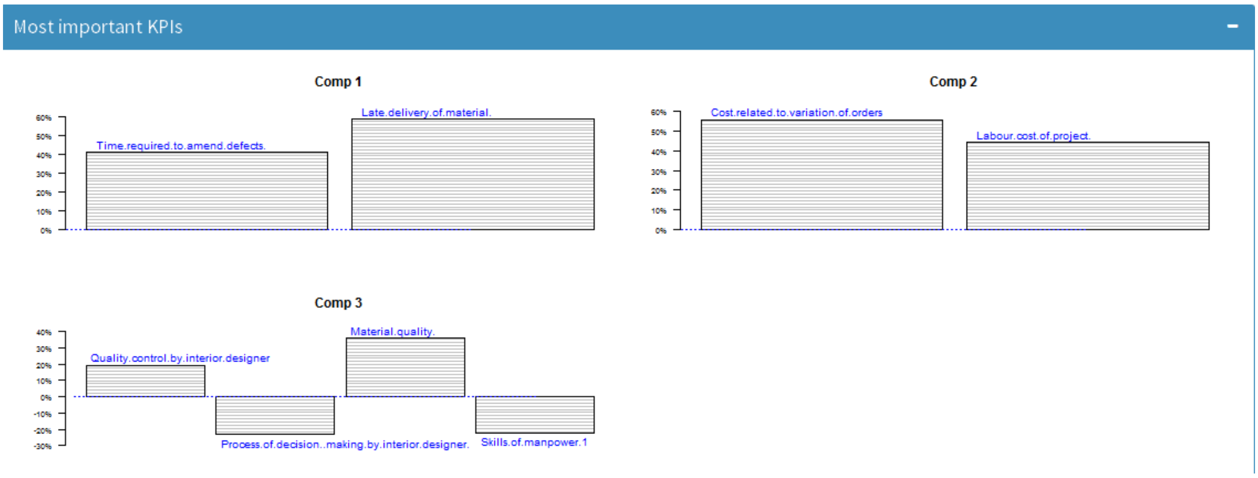

Figure 5-6 Visualize most important KPIs

Then, based on the selected KPIs, using execution of the SPCA algorithm, project managers should create a benchmark space which consists of the most important KPIs with a specific target (preferably selected from performance of best practice). Users should add the value of selected KPIs (derived from FM) from both ongoing projects and benchmark projects as the input of the positioning module. Figure 6-3 shows how the user can manage KPIs for feeding to the positioning module. In this case time, cost and quality are the most important KPIs that should be added into the subsection of created KPIs, as shown in Figure 5-7, with their values from benchmark projects. In this case benchmark projects are collected from one of the top interior design companies. In this regard, an official email was sent to the Managing Director of the company asking her to send us the values of selected KPIs from Figure 5-7 for 20 residential interior design projects with two bedrooms. Then we collected the same type of data from a residential project from an interior design company in New Zealand to find the distance of this project from benchmark projects.

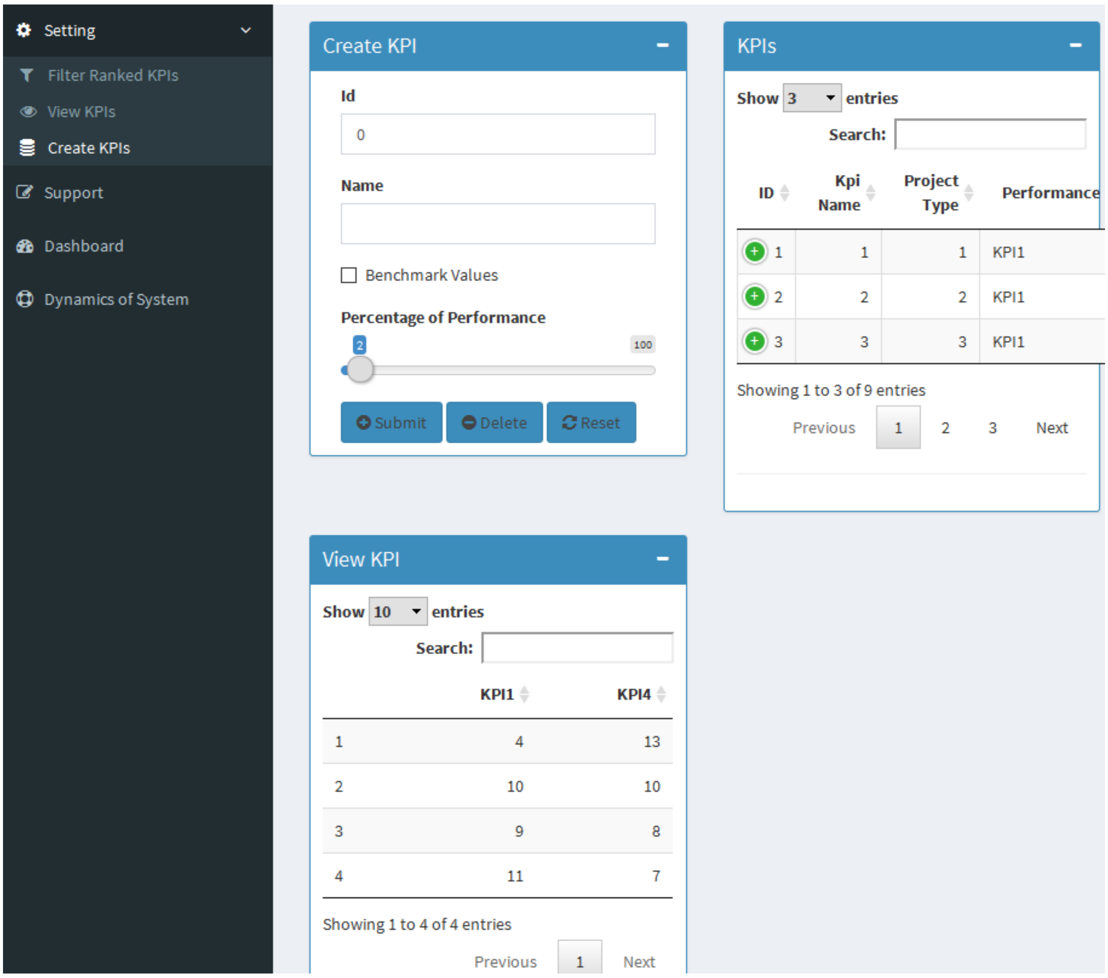

Figure 5-7 Managing key performance indicators for current project and benchmark projects

5.6.3 Positioning Module (PM)

The second module is responsible for finding the position of ongoing project performance from best practice performance (benchmark projects performance). The input for this module are values of selected KPIs from benchmark projects performance (BPP) and ongoing project performance (OPP). Due to the strong correlation between different KPIs (Toor & Ogunlana, 2010), we have used the MD metric to find the distance of ongoing project performance (OPP) at the current time from benchmark projects performance (BPP) by taking into account the correlation between KPIs to create a benchmark space from benchmark data.

The MD to measure the difference between current project and benchmark projects values is given by:

$$\Delta^2 = (\mu_{(Current)} - \mu_{(Benchmark)})^T S^{-1} (\mu_{(Current)} - \mu_{(Benchmark)}) \qquad \textbf{Equation 5-1}$$

Where S denotes the correlation matrix of benchmark projects, Δ^2 is the distance of the current project from the benchmark project, and μ is the mean. As illustrated in Figure 5-8, the current project performance in terms of time and cost are both 22.5 units behind best practice. In this case benchmark projects are collected from one of the top interior design companies from the USA called Robeson Design. In this regard, an official email was sent to the Managing Director of the company asking her to send us the values of selected KPIs from 20 of their residential projects. It is noted that in MD there is no unit of measure for the KPIs. Also, in Figure 5-8, every point inside the ellipses shows the benchmark targets from benchmark projects and black ellipses shows the error for 99% confidence values. The direction of the oval shows that there is a strong positive correlation between time and cost.

The integration of MD and SPCA addresses the positioning problem of comparing current KPIs to benchmark KPIs, but it does not address the navigational problem of how to meet those benchmarks.

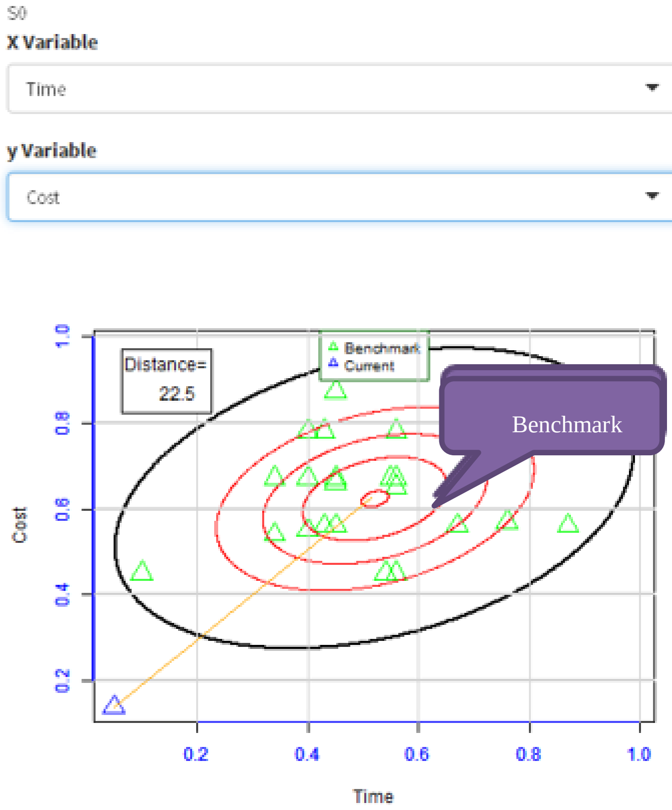

Figure 5-8 Distance of current project performance from benchmark projects

5.6.4 Dynamic Decision-Making Module (DDMM)

The last module of the NSS addresses the navigational problem of how to move from current project performance to benchmark performance. As mentioned earlier, this knowledge can be in the form of a mental model, a dynamic programming model, or a system dynamic model depending on the complexity of the system. Dynamic decision-making is a kind of decision-making in a situation where there are a series of decisions which are related to each other (dependent) and the state of the world changes over time (Brehmer, 1992). Because of the dynamic behaviour of projects, we have used a dynamic decision-making technique known as Markov Decision-Making Process (MDP) (Hernandez & Lasserre, 1991) to measure the dynamics of projects by considering the non-deterministic nature of project uncertainty (Maria Elena, Patrizia, Francesca, & Erika, 2011).

For example, a dynamic model of a project's performance using MDP (1957) can be created as illustrated in Figure 5-9:

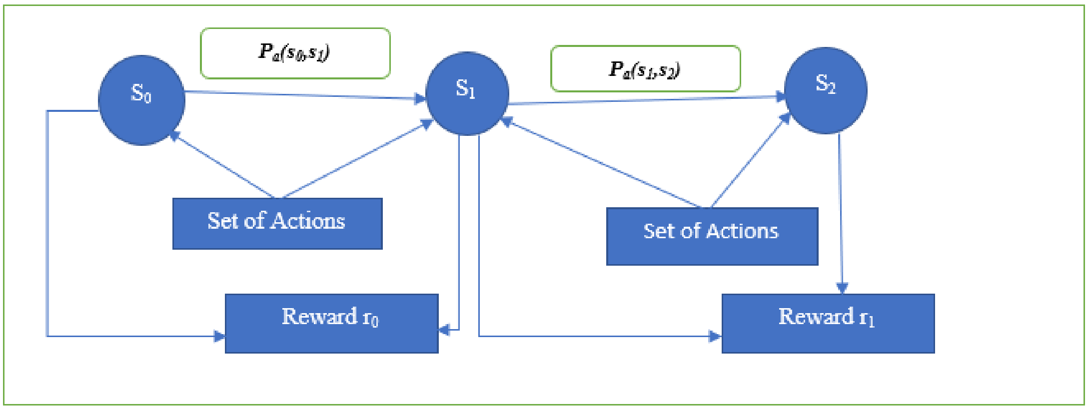

Figure 5-9 Dynamic model of a project

- Given a set of *k* policies $\{P_0, P_1, P_2, \ldots P_k\}$
- Policies are combinations of actions in different situations and they should be finite. For example, policies can be defined as {P_0= hire new staff and inject money, P_1 = labour work over time and reassign resources to a lower cost resources, P_2 = charge customers for any variations after signing off the project}.
- Given a set of *m* states $\{S_0, S_1, S_2, \ldots S_m\}$, states are considered to be different situations of project performance, such as { S_0 = project is under budget and over time, S_1 = project is within budget and within time and S_2 =within budget and low quality}.

- The probability of transiting from state ***s*** at time ***t*** to state $\boldsymbol{s'}$ at time ***t+1*** by taking policy could be shown as $P_a(s, s')$**.** Based on historical records regarding different actions taken by project managers in different situations, we can create a transition probability matrix for each action taken (Figure 5-10). We assume that we have a dynamic model of project performance. Then NSS recommends the best policy for project managers to take with the help of dynamic models. For recommending the best policy the NSS needs to know the current position of project performance, which is detected from the positioning module (PM).

$$
\begin{array}{c|cc}
 & & \text{Current state} \\
 & & \text{State } 1 \quad \cdots \quad \text{State } j \quad \cdots \quad \text{State } r \\
\text{Next state} & \begin{array}{c}\text{State } 1 \\ \vdots \\ \text{State } i \\ \vdots \\ \text{State } r\end{array} & \left[\begin{array}{c} \\ \\ \Pr(\text{next } i \mid \text{current } j) \\ \\ \\ \end{array}\right]
\end{array}
$$

Figure 5-10 Transition probability matrix by taking one particular action

Finally, r is the reward accumulated from moment t to moment t+1.

In this case the dynamic model of an interior design project is developed by interviews with interior designers and modelled as a stochastic Markov decision-making process as shown in Figure 5-11.

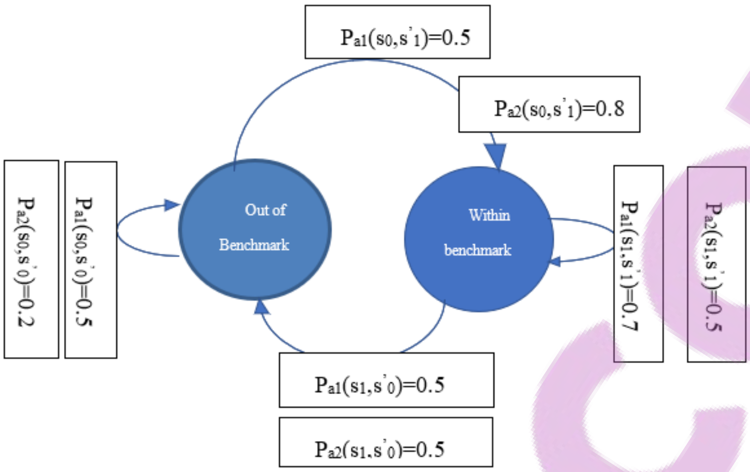

Figure 5-11 A dynamic model for an interior design project

According to Figure 5-11, the dynamic model of the interior design project consists of two possible actions: a1, labour work over time and use of low cost materials, and a2, hire more expert labour, and two states: s_1, within benchmark, and s_0, out of benchmark. Moreover, the probability of transiting from the out of benchmark state to the within benchmark state by taking actions a1 and a2 is shown in Figure 5-11. These probabilities are calculated based on the previous 10 similar projects done by the local interior design company. For example, if the project is out of benchmark (s_0) by taking action, a_1, the project will transit to the within benchmark state (s_1) with 0.5 chance and there is a 50% chance that it remains in the out of benchmark state.

We used the following range to classify the states from the current values of KPIs. These ranges can be determined by experts. For example, experts believed that if the performance of a project in terms of cost and time is less than 70% and 80% respectively, then the project status is considered as out of benchmark compared to benchmark projects.

For example, from Figure 5-8 based on the current values of KPI1 (time) and KPI2 (cost) from the ongoing project, the system detects that the time and cost status is out of benchmark compared to benchmark projects. Then, based on this situation, the best policy will be determined and recommended to the project managers (in this scenario the interior designers). The project managers can take the recommended actions or they can make their own decisions based on the situation. NSS only supports the decision-making process and the final decision will be taken by the decision makers.

The output of DDMM will determine the best action or set of actions (policy) that can be taken in any current situation by project managers to bring project performance closer to benchmark targets. Figure 5-12 shows a sample output of DDMM.

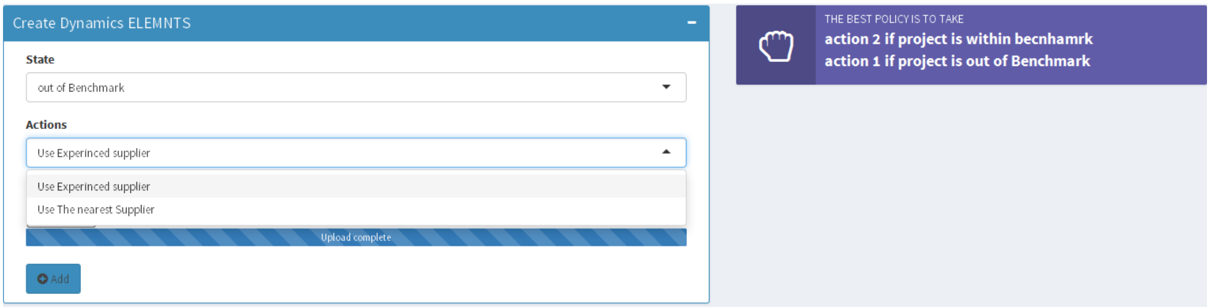

Figure 5-12 Output of dynamic decision-making module

Then, based on the action taken by the project managers, the project performance level at the next period of time will be saved into the ongoing project performance database. Afterwards, it will be compared to benchmark targets, again using MD in the PM to check the status of project. This process continues until the project performance reaches benchmark targets or the project is completed.

5.7 Evaluation of proposed framework

To implement the NSS, we used Microsoft Excel macros written in VBA and Shiny dashboards with R programming language. The system is designed for decision makers, such as project managers and interior designers that have a basic understanding of project control and monitoring, but not necessarily an understanding of the algorithms and parameters explained for this NSS in each module, i.e. it is designed for decision-makers with no understanding of programming, or the mathematical or statistical techniques employed by the NSS. When the system is open, they should upload the necessary data from a particular Microsoft Excel spreadsheet of evaluated data of KPIs into the system. Then by opening that spreadsheet, they will be asked to create KPIs related to that project at the beginning of the project life time; however, it can be revised during the project life time and entered into the ranked KPIs from experts from the structured interviews and surveys. After these values are entered, the user can view the most important KPIs. The system will prompt the user to go to the PM to view the distance of current project performance in contrast with benchmark targets. Then the user will be asked to upload the current values of project performance of the ongoing project and upload the performance related to benchmark projects. Then the user should click on the “calculate distance” button to see the closeness of the current project performance to best practice. There will be a system prompt for the user to click on the DDMM. In the DDMM, the best action or set of actions will be recommended to the project manager based on the current status of the project identified from PM. Appendix 3 illustrates this process as an activity diagram of NSS.

According to Offermann et al. (2009) we have used expert interviews to validate the application of NSS in the field of interior design projects.

We performed an evaluation of this tool by gaining some feedback from 10 interior designers working at different interior design companies in New Zealand. All of them were familiar with project monitoring and controlling. They expressed genuine interest in a controlling system that aids project managers in understanding where the project is and how managers can control it to increase its performance. We designed a questionnaire to get their feedback on the functionality, completeness, reliability and performance, and fit to the organization.

Hypothesis

H0a: By using NSS user acceptance is less than moderate

H0b: functionality of NSS is less than moderate

H0c: completeness and reliability of NSS is less than moderate

H0d: reliability of NSS is less than moderate

H0e: NSS moderately fits to the organization's need

According to Table 5-1, the null hypotheses will be rejected for user acceptance, functionality, completeness and reliability of NSS according to p-values less than 0.05, and the criteria of fit to the organization failed to be rejected. We concluded that in terms of user acceptance, functionality of the system, completeness and reliability, users were satisfied with NSS and in terms of fit to the organization that they were moderately satisfied and users mentioned that there was a huge potential to integrate NSS with existing project management software, such as MS Project or Primavera. Moreover, they mentioned some limitations in using NSS, such as collecting relevant data of dynamic decision-making modules, which is very time consuming, and needed an explanation as to how to collect relevant data.

Table 5-1 One sample T test to analyse the hypothesis on different validation criteria

	Mean	Standard deviation	P-value	Hypothesis status
User acceptance	3.94	0.38	0.000	H0: $\mu \leq 3$
Functionality	3.89	0.76	0.000	H0: $\mu \leq 3$
Completeness	3.78	0.28	0.000	H0: $\mu \leq 3$
Reliability and performance	4.05	0.38	0.000	H0: $\mu \leq 3$
Fit with the organization	3.28	0.28	0.104	H0: $\mu \leq 3$

We compared the final status of 10 interior design projects' performances which had used NSS at the middle stage of the project life time and some at the end stage with 10 interior design projects that did not use NSS to see if there was any dependency between using NSS or not using NSS to control and monitor the project performance. A cross tabulation table between final project status and the usage of NSS in controlling projects is shown in Table 5-2. According to p-value of 0.025, the null hypothesis is rejected, which confirms that there is a dependency on the usage of NSS in controlling project performance and it affects the final status of the project performance.

Table 5-2 Contingency table of final output of project performance and the usage of NSS to monitor and control project performance

		Applied NSS Yes	Applied NSS No	Total	Chi square P-value
Final Status of project	Out of benchmark	3	8	11	0.025
	Within benchmark	7	2	9	
Total		10	10	20	

We discuss some of the user feedback below.

- “Need a lot explanation how to collect relevant data of dynamic decision-making module”: however, we spent a considerable effort in explaining the different steps of dynamic decision-making module within the system. Reviewer 3 indicated that he still did not understand how to define some of these variables, such as sets of states and how to identify reward values. To address this issue, we decided to give users guidelines for collecting relevant data to create a dynamic model of the system, for example, a help button in the NSS to tell them how collect these data step-by-step.

- “The graph in the position module should shows time as another axis”: This suggestion was to improve the visualization of project performance in a time frame, then the project managers will know the project performance in each period of time and they can compare the performance gained by recommended action from DDMM in t+1 with the previous time to check the accuracy of the NSS. To address this issue, we added a time axis into the benchmark space graph in the positioning module.

5.8 Discussion and Conclusions

In this research, we aimed to create a novel controlling and monitoring system to improve the body of knowledge on controlling project performance. This paper discussed the problem of navigating in multidimensional benchmarking spaces. The main contribution of this research is the development of a generic NSS for navigating in a benchmarking space by integrating multivariate measurement systems and dynamic decision-making tools. The study was conducted to solve the problem of navigating a system in a benchmarking space. The developed artefact provides an environment for decision-makers to understand where they are with respect to targets, and then to take corrective action to meet targets. This NSS also automates all the calculations within the proposed framework, thus saving project managers from the complexities of statistical and analytical formulas, and calculations. The system only requires that decision makers enter relevant KPIs, values of KPIs from both benchmark projects, ongoing project values and historical values of dynamic models related to project performance. Then the system automatically visualizes the project performance in multidimensional space and supports the decision-making process by recommending the best action to take.

Some of the disadvantages of NSS are as follows: Using NSS is time consuming. Most of the data are not available in the company. To develop a dynamic model of NSS, a lot of time and resources are required. In addition, the filtration and distance modules and their algorithms are fixed. Updating the algorithm is not an easy option. Therefore, a new algorithm is needed to override the previous one and it needs an expert to do this. Finally, NSS is too data related.

Some of the advantages of NSS are as follows: for non-technical people, it is easy to use as it visualizes the performance of the projects so that they understand where the project performance is with reference to the targets. Furthermore, it helps the expert (e.g. project designers, decision makers) to recommend the best possible action to achieve the benchmark targets.

The NSS is applied to an interior design project to help interior designers to [1] understand which KPIs are the most important KPIs in interior design projects, [2] identify the distance of the current project performance from benchmark projects, and [3] help interior designers to make better decisions by recommending the best action that they can take based on the current position of project performance relative to benchmark targets. The interior designers were approached through the interior consultant of a tile and stone company, who introduced the project to them and convinced them about the possible benefits of the project for their company. The survey questionnaire was distributed among 32 interior designers from May 2017 to June 2017. The interior designers were asked to rank the KPIs in the questionnaire. The ranked KPIs were fed to NSS, which then identified the most important ones out of 37. A renowned overseas interior design company was contacted and asked to give the researcher the value of those KPIs for 20 similar residential interior design projects already completed. The above-mentioned project was used as a benchmark against which a New Zealand residential interior project was compared so that the distance between the two could be measured through a distance module in NSS. The interior designers were interviewed later to understand the dynamics of the interior design project. A model was developed based on the outcome of the interviews which was developed in DDMM in NSS. The best action was identified and recommended to the interior designers. One limitation of this research is related to validation of the system in construction companies: an ongoing project takes time and it is necessary to wait until data collection is completed before comparing estimated performance with actual performance. The other limitation was convincing the interior design company to give us their benchmark data to be used to create benchmark targets. Another limitation was that the interior design company did not have the values of the KPIs selected and identified by NSS.

Therefore, in Paper III we collected actual construction project data to apply NSS in construction projects for more validation. Then we intend to extend our system into different industries such as educational systems and healthcare systems to make it more generalisable.

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5.10 Appendices

5.10.1 Appendix 1

Number	Variables	1=NOT IMPORTANT	2=SLIGHTLY IMPORTANT	3=MODERATELY IMPORTANT	4=HIGHLY IMPORTANT	5=EXTREMELY IMPORTANT
1	Cash flow of project					
2	Delay due to shortage of material or equipment fault					
3	Rise in prices of material due to slow work progress					
4	Labour cost of project					
5	Experience of Labour					
6	Neighbour and site conditions					
7	Motivation of employees					
8	Regular payments in order to overcome delays, disputes and claims					
9	Amendments in bill of quantity (B.O.Q)					
10	Late delivery of material					
11	Time required to amend defects					
12	Site preparation time					

13	Delay in payment from client to contractors					
14	Material and equipment cost					
15	Material and equipment quality					
16	Skills of manpower					
17	Process of decision-making by interior designer					
18	Quality control by interior designer					
19	Management relationship with labour and other staff					
20	Wastage of material					
21	Rate of absents in project					
22	Leadership skills of project managers					
23	Completion of work according to plan					
24	Amendment of the design					
25	Speed and reliability of services					
26	Project overtime cost					
27	Number of disputes and delay on the project					
28	Attitude of employees at project					
29	Cost related to variation of orders					

30	Conflicts of ideas at construction site regarding interior design					
31	Coordination among project participants					
32	Rate of accidents in project					
33	Accessibility of site					
34	Climate conditions of site					
35	Hazardous Waste material at site					
36	Quality of air					
37	Level of noise					

5.10.2 Appendix 2

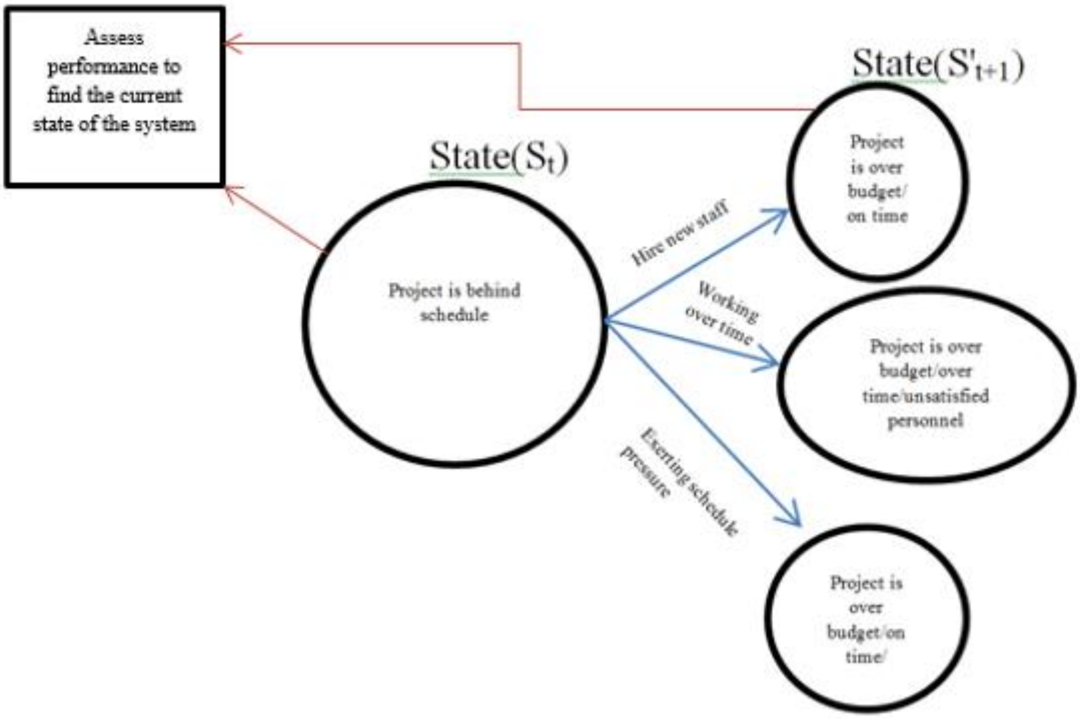

Figure 5-13 Dynamic model of Project Performance

5.10.3 Appendix 3

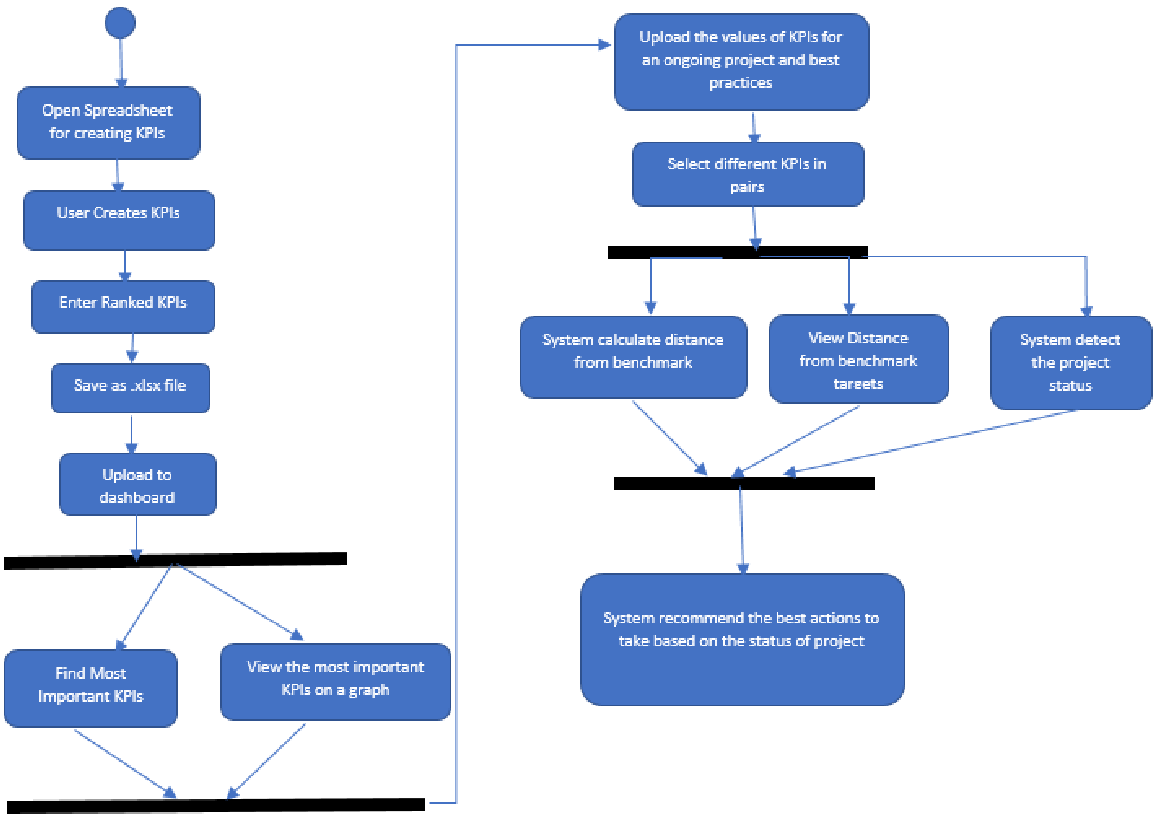

Figure 5-14 Activity diagram of NSS

6 Paper III

Application of Navigational Support System to Monitor and Control Project Performance in the Construction Industry

Foad Marzoughi and Tiru Arthanari

- Unpublished-Extended version of paper presented at ProjMan 2016 (Marzoughi & Arthanari, 2016b)

Abstract

In a globalized and dynamic world, the construction companies that survive are those able to adapt rapidly and successfully to new conditions. Measuring the performance of construction projects dynamically helps companies survive. Despite more than 20 years of research into project performance measurement, no one has explained how important it is to navigate and visualize project performance dynamically in different dimensions. Normally project performance is measured in more than one dimension, such as cost, quality, time, customer satisfaction, and safety. The purpose of this research is to apply a navigational support system in construction projects to control and monitor projects. A Navigational Support System (NSS) is a novel decision support system that [1] finds the most important key performance indicators of construction projects, [2] identifies the position of project performance in multidimensional space (selected KPIs) by considering the correlation between key performance indicators of construction projects, and [3] handles the decision-making process by using a dynamic model

of project performance to support project managers to choose corrective actions due to uncertainty in projects.

Keywords: construction project management, Navigational Support System, Key Performance indicators, control and monitor projects

6.1 Introduction

Most construction projects fail to meet their objectives and face cost overruns and time overruns (Aibinu & Jagboro, 2002; Memon et al., 2012). Delay in a construction project is caused by dynamic and uncertain behaviour of construction projects (Collyer & Warren, 2009), lack of resources caused by contractors during the drawing phase, financial difficulties, and changes to orders (Le-Hoai et al., 2008). According to Haseeb et al. (2011), the consequences of a delay in a construction project can be very serious and cause disputes, lawsuits, litigation, abandonment and the project to go over time and cost. Because of this, it is necessary for project managers to have a reliable computer system to monitor and control project performance to know where the project performance is now, and where it will be.

To monitor and control construction project performance, there are some tools available: key performance indicators in construction projects (Cox et al., 2003), benchmarking in construction projects which is defined by the Construction Industry Institute (CII), project auditing (Meredith & Mantel, 2010), project status reports (Boxwell, 1994), earn value management (Lipke, 1999), balanced scorecards (R. S. Kaplan & Norton, 1992) and dynamic balanced score cards (Henk & Kim van, 2002); (Sloper et al., 1999b). These are commonly used in the construction industry but none of them visualize the position of KPIs by considering the correlation between them. Also, they do not support decision makers dynamically

(Jalaliyoon, Taherdoost, & Zamani, 2011; Michail Kagioglou et al., 2001; Neely & Bourne, 2000; Zhang, 2012), except dynamic balanced score cards. However, the dynamic behaviour of a construction project is more abstract, needs high implementation requirements and is very time consuming (Zhang, 2012). Current performance measurement systems are static; however, the nature of a project is dynamic (Y. Chen et al., 2012; Huan, 2010; Lin & Shen, 2007). Therefore a static performance measurement system has a negative effect on the agility and responsiveness of organizations (Bititci., Turner., & Begemann, 2000). Effective performance measurement systems for projects will not only identify performance levels, but also identify ways in which to improve this in an uncertain environment (strategic level) (Azlan & Ismail, 2010). According to Oncu Hazir (2015), current performance measurement systems cannot determine the possible need for corrective action. They should be user friendly and have an early warning mechanism.

The objective of this study is to apply a developed generic decision support system called Navigational Support System (NSS) (Marzoughi & Arthanari, 2016a) for monitoring and controlling construction projects. The goals of NSS are as follows: [a] find the most important KPIs that can measure the performance of a construction project, [b] find the project position with respect to the selected KPIs and take into account the correlation between different KPIs, and [c] recommend the best action for project managers to take based on the available dynamic model of a construction project. To apply the NSS framework in the construction industry, we have used the following databases or information sources: [1] a knowledge base available to project managers (based on most actions that take in different situations), [2] a historical database related to the performance of the best construction projects, and [3] a database related to ongoing project performance. We have used the expert knowledge to validate the NSS framework after applied NSS in construction projects.

The rest of the paper is structured as follows: Section 6.2 reviews evaluation methods for measuring construction performance and decision support systems for controlling and monitoring project performance, particularly for construction projects. Section 6.3 briefly describes the methodology steps used in this research. Section 6.4 presents the framework of NSS for construction projects. In Section 6.5 we implement NSS in a building construction project. In Section 6.6 we evaluate the output of NSS with real data from construction projects. Finally, the concluding section summarises the results and limitations, and discusses future research directions.

6.2 Domain Background and Related Work

6.2.1 Evaluation methods for measuring construction project performance

According to previous studies, construction project performance evaluation methods are responsible for measuring the level of success of projects from different stakeholders' perspectives (A. Chan et al., 2002; Karen Young, 2010; Ko & Cheng, 2007; Nassar & AbouRizk, 2014). Project success is related to several internal and external factors ranging from manager related, contractor related, project management team/team related, institutional related and client related (Gudienė, Banaitis, Banaitienė, & Lopes, 2013). Also, these factors are correlated to each other (Y. Chen et al., 2012; Latorre, Roberts, & Riley, 2010). So, for measuring the project success, considering the correlation between KPIs is essential. For example, if a project manager wants a project to be delivered quickly with high quality, then the cost will be increased. If a project is to be fast and cheap, then the quality will be compromised, and if a project is to be delivered with high quality and cheaply, then it will take more time to complete (Karen Young, 2010; Ko & Cheng, 2007). Similarly changes to the design of construction projects affect the other KPIs, mostly time and cost. If the project is behind schedule, then the cost will increase to finish the project on time, or an increase in staff, materials and equipment would be made in an effort to decrease the time taken to do additional work and therefore maintain the time KPI for the project goal.

There are several methods commonly used in the construction industry to measure the overall performance of projects to support decision makers to control and monitor projects, such as, the program evaluation and review technique (PERT) (Fleming & Koppelman, 2010), the earn value management system (EVMS) (Christensen, 1994; Reifer, Fleming, & Koppelman, 2006), S-curve method (Osama. Moselhi, Li, & Alkass, 2004) and stochastic S-curves (SS) (Barraza et al., 2000). However, they are mostly used to control the cost and time of projects, and a large number of construction projects cannot meet their target time (Barraza et al., 2000; Kamaruzzaman & Ali, 2010; Memon et al., 2012). These methods only take into consideration cost and time, while the rest of the KPIs and the interrelationship between them are ignored.

6.2.2 Project Performance Measurement Systems in Construction Projects

Performance measurement in general is the process by which an organization reaches its desired goals or targets (Program, 2007). Performance measurement in construction emphasises project level factors, such as cost, time and quality (Michail Kagioglou et al., 2001; Ward, Curtis, & Chapman, 1991), and organizational and stakeholder levels, such as client satisfaction, health and safety, and the environment (I. Yu et al., 2007).

To measure the performance of a construction project with respect to different criteria, some performance indices are available, such as cost performance index, billing performance index, profitability performance index, safety performance index, quality performance index, team satisfaction index and client satisfaction index (Nassar & AbouRizk, 2014). Some existing performance measurement systems are listed in Table 6-1.

Table 6-1 Overview and limitations of existing performance measurement systems in the construction industry

Current tools	**Type**	**Monitor**	**Multiple perspective**	**Ease of extracting and analysing data to create insight into projects**	**Level of performance measurement in construction**	**Ability to deliver new insight through data analysis**
Key Performance Indicators for Construction Industry	Static	Productivity (Cox et al., 2003)	Yes (Lin & Shen, 2007)	No (Andersen & Langlo Jan, 2016)	Organizational/ project (Andersen & Langlo Jan, 2016; Huan, 2010)	No (Andersen & Langlo Jan, 2016)
National Benchmarking System	Static (Zhang, 2012)		Yes (Lin & Shen, 2007)	No (Andersen & Langlo Jan, 2016)	Company level, difficult to implement the system (Andersen & Langlo Jan, 2016; Huan, 2010)	No (Andersen & Langlo Jan, 2016)
Construction Industry Institute Benchmarking and Metrics (CII)	Real time evaluation using web based progress report (Institute, 2013)		Yes (Lin & Shen, 2007)	No (Andersen & Langlo Jan, 2016)	Organization/project (Andersen & Langlo Jan, 2016; Huan, 2010)	No (Andersen & Langlo Jan, 2016)

According to Table 6-1, none of the existing performance measurement tools is able to reduce the multidimensionality of KPIs and show the position of project performance from benchmark projects. However, the Construction Industry Institute (CII) is able to compare project performance with other projects and generate reports to show the performance quartiles for a visual comparison of performance between the projects (Institute, 2013). It does not, however, consider the correlation between the KPIs in generating reports and visualization. Moreover, it considers all KPIs, which makes it really difficult for a project manager to make decisions based on the status of a project, and to take corrective action (Haponava & Al-Jibouri, 2011). Also, according to Andersen and Langlo Jan (2016), a lot of work has been done this decade to improve performance in the construction industry without success, due to not having a common tool to measure productivity and performance, and recommend to decision makers how performance and productivity can be improved or dropped over time. KPIs only monitor project performance; they do not control the project (Haponava & Al-Jibouri, 2011). Another criticism about KPIs is related to the large number of different dimensions (KPIs) in the construction industry (see, for example (Beatham et al., 2004)). There is a need to reduce the high dimensionality of KPIs for better decision making to improve project performance.

Due to this fact, we have proposed a framework to identify the project status in multi-dimensional space and support the decision-making process during the execution of a project to guide the project to reach to its benchmark target.

6.3 Methodology

This research uses multiple methodologies for developing a model driven decision support system (called Navigational Support System) to monitor and control construction project performance. For this purpose, multivariate data analysis methods, such as sparse principal component analysis, distance metrics such as Mahalanobis distance, and dynamic decision-making tools, such as Markov decision-making process, and quantitative and qualitative data collection methods are used and integrated. For validating the proposed system, the real data from a construction project is collected and used. Experts' opinion on the importance of KPIs on construction project performance is an important input for NSS, so methods to elicit this information become important. Also, the values of ongoing project performance and best practice are another input of the system so that the system can identify the distance of current project performance from benchmark targets using appropriate distance metrics. Then the dynamic model of project performance should be created using dynamic decision-making tools to forecast the status of project performance. We have applied quantitative research methodology to collect data from experts (construction project managers), and information regarding the most important KPIs. Our target was project managers and the sample size was 103 experts, for whom we designed a questionnaire in two parts. The first relates to the background of the experts and demographic information, and the second relates to the importance of KPIs (see Appendix 1). The questionnaires were distributed to construction experts to identify the most important performance factors in the construction file. We then used secondary data to ascertain the values of selected KPIs from previous construction projects. Finally, we conducted in-depth interviews with three project managers to develop a dynamic model for measuring the performance of construction projects. Brief accounts of some of these methods are given.

6.3.1 Sparse Principal Component Analysis (SPCA)

Principal component analysis (PCA) is a multivariate statistical tool used to reduce the dimensionality of a data set on several variables and observations, by identifying a smaller number of underlying dimensions that explain most of the variability in the data (I. Jolliffe, 2005). PCA is widely used in dimensionality reduction (i.e., analyses to reduce the number of variables to those most important) and data processing, with several applications in engineering, biology and social science. However, it suffers from the fact that each principal component is a linear combination of all variables (Hui Zou et al., 2006). In other words, the true dimension reduction will not occur after executing PCA. To overcome this problem, Hui Zou et al. (2006) proposed a new method of dimension reduction called sparse principal component analysis (SPCA). SPCA considers the zero impact of variables on the components (sparsity) and is more efficient when the number of variables is much larger than the number of observations. We use SPCA in the filtration module of NSS to find the true dimension of KPIs out of 46 variables (see Appendix 1).

6.3.2 Mahalanobis Distance

Mahalanobis distance (MD) was introduced by Professor Mahalanobis (1936). MD is a general form of distance, and Euclidian distance is a special form of MD when variables are uncorrelated. MD can be used in original variables and considers the correlation between variables. According to Lande (2004), MD is used to distinguish patterns of certain groups from normal groups, and is a useful tool for determining the similarity of a known set of values with that of an unknown set. MD considers the variance and covariance of the measured variables instead of considering only the mean value. We used MD metrics to determine the closeness of ongoing project performance from the performance of best practice in positioning modules of NSS.

6.3.3 Markov Decision Process (MDP)

Dynamic decision making is a kind of decision making in a situation where there are a series of decisions which are related to each other (i.e. co-dependent), and where situations change over time (Brehmer, 1992). One of the decision-making techniques which can be used in dynamic environments and under uncertainty is MDP (Bellman, 1957; Leong, 1998). Dynamic decision-making modelling is widely used in real world applications, such as management of construction sites (Manjia et al., 2014), navigational control (Fakoor et al., 2016), battlefield decisions, medical emergencies (Ni et al., 2017), and so on. We used MDP in the decision-making module of NSS to support decision makers when taking the best action to reach the benchmark targets. A MDP algorithm will find the corrective action based on the available dynamic model of the system.

6.4 Conceptual Model of Navigational Support System

The idea of navigation in benchmark space was first introduced by Arthanari (2010), although the idea of physical navigation, on land, sea, or in the air is ancient, and navigation in space is done successfully these days. In general, the process of monitoring and controlling the movement of a vehicle from one place to another is called navigation (Bowditch, 1802). Benchmarking is common in organisational and individual settings. Navigating consists of two steps: finding the position of the system/object with respect to the benchmark, and [2] taking action to advance towards the benchmark. Similarly, in the construction industry, project managers are responsible for project success; therefore, project managers should continuously monitor project performance in order to take appropriate action to regulate the project. Continuous monitoring and control procedures in construction can help projects to be accomplished successfully (Ko & Cheng, 2007). Due to the dynamic and stochastic nature of construction projects (Albert. Chan & Chan, 2004), deterministic control methods are not efficient in controlling them (Alberto, 2006; Barraza et al., 2000).

Project managers are keen to know where project performance stands with respect to the performance of best projects (benchmark projects) and where project performance will go by taking action with respect to best practice. In the construction field, project performance is like an object in multi-dimensional intangible space (cost, time, quality, health and safety, productivity, client satisfaction and the environment) (Enshassi et al., 2009) that moves from its current position to another position to reach benchmark targets in the benchmark space. Benchmark space is defined as a space consisting of the factors that affect project performance for best practice. For the first step we use existing knowledge of the area that defines benchmark space. To apply this framework in the construction area, we first gathered knowledge of construction project performance from a literature review to identify the benchmark space.

To develop a generic engine to implement the NSS framework given in Figure 6-1, we should find the true dimension of the subset of important KPIs from the expertly evaluated KPIs to obtain a sparse representation using a multivariate measurement method. This phase is called *filtering*. The second phase is *positioning*. After finding the true dimensions of benchmark space or the most important variables from the given benchmark space, we then determine the current position of construction project performance from that space. At this stage, we try to find the position of the ongoing performance of the construction project with respect to benchmark space. Furthermore, we consider the correlation among the variables for finding the proper distance between the current state and the desired state. In the third phase (dynamic decision-making phase) we use the dynamic behaviour of the performance of construction projects for a dynamic decision-making approach. We will use dynamic models of construction project performance, such as system dynamic models or a multistage decision-making approach. Our choice depends on the complexity of the system; for example, in this research we chose very simple construction projects (one-storey residential projects), so that the dynamic of the system is available in the form of both a stochastic dynamic decision-making model and system dynamic models. The goal of the dynamic decision-making phase is to determine the best action to take to reach the benchmark targets. This process continues until the project meets its targets.

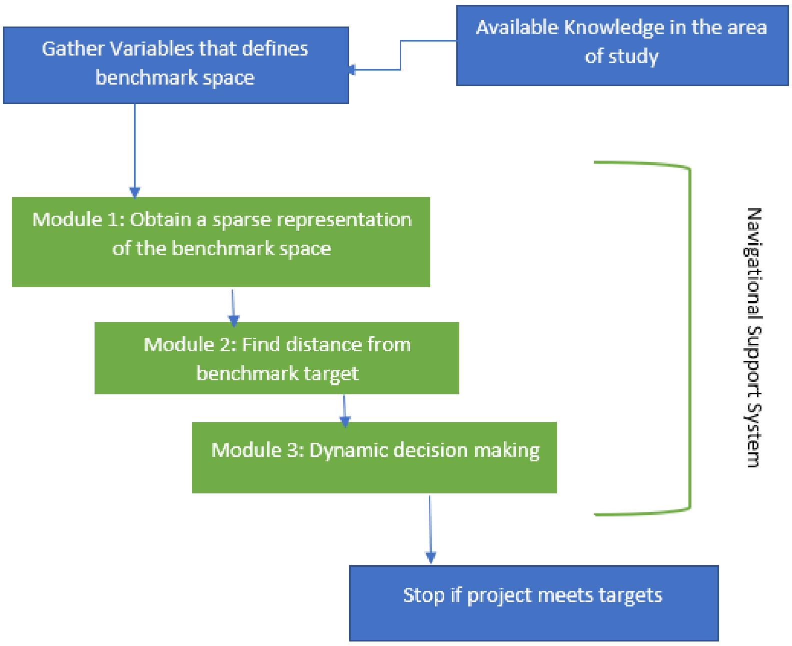

Figure 6-1 Generic framework for navigational support systems

6.5 Framework of Navigational Support System for Construction Projects

In order to use NSS in the construction field, we should collect relevant data to use in the system to help project managers in monitoring and controlling project performance. To evaluate NSS we used real data from a construction project and compared it with the forecast status of the project with the system. Figure 6-2 shows the framework of NSS for construction projects.

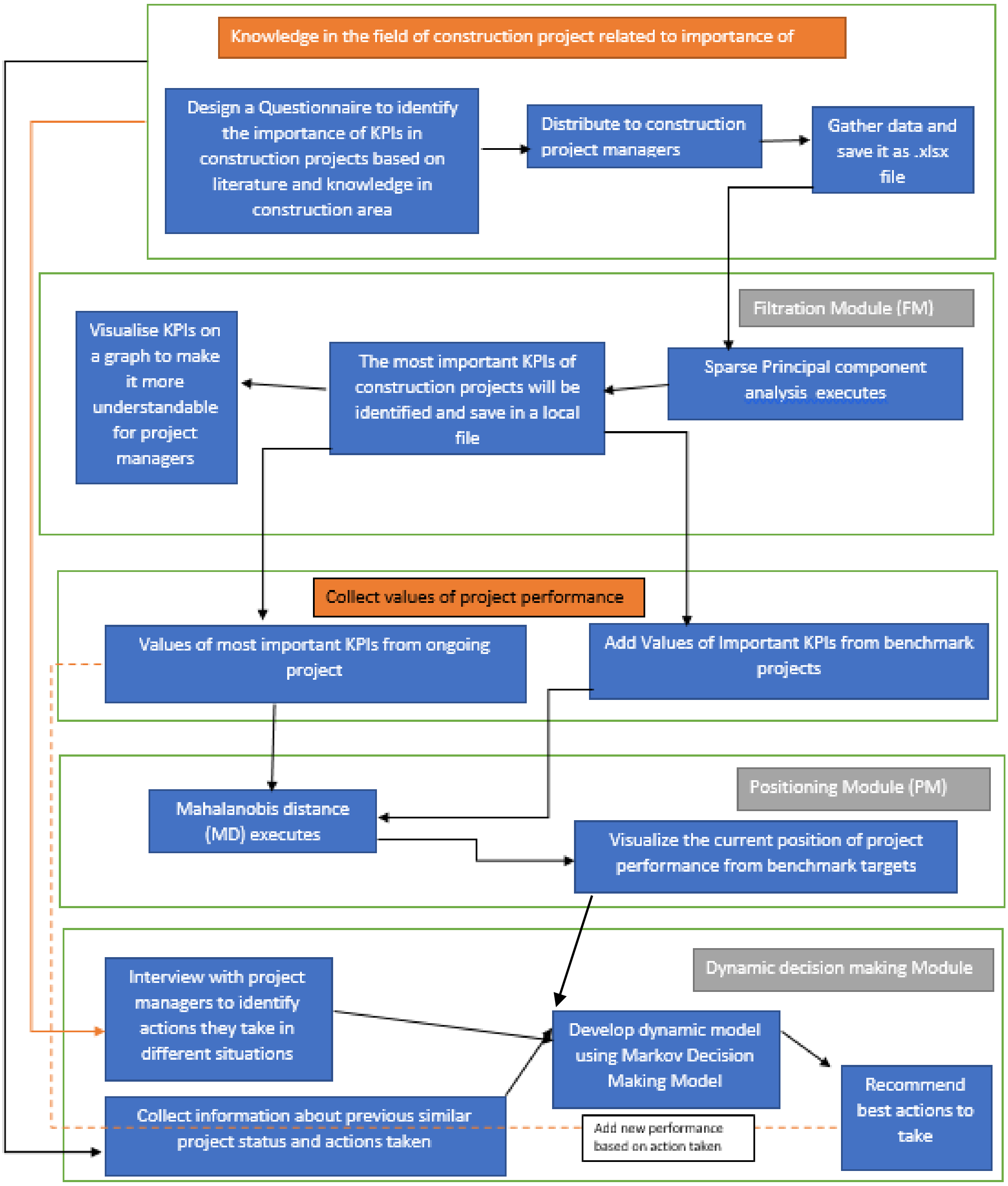

Figure 6-2 Framework of NSS for construction projects

6.5.1 Gather Data Related to Ranked KPIs

We designed a questionnaire based on the literature in order to create a benchmark space with the most important KPIs for monitoring construction project performance (Appendix 1). This questionnaire was distributed to experts (mostly construction project managers) to rank the KPIs in terms of their importance. A total of 103 experts were asked to complete the questionnaire; the response rate was 78%, or around 80 in total. According to Figure 6-3, the respondents comprised 43 project managers (53%), 16 site engineers (20%), 10 civil technicians (12%), 5 property owners (6%) and 7 architects (9%). Most of the respondents had 5 to 7 years' working experience in the construction industry. Further, half of the respondents were from building construction projects.

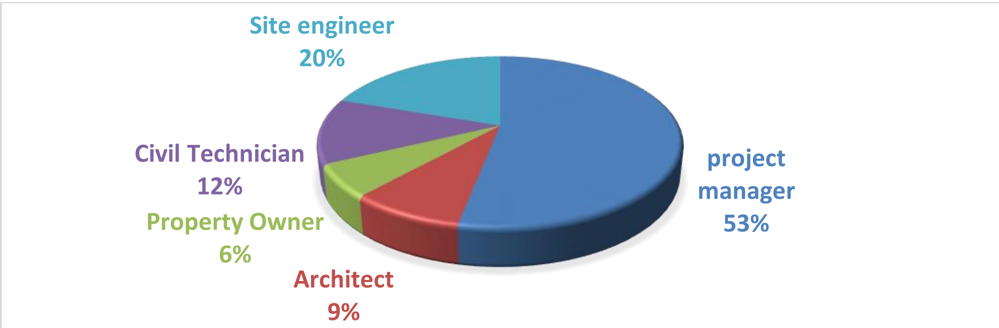

Figure 6-3 Respondents' profiles

Responses collected were based on a five-point Likert scale (1- Not important; 5- very important). The completed questionnaires were saved as an Excel file and imported to the filtration module to reduce the dimensions of the study. Due to the high dimensionality of KPIs (46 variables), it was difficult for project managers to understand where the project was with respect to all of the KPIs. Hence the Filtration Module (FM) was responsible for reducing the dimensions (KPIs) for easier decision making.

6.5.2 Filtration Module

In this module, evaluated KPIs should be uploaded to the system and the most important KPIs will be identified using execution of SCPA. Before uploading ranked KPIs, we tested the validity and reliability of the data using Cronbach's alpha and Kaiser-Meyer-Olkin (KMO) respectively. It is very important to test reliability because it indicates that the data is reliable (more than 0.6) (Cronbach, 1951) to produce consistent results. Also, the validity test indicates that the sample size is adequate if it is greater than 0.5 (Kaiser, 1974). In this case, Cronbach alpha was 0.87 meaning that data was reliable, and KMO was 0.62 which indicates that the sample size was adequate. Then it was possible to derive logical conclusions from the analysis of the variables under consideration. The output of the Filtration Module shows the most important KPIs, as shown in Figure 6-4:

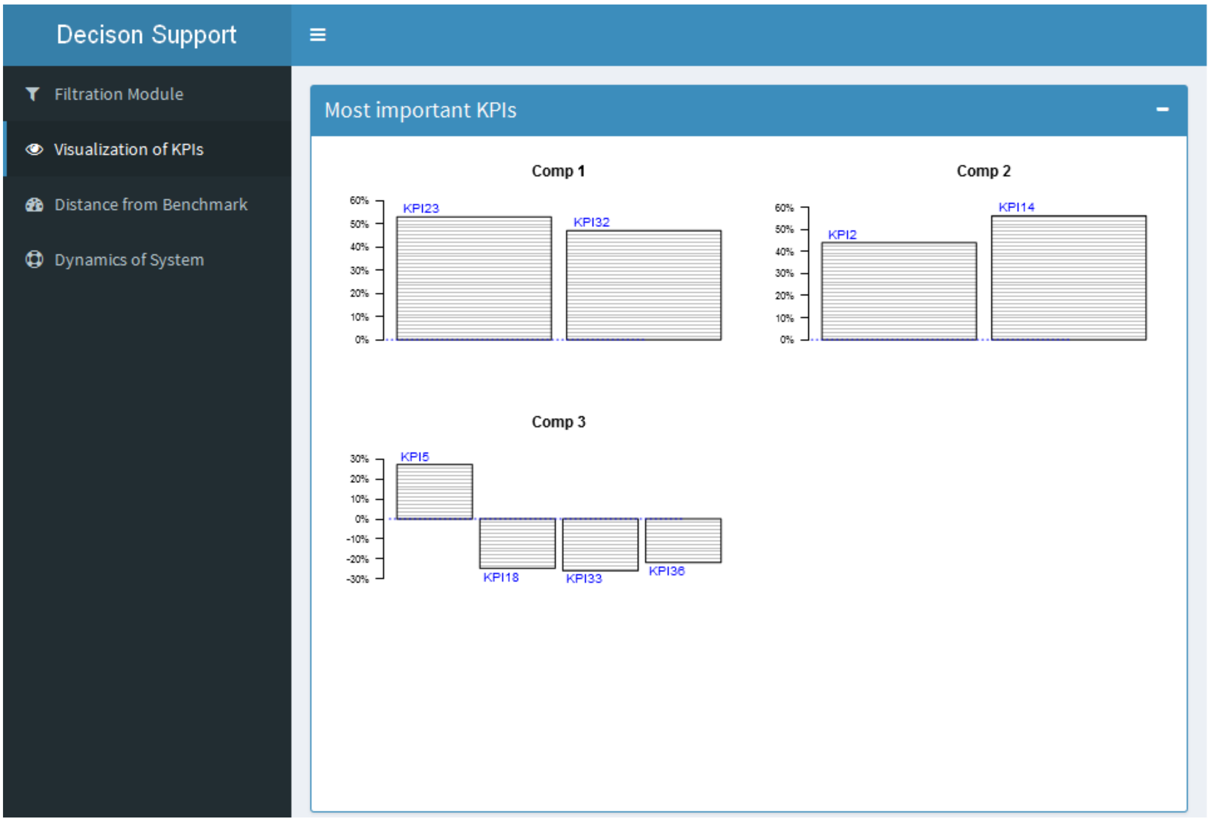

Figure 6-4 The most important KPIs of construction project performance

According to Figure 6-4 and the questionnaire in Appendix 1, the first principal component (Comp1) consists of variable 23 (waste of materials) and variable 32 (project over cost). These are the most important variables loading on Comp1 and these variables related to the financial perspective in similar construction projects. Hence the first important KPI is cost in the same construction projects. Similarly, the second principal component (Comp2) consists of variable 2 and variable 14, which are delays due to shortage of materials, and delays in payment from the host respectively. So, the second principal component represents the scheduled perspective of construction projects. Finally, the last principal component consists of variable 5 (experience and qualifications of staff), variable 18 (material and equipment quality), variable 33 (disputes and delays) and variable 36 (variation of orders), which are the most important variables; the loading on the third principal component related to the quality perspective in the construction field. However, the importance of KPIs on accessing project performance varies between projects, particularly across various disciplines.

Accordingly, the indicators and units of measures of cost, time and quality performance can be defined as shown in Table 6-2 (Ramı´re, Alarco´n, & Knights, 2004):

Table 6-2 Performance indicators

Area	**Indicator**	**Units**
Cost	Deviation of Cost by project	(Real Cost-Budgeted Cost)/Budgeted Cost
Time	Deviation of project due date	(planned schedule- completed schedule) /Planned schedule
Quality	Rework rate	Number of rework Items/Number of registered non-conformance
Safety	Accident rate	(number of accidents) *100/Total number of Workers

The values of KPIs for the ongoing project and the benchmark project should be collected for identifying the project status with respect to benchmark targets, then the positioning module is responsible for identifying the status of the ongoing project in a given time.

6.5.3 Positioning Module

Actual and benchmark data will be imported into this module (positioning) and the current position of the construction project performance from benchmark targets will be determined. This is so that the project manager can visualize the differences between the actual project performance and the benchmarked performance in a 2-dimensional format. According to previous research, KPIs of construction projects are not independent, but are interrelated (Latorre et al., 2010). For example, changes to the design of a construction project affects the KPIs of time and cost. If the project is behind schedule, then the cost will increase to finish the project on time. For instance, an increase in staff, materials and equipment would be made in an effort to decrease the time taken to do additional work and therefore maintain the time KPI to the project goal. An increase in safety means an increase in cost. So, we need to consider a metric to find the distance between an ongoing project from best practice by taking into account the relationship between KPIs. In other words, correlation between KPIs should be taken into account to find the proper distance from benchmark targets.

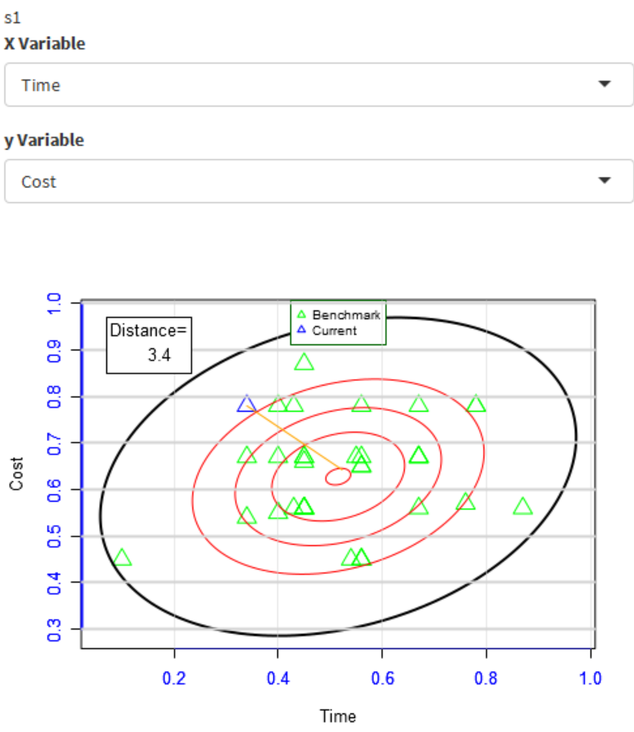

Figure 6-5 **Distance of an ongoing project from best practice**

NSS will calculate the distance of an ongoing project from benchmark projects gathered from UK performance reports (Glenigan, Construction Excellence, & BIS, 2012). For example, the distance between construction cost and time performance of an ongoing project from best practice is 20.3, and Figure 6-5 shows that there is a negative correlation between construction cost and time. Also, the status of project performance will be determined by NSS to be used in the decision-making module for forecasting the next state of the project based on the current status of the project using the Markov decision process (MDP) (Bellman, 1957). NSS detects that the position of project performance in Figure 6-5 is behind schedule and over cost, based on the threshold identified in Table 6-3.

Table 6-3 Project status threshold

Project KPIs	**Threshold**	**Status**
Time	<65%	Behind schedule (BS)
	>65%	Within schedule (WS)
Cost	<73%	Over cost (OC)
	>73%	Within budget (WB)
Quality	<55%	Low quality (LQ)
	>55%	High quality (HQ)
Safety	<80%	Low safety (LS)
	>80%	High Safety (HS)

6.5.4 Dynamic Decision-Making Module

The final module of NSS is the dynamic decision-making module (DDMM) responsible for finding the best action that the user can take to get closer to benchmark targets, based on the available dynamic model. As mentioned earlier, the dynamic model can be available in terms of stochastic decision-making processes or system dynamic models. We have developed a dynamic model based on interviews with five project managers (Appendix 2) for construction project performance using the Markov decision process (MDP), illustrated in Figure 6-6. This is only model with one action and the transition probability of the rest of the actions are demonstrated in Table 6-4.

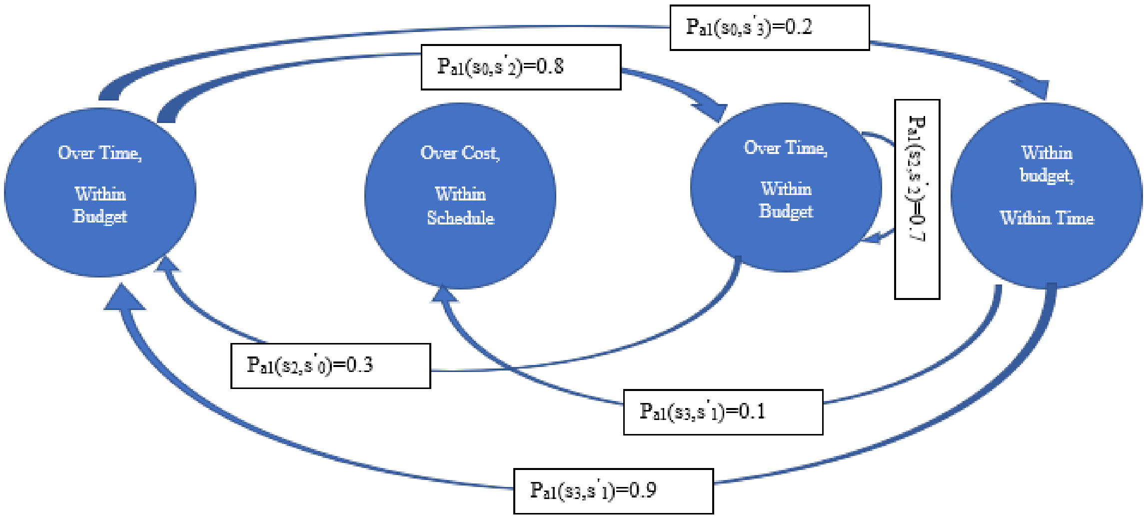

Figure 6-6 Markov decision process

In this regard four possible actions are considered:

- Labour worked over time (LWT)
- Hire new labour (HNL)
- Inject money (IM)
- Charge customers extra for any type of variation (CV)

We assume that these are possible actions that project managers take most of the time when a project is over cost and over time. The main policies that are available to a project manager between any two actions can be summarised by the following set:

(1:(LWT, CV), 2:(HNL,CV), 3:(LWT, IM), 4:(HNL,IM))

Also, we have considered a finite state to create a dynamic model of construction project performance. The states are defined based on the status defined in Table 6-3. For example, (S_0=BS and OC, S_1=BS and WB, S_2 = WS and OC, S_3 = WS and WB).

For considering uncertainty, we used the quantification methods and classification of particular risk as follows:

- Extremely Likely ($0.7 \leq p \leq 1$);
- Very Likely ($0.4 < p \leq 0.7$);
- Probable ($0.1 < p \leq 0.4$);
- Unlikely ($0 \leq p \leq 0.1$);

These thresholds were identified by the five project managers who have had more than 20 years' experience.

Table 6-4 displays the transition matrices for four states in relation to four possible policies (sets of actions), where the probability of transiting from state s_i to state s'_j is gathered from a historical database based on similar previous projects.

Table 6-4 Sample transition matrices for 4 states and 4 policies

Policy 1

	S'_0	S'_1	S'_2	S'_3
S_0	0	0	0.8	0.2
S_1	0.1	0	0.9	0
S_2	0.3	0	0.7	0
S_3	0.9	0.1	0	0

Policy 2

	S'_0	S'_1	S'_2	S'_3
S_0	0	0.4	0.1	0.5
S_1	0.2	0.5	0	0.3
S_2	0.8	0.2	0	0
S_3	0	0.5	0	0.5

Policy 3

	S'_0	S'_1	S'_2	S'_3
S_0	0	0.4	0	0.6
S_1	0	1	0	0
S_2	0	0	1	0
S_3	0.2	0	0.8	0

Policy 4

	S'_0	S'_1	S'_2	S'_3
S_0	0.6	0	0.4	0
S_1	0.5	0	0.5	0
S_2	0.5	0	0.5	0
S_3	1	0	0	0

The immediate reward due to the selection of a policy is shown in Table 6-5:

Table 6-5 Sample reward matrix for 4 states and 4 policies

	P_1	P2	P_3	P_4
S'_0	0	0	0	0
S'_1	0	0	0	0
S'_2	0	0	0	0
S'_3	1	1	1	1

These are four elements of MDP for developing a dynamic model for a construction project. By executing the dynamic decision-making module, the current position of project performance will be detected and imported from the positioning module to DDMM to set the initial state of the Markov decision-making process. Then NSS finds the best policy or set of actions to take. Figure 6-7 shows the output of DDMM. According to that, the best action to take, based on the current state of the project, is S_1=BS and WB from the positioning module at the current time, and the best policy to take is policy 2, which is hire new staff and charge customers extra for any type of variation.

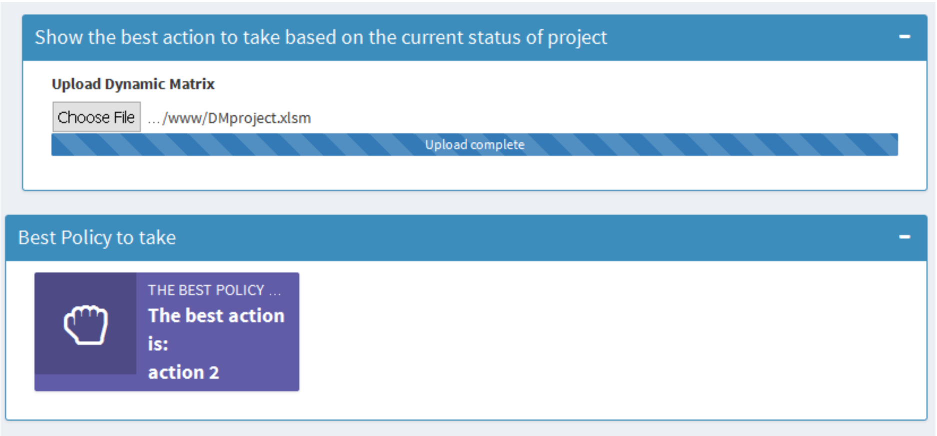

Figure 6-7 **Recommended actions to project manager**

6.6 Evaluation

According to March and Smith (1995), evaluating an artefact in Information Systems should answer the following question: "How well does the artefact work?" In this section, we examine the efficacy, validity and ease of use of NSS by implementing it in the construction field. According to Offermann et al. (2009) they type validation which is applied in this paper is expert surveys. According to Siau and Tan (2008), artefact evaluation techniques divided into the following categories, feature comparison, theoretical and conceptual investigation and empirical evaluation. In this research, we have applied empirical evaluation techniques to validate our artefacts which were field experiment technique. This type of evaluation in the design science research cycles (A. Hevner & Chatterjee, 2010) is a transition between design science research and environment (people, organization, and technology). The efficiency, effectiveness, and impact are all context-dependent and can only be fully assessed after the instantiation has been deployed. Also, it is possible that some of the features test in advance in the lab. So, we adopt potential user assessments through field testing (project managers). Hence we have used positivism epistemological approach (Gonzalez & Sol, 2012) to validate NSS because we assumed the reality could be objectively and empirically amenable to study to produce generalizations.

6.6.1 Evaluation of NSS Efficacy

Efficacy is defined as the degree to which an artefact reaches its goal (Venable, Pries-Heje, & Baskerville, 2012). We evaluated the efficacy of NSS by implementing it in a construction project. As is shown in the previous section, NSS filtered the evaluated KPIs (Filtration Module), identified the position of project performance from benchmark targets (positioning module), and supported project managers to select the best action to take (Dynamic decision-making module). All of the modules integrate with each other and NSS reached its goal in each module.

6.6.2 Evaluation of NSS Validity

According to Gregor and Hevner (2013), the validity of the information system artefact is defined as the degree to which the artefact works correctly. We have used a manipulation check

(Boudreau, Gefen, & Straub, 2001) to test that each module of NSS works correctly. We used dummy data during the development of the artefact to check the correctness.

6.6.3 Evaluation of NSS Ease of Use

Regarding evaluating the ease of use, we asked 19 project managers to use NSS and rank each module based on the ease of use. They ranked from 1=very easy to 5=very difficult to identify the complexity of the system. The descriptive statistics of ease of use for each module of NSS are presented in Table 6-6.

Table 6-6 Descriptive statistics of perceived ease of use

Module	Module Complexity	Perceived ease of Use		One sample T test
		Mean	Variance	P-value
Filtration	H_0:$\mu \geq 4$ H_1: $\mu < 4$	3.05	0.29	0.000
Positioning	H_0:$\mu \geq 3$ H_1: $\mu < 3$	1.33	0.23	0.000
Dynamic Decision Making	H_0:$\mu \geq 4$ H_1: $\mu < 4$	4.05	0.26	0.289

According to one sample t test, we concluded that for the filtration and position module, the null hypothesis is rejected. We concluded that in terms of complexity, FM and PM are easy to medium. However, for the dynamic decision-making module, the P-value is greater than 0.05 so there is not enough evidence to reject the null hypothesis. We also interviewed the project managers regarding the complexity of this module and we found that data gathering to create the dynamic model was time consuming and not an easy task. However, they agreed that if they created such a database to collect relevant information to create a dynamic model, it would be very useful to support decision making for projects.

6.7 Conclusion

This paper provides a computer system for monitoring and controlling KPIs for any project. By using NSS, a project can be monitored in a dynamic environment. The goal of this research is to create an engine for all types of project to be monitored and controlled. Hence, NSS is a generic engine that can monitor and control project KPIs with respect to best practice. Moreover, it recommends driving projects toward benchmark space by taking proper action. NSS was tested and evaluated in construction project fields to identify the most important KPIs of building construction projects. Thereafter the system automatically found the position of current project performance from benchmark projects. Finally, the system recommended the best action for project managers to take to get closer to the benchmark target. By applying NSS in the construction project field, cost, time, quality and community satisfaction were selected as the most important KPIs. Thereafter, benchmark space was created from the secondary data based on the most important KPIs. Any ongoing construction project can be evaluated based on the created benchmark space, and the dynamic model of the system is developed based on a stochastic decision-making model.

One limitation of this research is that some KPI data relating to the people and environment of the benchmark project is not available. Another is related to ongoing project performance that is not available in the organization because not all KPIs are measured regularly by project managers. Also, historical data related to actions that the project managers take to make the project align is difficult to gather. For future research, developing a decision-making module of NSS using system dynamic models is recommended to overcome the aforementioned limitations.

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6.9 Appendices

6.9.1 Appendix 1

QUESTIONNAIRE

Maintaining the confidentiality of your company and personal information is of utmost concern to us. This information will be kept anonymous and will be used in our research to identify the factors which affect the performance of construction projects. This research is about creating a decision support system for construction companies to ease the process of decision making for project managers. The identity of the respondents will be kept confidential. After the data is collected and analysed appropriately the respondents will be informed about the results of the research. While answering this survey if the respondent feels the need to withdraw at any time, they may do so.

The information collected will **not** be used to identify individuals and will **not** be placed on your personal file.

PART 1: Personal questions

1. Respondent is
    - Project manager
    - Architect
    - Building or property owner
    - Civil technician
    - Site engineer
2. You handle which part of construction industry
    - transportation
    - water supply
    - building maintenance
    - building construction
    - Others…………………………
3. Number of employees in your company
    - Less than 100

- 100-200
- 200-300
- 300-500

4. Experience of respondent
    - Less than 3 years
    - 3-5 years
    - 5-7 years
    - 7-10 years
    - More than 10 years

PART 2: FACTORS AFFECTING PERFORMANCE IN CONSTRUCTION INDUSTRY

PLEASE (√) MARK THE FOLLOWING FACTORS ACCORDING TO THEIR IMPORTANCE:

Number	Variables	1=NOT IMPORTANT	2=SLIGHTLY IMPORTANT	3=MODERATELY IMPORTANT	4=HIGHLY IMPORTANT	5=EXTREMELY IMPORTANT
1	Cash flow of project					
2	Delay due to shortage of material or equipment fault					
3	Rise in prices of material due to slow work progress					
4	Labour cost of project					
5	Experience and qualifications of staff					
6	Neighbour and site conditions					

7	Difference in currency of imported material					
8	Motivation of employees					
9	Regular payments in order to overcome delays, disputes and claims					
10	Amendments in bill of quantity (B.O.Q)					
11	Late delivery of material					
12	Time required to amend defects					
13	Site preparation time					
14	Delay in payment from host organization to contractors					
15	Timeframe for construction of project					
16	Material and equipment cost					
17	Conformity in material specification					
18	Material and equipment quality					
19	Skills of manpower					
20	Process of decision-making by company leaders					
21	Quality control by the management					
22	Management relationship with labour and other staff					

23	Wastage of material					
24	Rate of absences in project					
25	Leadership skills of project managers					
26	Completion of work according to plan					
27	Amendment of the design and drawing of building					
28	Delay in receiving building drawings					
29	Cost of compliance to regulators requirements					
30	Information exchange between host organization and contractors					
31	Speed and reliability of services					
32	Project overtime cost					
33	Number of disputes and delays on the project					
34	Number of non-compliance to regulation					
35	Attitude of employees at project					
36	Cost related to variation of orders					
37	Engagement of executives or staff					
38	Conflicts of ideas at					

	construction site					
39	Coordination among project participants					
40	Application of Health and safety factors in organization					
41	Rate of accidents in project					
42	Accessibility of site					
43	Climate conditions of site					
44	Hazardous Waste material at site					
45	Quality of air					
46	Level of noise					

6.9.2 Appendix 2

The list of semi-structured interview questions.

Question 1): What are possible actions that project manager can take when a construction project is not within budget?

Question 2): What are possible actions that project manager can take when a construction project is not within time?

Question 3): What are possible actions that project manager can take when a construction project is not within budget and is not within time?

Question 4): What are possible actions that project manager can take when a construction project is within budget but is not within time?

Question 5): What are possible actions that project manager can take when a construction project is not within budget but it is within time?

Question 6): What are possible actions that project manager can take when a construction project is within budget and it is within time?

7 Discussion and Conclusion

In Paper I, we have proposed a decision support framework to estimate the duration of construction project activities affected by weather factors. According to previous studies, inclement weather is one of the three most important factors that cause time overruns in construction projects (Wasiu et al., 2012). Inclement weather has a direct effect on the health and safety of site labourers and can affect human resource productivity, supplier effectiveness and material damage (E. H. W. Chan & Au, 2008; Huang & W. Halpin, 1995; Koehn & Brown, 1985; O. Moselhi et al., 1997). The estimation of project duration at the project planning and scheduling stage is somewhat subjective and depends on engineering judgment (Hendrickson et al., 1987). However, there are some tools to estimate the duration of project activities, such as critical path method, and programme evaluation research task, but these techniques cannot handle uncertainties. There are some other tools available to overcome this problem, such as the probabilistic network evaluation technique and critical chain scheduling but they ignore the correlational impact between activities and risk factors (Hendrickson & Au, 1989; L-P Kerkhove & Mario Vanhoucke, 2017; Omar, 2009; W. Wang & Demsetz, 2000). The aim of this paper is to create a more comprehensive decision support framework to consider the correlations between activities and weather risk, to be able to estimate the duration of construction activities in the initial stage of the project (planning phase).

For developing this framework, multiple methodologies have been used and applied in a construction project to validate the framework. The methods used for developing the five-module framework are multivariate data analysis methods, time series model building approach, multicriteria decision-making tools, non-linear multiple regression and qualitative and quantitative data collection methods integrated into a framework. We have validated the model developed from the framework in a real case, but there is still a need to apply the framework to different construction project types in different locations for more validation. One of the big assumptions of this framework is the availability of data related to weather, construction performance and activities duration, and if those data are not available then the framework will be unworkable. Moreover, this framework needs to be developed as a computer system to make it easier for project managers to use. The integration between different databases used in this framework such as weather-related data, project performance and project duration databases is vital to make the system a real-time system. Due to lack of time and limited resources, we will develop a computer system for the proposed framework and apply it to more construction projects for further validation.

Our proposed framework is generic and the model implemented based on the framework is for illustration purposes only. It is only one among many possible alternatives. We also do not claim that the methods which we used in the proposed model are the best way of implementing the framework. For example, in the second module of the framework (Filtration Module), we have used principal component analysis to identify the most important activities: weather variables and performance variables. However according to Hui Zou et al. (2006), in PCA each component is a combination of all the variables and does not truly reduce the dimensions. One of the proper dimension reduction methods to find the true dimension of variables is sparse principal component analysis introduced by Hui Zou et al. (2006) The other important area that we have not been able to cover are the other risk factors that affect activity durations, such as economic downturn, corruption and natural disasters. In future research we will develop a system dynamic model to consider more risk factors to make the prediction more accurate, because in the current framework we considered only weather factors that affect the construction durations, but other factors can also cause delay in project activities.

Following the development of the framework in Paper I to estimate the project duration in the planning phase of the project, we continued our work to develop a framework to monitor and control project performance in the execution phase of the project.

According to previous studies (Cândido et al., 2014; Hall, 2012; Kim & Ballard, 2000; Narbaev & De Marco, 2014; White & Fortune, 2002), most current performance measurements, such as earned value analysis (EVA), national benchmarking system (Zhang, 2012), key performance indicators for the construction industry (Andersen & Langlo Jan, 2016) and balanced scorecards (BSC) (Bontis et al., 1999) are not dynamic. However, dynamic balanced scorecards filled this gap but still it only measures the performance of the whole organization at strategic levels and does not identify the project performance for benchmark projects. In Paper II we developed a decision support system called NSS to help project managers to understand where the project performance was compared to benchmark projects. Moreover, the developed system helps the project manager to choose the best action to reach the benchmark targets.

However, this system is completely dependent on the availability of data and the dynamic model of the project, such as expert knowledge regarding the priority of project performance variables, benchmark projects and an ongoing project performance value related to the most important key performance indicators. For the decision-making process to select the best course of action, the availability of a dynamic model is vital to make the system efficient.

In NSS, the first module is related to filtration of KPIs to select the most important ones. From the decision support framework in Paper I, we realized that PCA did not truly reduce the dimensions and we have used SPCA to consider the sparse loading factors. In the next module of NSS, we used the Mahalanobis distance to take into account the correlations between the KPIs, and in the last module we used the Markov decision-making process to develop a dynamic model for a particular project performance. The last module of NSS is very time consuming and we could not develop a generic model for all types of projects. We only developed a model for a very simple interior design project but it needs to be developed more holistically.

In the Markov decision process model, identifying the transition probability matrix is a challenge and we spent a lot time collecting previous data which caused delay in validation of NSS. In future studies, we have decided to develop and use system dynamic models to capture the underlying dynamics.

The other issue with NSS is related to overriding a new method with an existing method which the user cannot manage, and only a developer can revise the existing methods and algorithms. For more validation we applied NSS in the construction industry in Paper III. One limitation of this research is that some KPI values related to the people and environment of the benchmark project were not available so we could not compare those values from an ongoing project with benchmark projects. Another is related to the values of KPIs from an ongoing project performance which were not measured regularly by project managers. Also, historical data related to actions that the project managers take to make the project align is difficult to gather. Creating a transition probability matrix is based on previous similar projects (empirical data) and gathering this data was very time consuming.

7.1 Summary of Research Results

Paper I proposed a decision support framework for estimating project duration under the impact of weather. Moreover, it provided a literature review on the causes of delays in construction projects, the weather impact on project performance and the impact of project performance on project activities. The framework considered the effect of inclement weather on construction project performance and classified the most important factors which are influenced by weather; then it estimated the project duration based on the value of performance after considering the effect of inclement weather. This paper focused on the weather risk but it can be expanded to other risk factors that affect project duration for estimating project duration. This paper fills a gap in the body of knowledge for project management by developing a decision support framework with consideration of weather risk. As a complementary study to Paper II and Paper III, this paper provided a literature review on the project performance by considering risk factors.

Paper II was related to a conceptual framework for a Navigational Support System (NSS) as a generic engine for a construction project. We created a tool called NSS to monitor and control project performance in a multidimensional space. It considers the dynamic nature of construction projects and the relationship between the KPIs. It then visualizes the current position of project performance and the current state of project performance with respect to best practice to help the project manager to understand where the project stands in the benchmark space. Also, it provides a recommendation for the project manager to select the nearly ‘best’ action that they can take to get closer to the benchmark space. Follow-up research was done in Paper III to implement the conceptual framework of NSS.

Paper III is about implementing NSS in the area of construction projects. The most important KPIs in the construction projects field are identified from the filtration module of NSS. Then the benchmark space and the distance from the benchmark space is determined from the positioning module. Finally, the nearly best action is chosen from the decision-making module. In this paper, we illustrated the different modules of the proposed framework in Paper II using a real case from a construction project.

7.2 Link Between Papers I, II and III

The first part of this research provides a literature review on the factors that cause delays in construction projects. It then goes on to focus on only one of the risk factors (weather risk) which affects construction project performance, and which ultimately causes delay. The research emphasises filling the gap in project duration estimation by considering dependency between the variables that affect project performance and project duration. An estimation model was developed using multivariate statistical techniques and analytical techniques to identify weather-related factors and project resources that are influenced by these factors. The proposed five-module framework integrates weather variables, project performance variables and project activity duration. This framework uses expert knowledge about the importance of weather variables, pairwise comparisons of weather variables with respect to different performance criteria, and, similarly, pairwise comparisons of performance variables with respect to project activities. A model based on this framework using multivariate statistical techniques and an analytical network process (ANP) was developed to estimate the duration of project activity, taking into account the impact of weather. The proposed model was illustrated with data from a construction project in Iran. Validation of the model was provided by comparing the actual duration of an activity from similar construction projects with the estimated duration using the proposed framework.

As a complementary study, the architecture of a Navigational Support System was created to show project performance compared with benchmark values (Marzoughi & Arthanari, 2016a). It helps decision makers get a better picture from the position of current project status in multi-dimensional space. The conceptual framework of the decision support framework and generic engine of navigational support system are illustrated in Figures 1 and 2 respectively. To develop a generic engine, we should find the true dimension of a subset of important KPIs from the data set to obtain a sparse representation using a multivariate measurement method which we call ‘filtering’. The second module is about positioning. After finding the true dimensions of the benchmark space or the most important variables from the given benchmark space, NSS determines the current position of KPIs from the benchmark space. NSS attempts to ascertain any correlation among the variables for finding the proper distance between the current and desired state. In the final module or dynamic decision-making phase, the dynamic behaviour of project performance is used for a dynamic decision-making approach. The estimation of construction performance in the Estimation Module in Figure 7-1 can be used as an input in the Distance Module in Figure 7-2, if the current values of project performance are not available. In Paper II the initial values of the project performance level can be gathered from the estimated project performance from Paper I under the impact of weather risk. Finally, the proposed framework of NSS is illustrated in a real construction project in Paper III.

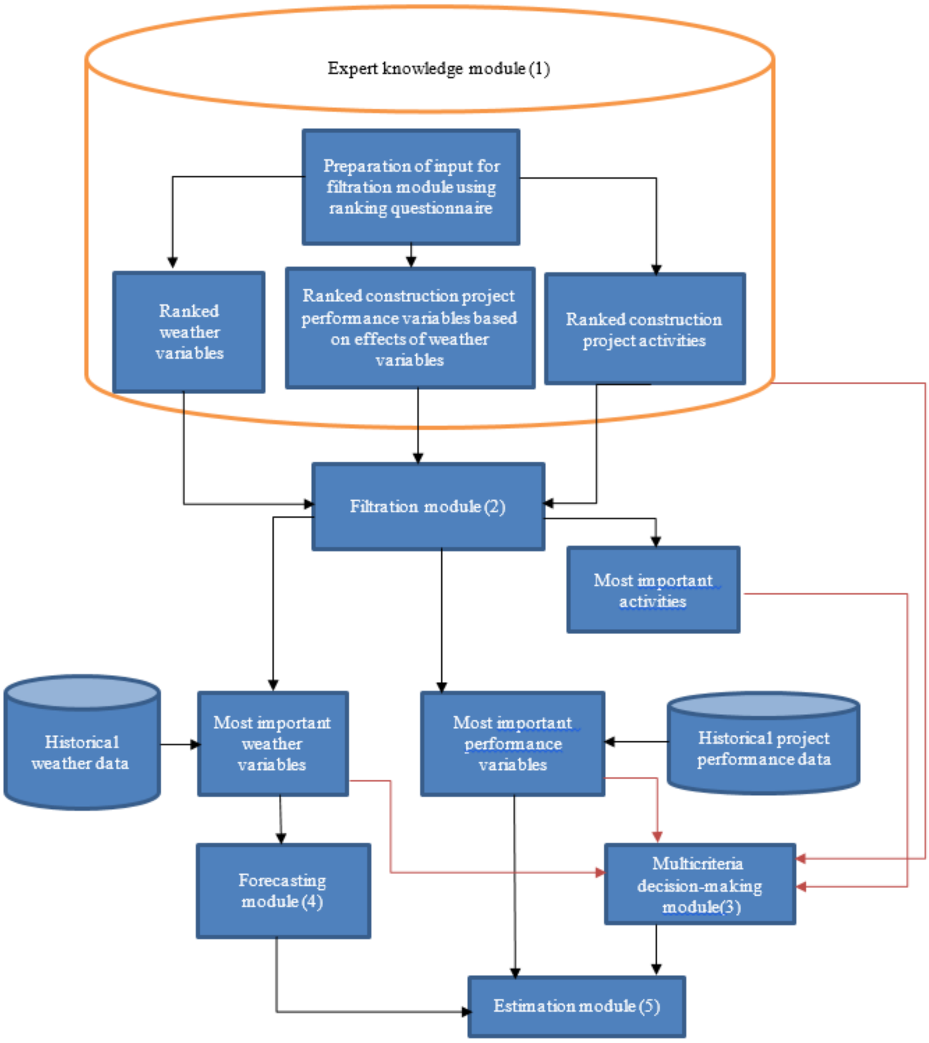

Figure 7-1 A framework of decision support framework to estimate project duration

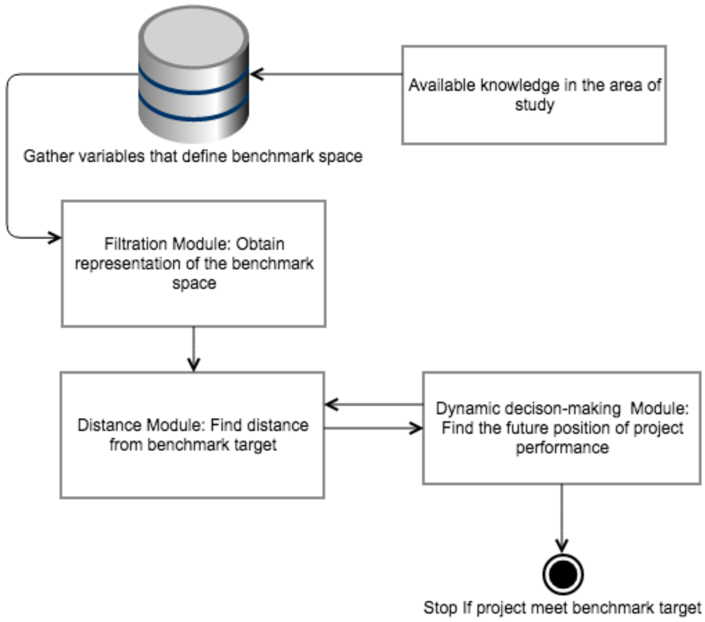

Figure 7-2 Generic framework for navigational support systems

7.3 Contribution to Research

First, the contribution of Paper I is in proposing a framework to estimate project duration under the effect of inclement weather. This paper tried to address estimating the time problem for a construction project in a systematic manner. We have validated the framework using a case from construction. However, the model implemented based on this framework is not significant; it is only for illustration and this framework is generic. This model is one among many possible alternatives. We do not claim that this is the best way of implementing the framework. In this framework we only consider weather risk but we believe a similar approach is possible to incorporate other risk factors that affect activity duration, such as political instability, economic downturn, corruption and natural disasters.

Second, the contribution of Paper II is in proposing a framework based on the idea of navigation in benchmark space (Kastor & Sirakoulis, 2009). In this paper, we proposed the NSS framework as a generic engine to monitor and control the project performance. We have integrated multivariate statistical tools and dynamic decision-making tools to develop NSS. As discussed earlier, NSS can be used for monitoring project performance in a multi-dimensional space and controlling it by recommending the best action to take. The main contribution of this paper is to design such a system, implementing the idea of navigation in benchmark space and make it practical to use (illustrated in Paper III).

Finally, the contribution of Paper III is illustrating the implementation of three different modules of NSS, including [1] filtration, [2] positioning and [3] decision-making for a real-life construction project. However, NSS framework is a generic engine that can be applied in different areas of study. We have provided a computer system for monitoring and controlling KPIs for a construction project for validation. This artefact informs project managers about the distance of the current situation of the project from best projects performance and recommends where the project will be if they take different possible actions.

7.4 Contribution to Practice

As discussed in Paper III, the NSS is applied to case construction projects. Through the output of NSS in the filtration Module, it confirms that four KPIs were selected as the most important KPIs, which are cost, time, quality and community satisfaction. These KPIs are the most important for only selected project and cannot be generalised to all projects due to the uniqueness of each project. Through the second module of NSS, the project managers get a clear picture from the position of project performance with respect to benchmark targets. However, in this system only two KPIs can be selected at a time and visualize them in a graph; we believe that we should develop a visualization module to show more KPIs in one graph. The third module helped project managers to make better decisions based on the dynamics of the system. NSS needs to apply to different similar projects to increase the accuracy of decision making. For this purpose, we need to create a comprehensive knowledge based system and integrate it into the dynamic of the projects. One of the approaches that we believe can be applied in the dynamic decision-making module is the system dynamic approach.

8 Future Research Direction

The objective of the development of a decision support framework is to estimate project duration by considering weather risk variables. The first limitation of the proposed framework in Paper I is that because of lack of time, the implemented model based on the framework is only validated for a particular activity. Secondly, there are many possible tools that can be used in the proposed generic framework. We have used the mentioned tools for illustration purposes only. We are therefore not claiming that this is the best way of implementing the framework. Other limitations include: [1] the validation of a model that might consider multiple construction projects with different complexities or types, [2] the non-availability of some of the databases required that might prevent the use of this framework, [3] difficulties in finding experts to provide the knowledge base, and [4] the system has not been applied to make predictions for real on-going projects. The lack of empirical data makes the current validation not that much strong.

Further research in this area could create an integrated computer system which obeys design science principles and automates the integration of the different modules within the frameworks. Also, such a system might offer different tools to choose from in each of the modules, which would give users a wider choice. We believe a similar approach is possible to incorporate other risk factors that affect activity duration, such as political instability, economic downturn, corruption and natural disasters (Li & Liao, 2007; Sambasivan & Soon, 2007).

The objective of Paper II was to design a novel artefact to monitor and control project performance in multi-dimensional space. The proposed framework is a generic engine and many other tools can be used in different modules. The limitation in this research is related to not integrating NSS to available software for project management such as MSP because of lack of time and certain tools in each module used for implementation. Therefore, for future research we have a plan to give a chance to users to select different tools in each module and integrate NSS to Microsoft Projects, a new module for commercialization purposes.

In Paper III, the proposed framework is validated in an ongoing construction project and there are some limitations for this research such as [1] limitation, related to non-availability of some of project performance variables for an ongoing project, [2] some data related to benchmark projects were not available for validating the proposed framework and [3] historical data related to actions that project managers take to make the project align, is difficult to gather.

According to Sheffield, Sankaran, and Haslett (2012) one way of controlling the complexity in project management is using the system thinking approach in the context of software projects. Hence for future research, developing a decision-making module of NSS using system dynamic models is recommended to overcome the aforementioned limitations. It is hoped that follow-up research can address the limitations of this research. Also, for future research, NSS can be applied in different areas such as educational systems, healthcare systems and real-time systems.

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