Scheduling and staffing of multiskilling of workforce in the context of off-side construction

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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Oct 2019
Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the project is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

Araz Nasirian

5 Oct, 2019
Acknowledgements

I wish to express my profound gratitude to my supervisory team Professor Babak Abbasi and Dr. Mehrdad Arashpour. Their invaluable support, advice, proper guidance, and continuous inspiration enhanced my confidence to accomplish this research. I am indebted for their encouragement and inspirational advices received throughout the association.
Dedication

I dedicate this thesis to the memory of my beloved grandfather Ali Asghar Rasouli.
List of publications arising


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Abstract

**Aim:** There is an increase of interest in multiskilling research from the academy, industry and governmental authorities. Multiskilling of a workforce refers to enhancing flexibility of production by enabling labor to be reallocated in response to change in production priorities during the production horizon. Production priorities can change for several reasons; however, this study considers changes due to alterations in bottleneck configurations. The aim of this research is to investigate the extent to which operational benefits associated with different multiskilled resource management policies pertaining to bottleneck configurations can be achieved in off-site construction. To achieve this aim, first the multiskilling of a workforce in an off-site construction context should be understood as it is a complex matter in both conception and application. Second, an appropriate scheduling method should be developed to allocate an existing workforce to the right tasks, based on their skill level and set, during the production makespan. Third, a staffing platform should be developed to facilitate recruiting and hiring of a multiskilled workforce with an appropriate skill level and set.

**Methodology:** In the Chapter 2 a two-stage paper-screening methodology was used to collect relevant papers in the literature review section. A flow-shop-based optimization methodology is used in the Chapter 3 to schedule multiskilled crew during the production makespan to achieve the production objective. A quadratic resource allocation model was developed to allocate a workforce to different tasks with consideration of the scheduling cost. A piece-wise linearization method is deployed to linearize quadratic constraints and decrease solution time. The Chapter 4 adopts a hybrid method including optimization and multi-criteria decision-making techniques to advise the best multiskilling strategy by comparing the performance of existing multiskilling staffing
configurations based upon a range of existing qualitative and quantitative criteria. PROMETHEE is recognized as a suitable multicriteria decision-making approach to incorporate qualitative criteria. A flow shop scheduling method is used to obtain an optimized performance from alternatives pertaining to quantitative criteria. The Chapter 5 of this thesis presents a decision-support tool to optimize a multiskilled staffing strategy. The methodology in this chapter differs from that in Chapter 3 in that the developed staffing optimization platform explores every possible multiskilling strategy to find the optimal staffing configuration.

**Findings:** In Chapter 2, the literature review results in the development of a construction multiskilling framework. This framework investigates multiskilling literature in conception and application. Multiskilling framework includes four main categories of multiskilling context, collateral effects, Mainstream research and strategy. A developed scheduling platform in Chapter 3 indicates that an optimal multiskilled labor allocation can lead to significantly different outcomes in terms of cost and time, based upon whether the location of the bottleneck is fixed or variable. The findings in Chapter 4 indicate that chaining and hiring a multiskilled workforce which is able to contribute to four different tasks, are the best multiskilling staffing strategies among existing ones. Sensitivity analysis pertaining to different criteria weight illustrates that the results of this investigation are stable in a wide range of alterations in the weight allocation. In Chapter 5 the decision-support tool illustrates that the optimal multiskilling strategy is highly context specific and should be customized in relation to production circumstances and data, especially the magnitude of bottlenecks. A slight alteration in the production characteristics can lead to significant changes in the optimal cross-training policy. Subjective multiskilling of a workforce could lead to counterproductive results such as a significant cost overrun. Numerical experiments indicate that if there is no extra capacity to allocate more workers to a bottleneck workstation,
multiskilling of the workforce in the workstation immediately preceding the bottleneck workstation can lead to enhancement in the productivity.

**Contribution:** The main contribution of the Chapter 2 is to identify theoretical gaps in the cross-training research and pave the way for comprehensive studies to produce more realistic multiskilling knowledge that considers both technical and managerial details. Research findings in Chapter 3, contribute to the scheduling literature by presenting an optimization platform for multi-skilled resource allocation and relocation during the makespan pertaining to the project objective. Research findings in Chapter 4 contribute to staffing literature by presenting a hybrid methodology which can encompass qualitative criteria as well. Research findings in Chapter 5 contribute to staffing literature by presenting a novel optimization platform to optimize configuration of multiskilled labor pertaining to their skill set. Chapter 3, 4 and 5 make another important contribution to the body of knowledge which is quantifying how performance measures and labor skill sets interact with each other. The decision-support tool, which is incorporated in Chapter 5, can help off-site construction industry practitioners, without a relevant academic background, to staff and schedule a workforce to achieve their production objective.

*Keywords: Multiskilling, Optimization, Staffing, Scheduling, Construction Management, Prefabrication.*
Chapter 1

1. Introduction

1.1. Background

Rapid rises in construction costs and times, which are attributed to inefficient resource management, have attracted significant attention in the current decade (Arashpour et al. 2018b). Despite the considerable advances in automation and digitalization of construction production to increase the productivity of construction projects, increasing labor productivity as a crucial aspect of resource management has attracted negligible attention (Arashpour et al. 2019). The academic research indicates that enhancing labor productivity by appropriate training of labor to achieve a predetermined skill set and level is a critical demand of the current construction industry (Arashpour et al. 2015). Alterations in strategies of labor utilization and improvement of labor practice can address and tackle construction pitfalls in terms of low productivity and cost overrun.

Inclusion of a wide variety of resources such as financial, machinery and human resources in every construction project makes resource management notoriously difficult in the construction context (Arashpour et al. 2019). Usually, the management of resources involves the interaction of two components—productivity and cost. In comparison with other resources, managing workers in the construction context demands the most commitment from a management team because of workforce variability and unpredictability in terms of productivity, expenses, and supply.

1.1.1. Research problem

Considering the vast variety of construction projects, it is helpful to classify different projects. From a spatial perspective, construction processes can be divided into two categories of on-site and off-site fabrication (Mcguinness and Bennett 2006). On-site fabrication is the traditional
method of fabrication. With off-site construction, different components of the final structure are produced in off-site factories and then are transported to the construction site to be assembled. Off-site logistics in building construction can be categorized as modular and panelized.

The on-site construction industry has long dealt with problems such as insufficient productivity, deadline overruns, and quality pitfalls (Arashpour et al. 2015). Additionally, the industry encounters major challenges with regard to increase in workforce wages (Leu and Hwang, 2002) and shortage of skilled workforces (Ho, 2016). Also, adverse weather condition (Arashpour et al. 2016) and subcontracting issues (Arashpour et al. 2018b) can downgrade on-site construction productivity. The results of decreased productivity can be seen in projects expanding beyond the determined deadline and violating budget limitations.

To deal with the aforementioned challenges, many managerial and technological innovations have been used to enhance construction performance. Transferring a majority of production to prefabricated construction is one of these innovations, which is well supported in the literature (Leu and Hwang 2002). This locational change is associated with significant benefits including, but not limited to, decreasing on-site operation (Alvanchi et al. 2012), quality assurance (Ko and Wang 2010), enhancing general performance of the system (Arashpour et al. 2018a), better on-site logistics (Arashpour et al. 2016), and reduction in construction time (Pan et al. 2013).

Variability and imbalance in off-site production are common drawbacks of manufacturing and semi-manufacturing production lines. Variability can be caused by random customization of product by the customer, seasonal demand, significant alteration in the market trend, and workforce absenteeism. Alterations in the product mix is an example of imbalance. Variability and imbalance lead to creation of bottlenecks inside the production line (Qin et al. 2015). In this study, a bottleneck is defined as a task in a chain of tasks for which the labor is insufficient resulting in
decrease in the capacity of the whole production line. Off-site construction is criticized for its insufficient capability to tackle bottlenecks. Inability in managing bottlenecks leads to impairing productivity that can be manifested in terms of cost and time overruns (Arashpour et al. 2018a). This pitfall of prefabricated construction is mainly attributed to insufficient coordination between its operations, resulting in a lack of integration of the flow of production which is originated in traditional construction approach.

The conventional approach in an off-site construction management context is to allocate a single-skilled trade contractor to a specialized task. One potential solution to tackle the negative effects of production bottlenecks resulting from variability and imbalance in the production line in manufacturing or semi-manufacturing environments encompassing off-site construction (Arashpour et al. 2018b), is the multiskilling of construction workers (Hopp and Oyen 2004). Multiskilling of a workforce can be defined as training the single-skilled worker in one or more extra skills in addition to their initial skill to enable them to be allocated or reallocated to different tasks during the production makespan. The terms cross-training and multiskilling are used interchangeably in the literature.

1.1.2. Motivation

The concept of multiskilling of a workforce first became popular in 1991 in manufacturing and three years later in 1994 it slowly started to influence construction. Multiskilling in construction was proposed by the Construction Industry Institute (CII) and the Centre for Construction Industry Studies (CCIS) in 1998 as a workforce management policy to enhance productivity and deal with workforce shortage (Burleson et al. 1998). Within the domain of academic publications, the multiskilling of a workforce was investigated by Burleson et al. (1998) for the first time. The
concept of multiskilling in construction attracted significant attention after a regulation was enacted in the United Kingdom which forced firms to decrease the cost of construction by 30 percent by the year 2000. Workforce cross-training in the construction context has recently attracted considerable attention from governmental bodies (MoM 2016), and the academy (Ahmadian Fard Fini et al. 2017) as it is aligned with the structures and principles of modern economies (Ofori 2002).

Multiskilling of a workforce can provide benefits for a project as well as for the workers involved. The benefits of multiskilling in terms of enhancing project productivity are achieved mainly through improved flexibility in optimizing resource use in projects (Arashpour et al. 2015). This stream of benefits can be categorized into three different subcategories. Firstly, it has the ability to provide line capacity balancing and optimize capacity location; secondly it has the ability to buffer variability in the workload process; and finally, it can eliminate or at least reduce the effect of absenteeism. Multiskilling has been reported to considerably benefit construction workers by improving their employment duration (Burleson et al. 1998), employability (Haas et al. 2001), job satisfaction (Carley et al., 2003), and safety (Teizer et al., 2013). However, the extent to which it is feasible to implement multiskilling in the production line and how it should be implemented are complicated matters, highly context specific and dependent on many factors (Arashpour et al. 2017).

1.2. Research questions and objectives:

This study tries to investigate the following research objectives:

- To present a multiskilling framework which facilitates understanding of the cross-training concept and its application under different situations.
• To present a scheduling strategy to facilitate the appropriate allocation of multiskilled human resources to different operations to achieve a specific aim in the production environment.
• To present a multiskilling staffing strategy to choose appropriate labor with an appropriate skill set.

Different research objectives are investigated in different chapters of this thesis. To tackle the above research objectives, the following research question is formulated:

How productivity can be enhanced in prefabricated construction by incorporating multiskilled human resources?

The above research question is divided into three different research sub-questions:

• How can the concept and application of multiskilling a crew be understood in the context of off-site construction?
• How should a multiskilled crew be allocated or reallocated to different tasks during the production horizon?
• Should a multiskilled crew be recruited as employees or temporarily hired and what should be their skill set and level?

1.3. Rational and the Significance of the Research

The significance of investigating multiskilling of labor in off-site construction originates from four different matters:

First, there is a need to increase building affordability and decrease construction lead-time, which are necessary considering the growing world population and increasing Australian housing
demand. A review of the literature on the housing construction industry in Australia shows that average time and cost of construction for new housing have increased in comparison with the previous decade (Dalton et al. 2013). Several different factors, including the limited capacity of supervisors and quality issues with on-site work, contribute to overrunning construction time and cost (Dalton et al. 2013). Multiskilling of labor can be used as a strategy to increase productivity in off-site construction through shorter lead times which will consequently affect price and delivery time in the whole construction sector.

Second, off-site construction capability needs to be increased in response to demand customization in the Australian building sector. Both standardization, which leads to efficiency, and customization, which requires flexibility, are needed to keep a sector alive in view of market conditions nowadays (Roy et al. 2003). Conventionally, off-site construction is highly efficient because of its high degree of standardization. On the other hand, bringing in customization is essential to keep the sector viable. However, this decreases the amount of standardization and makes production less efficient mainly due to resulting bottlenecks across different tasks (Pan et al. 2013). By changing a workforce from specialists to a cross-trained crew, off-site construction has the potential to have both efficiency and customization embedded in it, which gives a great competitive advantage (Roy et al. 2003). Without multiskilling of a crew, customization and variability will lead to decreased off-site construction profitability.

Third, the principles of multiskilling which are investigated and learned in off-site construction are applicable to other similar sectors such as manufacturing, to make them capable of dealing with variation and customization (Arashpour et al. 2015). Therefore, this research has potential economic benefits for Australian manufacturing. In recent years, several manufacturing production lines such as Toyota Camry, as well as a few prefabrication factories, have shut down due to low
productivity and it is important to enhance manufacturing performance by using different methods (Arashpour et al. 2016). Manufacturing closely resembles off-site construction in relation to production characteristics and productivity pitfalls. This potentially include production layout, distribution of resources, and problems that are made by bottlenecks pertaining to resource utilization. Therefore, despite this study being concentrated on the construction sector, its results can be beneficial for manufacturing as well. Considering the high labor cost in the Australian context, multiskilling of labor can enhance manufacturing productivity by allocating idle workers to bottleneck locations. Also, an unoccupied multiskilled worker can be reallocated to another workstation according to scheduling priorities to achieve a specific goal.

Forth, alterations in labor skill sets are needed to complete construction projects within limited periods of time. Construction market demand for a skilled workforce with a range of skill sets and skill levels has changed over the past few years. The Australian Bureau of Statistics annual report of unemployment reveals that despite many vacant positions for construction trades and a considerable number of applicants for every vacant position, the majority of vacant positions remain unfilled (ABS 2019). The reason is that many trade position applicants do not have the combination of skills which is demanded by the employer. This is attributed to the increased use of prefabricated construction as the majority of production is outsourced to off-site construction factories and instead of a single-skilled crew, a multiskilled crew, which is able to handle several prefabricated components, is needed (Mcguinness et al. 2006). Additionally, increased automation in off-site construction requires a workforce to deal with several machines at different work stations, instead of working in just one station. Multiskilling of a workforce can address these skill mismatches (Mcguinness and Bennett 2006).
1.4. The structure of the thesis

Research questions 1 and 2 are answered in Chapters 2 and 3, respectively. Research question 3 is investigated from two different perspectives and each perspective is incorporated in either of the chapters four or five.

Chapter 2 tries to facilitate understanding of multiskilling concept and application in the off-site construction context. This chapter identifies multiskilling of a workforce as a complicated issue in conception and application and it develops a framework to facilitate understanding of multiskilling a crew.

Chapter 3 of this phases is dedicated for developing a multiskilling scheduling framework. In this chapter, a quadratic scheduling framework is developed to allocate a multi-skilled workforce to appropriate tasks to minimize production makespan as one of the most important productivity measures in off-site construction. The quadratic scheduling framework is linearized to decrease the computational effort. The developed scheduling approach also provides opportunity for comparing different multiskilling strategies with regard to their contribution to makespan reduction, taking into account labor cost.

Chapter 4 tries to investigate multi-skilled workforce staffing problem by a comparative approach. This chapter identifies that there is a wide range of qualitative and quantitative criteria which should be investigated to advise on a multiskilled staffing strategy. A comparative approach is used to compare the performance of different existing multiskilling staffing strategies and suggest the best alternative. Qualitative and quantitative criteria are approached by a multi-criteria decision-making technique and an optimization platform. Additionally, several other analyses are
performed in this study to investigate the sensitivity of different multiskilled staffing strategies pertaining to qualitative and quantitative criteria.

Chapter 4 and 5 investigates multiskilled labor staffing strategy. Chapter 4 adopts a comparative approach, however, the proposed methodology in chapter 5 tries to supplement shortcomings of comparative approach. The main objective of this Chapter 5 is to develop a mathematical model which gives an optimal cross-training staffing strategy in the prefabricated construction context. In this regard, different characteristics of multiskilling of a workforce, in terms of cost and benefit which are applicable in different contexts, are explored and translated into mathematical parameters and variables. Then, the interaction of multiskilling collateral effects and benefits is formulated. An optimal multiskilling strategy is presented as a two-dimensional matrix which can explain the extent to which a workforce is cross-trained, by binary variables. Additionally, a range of metrics are presented to compare different multiskilling strategies in terms of skill accumulation and distribution.
Chapter 2

2. Critical Literature Review of Labor Multiskilling in Construction

Research in multiskilling experiences an incremental trend. Different methodologies have been used in previous research to identify best practice in multiskilling. A comprehensive and critical review of literature creates an in-depth insight into the dynamics of multiskilling in different settings. Accordingly, the aim of this literature review is twofold. Firstly, it sets out to present appropriate classifications to illustrate ramifications of cross-training, to help better understanding of this concept. Secondly, it aims to identify research gaps that can be the focus of future research. A two-stage paper screening methodology is used to collect relevant papers. This chapter classifies papers from the early introduction of multiskilling in the construction industry until now and categorizes cross-training based on configuration, strategy, collateral effects, context and mainstream research. The main contribution of this chapter is to identify theoretical gaps in cross-training research and to discuss interaction and dependency between different studies. Furthermore, it paves the ground for comprehensive studies to produce more realistic knowledge that considers both technical and managerial details.

2.1. Introduction

Within domain of construction industry multiskilling of workforce is introduced by Burleson et al. (1998). Multiskilling or cross-training refers to making use of crews who are enabled to perform more than one task (Gomar et al. 2002). An initial review of literature revealed that several studies, which investigate multiskilling in construction, borrow techniques from research in the service or manufacturing industry (Arashpour et al. 2017). There are fundamental differences between the

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construction industry and the service and manufacturing sectors, such as in production layout, subcontracting issues, level of automation, and required training time in order to become multiskilled (Arashpour et al. 2015). These factors suggest that it would be valuable to survey literature which focuses only on construction as the context in order to facilitate future research in the multiskilling domain.

A few studies have focused on dual resource constrained systems (Hottenstein and Bowman 1998; Treleven 1989). Hopp and Oyen (2004) reviewed the literature on crosstraining in manufacturing and service operations. Crosstraining literature in the service industry was reviewed by Aksin et al. (2007). A survey by De Bruecker et al. (2015) and Qin et al. (2015) investigated crosstraining in the operations research and management science context. However, there is a research gap in the investigation of crosstraining in the construction context.

Further complexity in research arises from: the breadth of existing knowledge about cross-training, the broad range of multiskilling methods available, and the application of cross-training with a variety of other tools. These include: using multiskilling with work study and dynamic scheduling to increase productivity (Pagano and Heathcote 2003), shaping the composition of multiskilling and control buffers to achieve the target of lean production (de Miranda Filho et al. 2007) and combining multiskilling and learning to achieve a knowledge-based construction economy (Ofori 2002).

Therefore, it is aimed to provide a literature review based upon various aspects of multiskilling methodologies and applications used in construction. This chapter raises the question of how to classify different studies in appropriate categories to streamline the examination of research about cross-training in construction. To achieve this, a dataset has been established including all the papers written in the English language that have been published since 1998, when the concept of
multiskilling was first introduced into the construction arena by Burleson et al. (1998). A multiskilling framework developed which classifies papers in this scheme based upon: application context, strategy, collateral effects, and mainstream research. The results of this classification are informative for academics by identifying connections, overlaps and gaps in the literature. It is also of importance to the industry as a guide to choosing appropriate multiskilling approaches in different situations.

In the next section the concept of cross-training is briefly described in general including multiskilling in service, manufacturing and other areas. Later, it is narrowed down to the construction sector and findings are presented by developing a multiskilling framework and arguments around how different papers are relevant to different elements of this framework. In discussion section independence, interaction, and interrelation of different elements of multiskilling scheme are investigated. Finally, conclusions and opportunities for future studies are presented.

2.2. Anatomy of Multiskilling

Resource flexibility is defined as the ability to dynamically reallocate renewable resources during delivery of a product or a specific process. According to Qin et al. (2015), there are five different ways to achieve workforce flexibility: having flexible working times, using floaters, having a cross-trained workforce, working in teams, and having a temporary workforce. Flexible working time is achieved by relaxing the duration of shifts. Floaters are deployed at points with greater needs. Cross-trained workers are trained to be able to perform a number of tasks. Teamwork achieves flexibility through the systematic collaboration of laborers. Contracting provides short-term labor to meet the demands, which arise in an ad hoc manner. In Singapore, workforce cross-training has currently attracted considerable attention from governmental bodies such as the
Ministry of Manpower (MOM 2016) and the Building and Construction Authority (BCA 2016) because it can be customized for the construction context (Ofori 2002).

Multiskilling in construction was primarily proposed by the Construction Industry Institute (CII) and the Centre for Construction Industry Studies in 1998 as a workforce management policy to enhance productivity and deal with workforce shortage (Burleson et al. 1998). Multiskilling is a workforce management strategy with the aim of increasing flexibility via expanding skill sets to cover a diverse range of trades (Haas et al. 2001). Cross-trained staff are trained to deal with multiple tasks, so that they can be assigned wherever and whenever needed (Burleson et al. 1998).

Multiskilling in construction plays a significant role in enhancement of construction performance and productivity (Ahmadian Fard Fini et al. 2017).

So far, a wide range of multiskilling strategies have been developed and incorporated in construction literature. These include: dual-skill (Burleson et al. 1998), tier 1 (Brandenburg et al. 2003), cross-trained teams (Thomas and Horman 2006), chaining (Arashpour et al. 2015), and upstream cross-training (Arashpour et al. 2017).

These multiskilling strategies are adopted to gain one or more predetermined objectives including, but not limited to: increasing employment prospects of labor (Haas et al. 2001; Wang et al. 2009), minimizing labor costs (Gomar et al. 2002; Srour et al. 2006), decreasing workforce shortages (Pollitt 2010), enhancement of safety (MOM 2016), and enhancement of labor productivity (Florez 2017).

Despite multiskilling being able to satisfy several objectives for both employer and employee, implementation of multiskilling can have limitations and collateral effects. A workforce may be unwilling to undertake additional training because its workers believe they have adequate knowledge or they may have concerns regarding sufficient compensation for the extra training
(Carley et al. 2003). There may also be decreasing efficiency as a result of learning and forgetting effects (Wang et al. 2009), licensing limitations (Lobo and Wilkinson 2012) and a perception of high specialization being more beneficial than multiskilling (Ho 2016). Additionally, finding appropriate funding to cover training expenses has been identified as the main barrier for employees and employers becoming involved in multiskilling (BCA 2016).

Additionally, cross-training contexts may vary in the degree of similarity between different tasks (Liu and Wang 2012) and production layout and features (McGuiness and Bennett, 2006), all of which affect the extent to which cross-training strategies are feasible, and allow objectives to be achieved while minimizing undesirable collateral effects.

All of the above factors exacerbate the complexity of selecting an appropriate cross-training strategy, which so far, has not been investigated together with the associated contexts, objectives and collateral effects.

2.3. Methodology

This literature review follows the methodology adopted by Chan and Owusu (2017) for selecting the relevant papers. Consequently, a two-step approach is followed to aggregate the final collection of papers. In the first step, related journals are shortlisted based upon Chau’s (1997) construction management journal ranking list. In the second step, a desktop search is conducted, employing powerful search engines such as Google Scholar, Web of Science and Scopus and using appropriate keywords.

In the first step relevant publications were identified from Chau's (1997) construction management journal ranking list. Accordingly, virtual libraries were employed to access journal papers with related keywords including “crosstrain”, “multiskill” and “multitask”, with consideration for
different spellings and different tenses, in the whole body of the paper. Search results showed that only 7 out of 22 of Chau's (1997) journals list had one or more papers related to the subject. Afterward, an in-depth visual investigation of selected papers was conducted to identify the papers more aligned with the purpose of this literature review. The abstract and conclusion were first scanned and if the paper was considered appropriate, the whole paper was evaluated.

In the second step of this methodology, as in the literature review of Chan and Owusu (2017), the authors realized that multiskilling research in the area of construction management is not limited to the boundaries of construction management journals, listed in Chau (1997). Therefore, methodologies from Chan and Owusu (2017) were employed to identify papers which are published in the journals of other disciplines such as human resource management and operations research. Publications from credible construction management conferences and journals which are not listed in Chau (1997) were also consulted.

This gave rise to a second cluster of papers collected through using search engines in Google Scholar and different databases especially Scopus. In selecting journals subsequent criteria were considered. First, the journal or conference should be indexed in a credible database like Web of Science or Scopus. Second, journals that were already indexed in Chau (1997) were excluded to decrease the volume of retrieved papers. Third, papers that partially or fully dealt with multiskilling were presumed to be relevant even though they were not published in construction management journals. Then, as in the first step, selected papers went through a visual investigation of the abstract and conclusion and, if appropriate, the whole body of the paper.

Finally, three reports CII (1998), BCA (2016) and MOM (2016) were identified as appropriate and added to previous data sets, for several reasons. BCA (2016) and MOM (2016) are the first government reports at ministry level in this area which recognize multiskilling as a professional
way of working in construction and recommend the use of motivational and deprivation policies to encourage contractors to shift towards using a multiskilled workforce. These two reports have been evaluated in academic publications several times. There is a comprehensive categorization of skill sets in these reports, which cannot be found elsewhere. CII (1998) was the first report to introduce the concept of multiskilling to the construction industry along with the investigations of Burleson et al. (1998). This report contains a comprehensive data set and suggests innovative methods for multiskilling. In the last stage of the selection of publications, citations of all collected publications were analyzed, which led to adding few more publications.

A total of 61 papers were recognized as meeting the requirements of this study, thus providing a suitable basis for the analysis of literature and for developing a multiskilling framework which will be explained in the next section. All of the publications with their corresponding journal, year of publication and authors are listed in Table 2-1.
<table>
<thead>
<tr>
<th>Step</th>
<th>Source title</th>
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<td>(2012), Ahmadian Fard Fini et al. (2017)</td>
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<td><strong>Total</strong></td>
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2.4. Results
The results section is in two parts. The first provides a summary of the journals publishing papers in multiskilling and the topics being considered. In the second, a conceptual framework for multiskilling in the construction industry is developed and a comprehensive argument regarding different elements of the multiskilling framework presented.

2.4.1. Distribution of Multiskilling Publications by Journal

This review revealed that there are ten sources that published more than one paper in the area of multiskilling in construction (see Fig. 2-1). The Journal of Construction Engineering and Management has published by far the most papers in this area, corresponding to 17% of all publications. This is followed by Construction Management and Economics, and Automation in Construction which contributed seven and five papers, respectively, to the multiskilling body of literature. Innovative ideas such as skill configuration (Burleson et al., 1998), skill affinity (Wang et al., 2009) and consideration of effective learning (Ahmadian Fard Fini et al., 2016) have been presented in the Journal of Construction Engineering and Management. Automation in Construction publishes papers which are mainly related to scheduling and planning of multiskilled workforce by mathematical programming such as the heuristic algorithm presented by Wongwai and Malaikrisanachalee (2011). Construction Management and Economics publishes a wide range of studies, including resolution methods (Tam et al., 2001), which examine multiskilling from a mathematical modelling perspective, and qualitative and quantitative methods in social science to understand successful implementation of multiskilling (Haas et al., 2001).
Fig. 2-1. Distribution of papers based on source of publication

2.4.2. Multiskilling Framework

As previously discussed, multiskilling in the construction context is a complicated and controversial matter (Arashpour et al. 2017). To better understand multiskilling, a framework has been devised, which incorporates the key elements that need to be considered when devising appropriate cross-training strategies. See Fig. 2-2. The development of this framework originates from reviewing existing body of knowledge and identifying the elements that significantly influence multiskilling conception and application in the literature. The four main elements of the framework are: context, strategy, collateral effects, and mainstream research. Each element includes a number of sub-elements discussed in detail in subsequent sections of this article.
2.4.3. Multiskilling Context

Multiskilling within construction has been implemented in three different contexts categorized as: repetitive construction projects, off-site construction, and on-site construction. Table 2-2 gathers different publications which directly or indirectly analyzed cross-training in construction. Direct cross-training papers investigated conception and application of cross-training as the main purpose of the paper. For example, Haas et al. (2001) studied how implementation of cross-training can be affected according to the nature of different construction projects. As another example, Carley et al. (2003) explored how different skills should be combined to each other to compose a cross-training structure. However, in indirect cross-training publications investigation of cross-training is not the main purpose of the paper. In this stream of literature cross-training of workforce is used as a tool,
Table 2-2. Distribution of multiskilling publications by context

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<th>Reference</th>
<th>Papers directly related to multiskilling</th>
<th>Papers indirectly related to multiskilling</th>
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<td>Burleson et al. (1998)</td>
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<td>Michael et al. (2017)</td>
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RC=Repetitive construction, OfC=Off-site construction, OnC=On-site construction
usually in composition with other tools, to achieve a specific purpose. For example, Dainty et al. 2005 investigates skilled workforce shortage and propose multiskilling along with several other measures such as importing skilled workforce as potential solutions. Each of these contexts has distinct characteristics which affect the adaptation of multiskilling strategies. In repetitive construction projects, targeted tasks have similar characteristics. Off-site construction has a lot of resemblance to manufacturing. Multiskilling in construction sites could be approached from a project perspective.

Basically, in repetitive construction projects the similarity of different tasks enables the same group of workers to execute activities from the start to the end of the project, resulting in productivity enhancements (Liu and Wang 2011). The literature review identified two different types of projects considered as repetitive construction. The first type is repetitive by essence such as pipeline and gas line projects, which include repetitive activities in different sections. The second type of repetitive construction takes place within a small portion of a big project. An example, which include repetitive tasks, is concrete work in residential buildings. However, it should be noted that construction of whole residential buildings does not necessarily involve repetitive construction work.

With the introduction of multiskilling to construction, Hegazy et al. (2000) proposed a heuristic algorithm which suits repetitive construction and provides an appropriate foundation for future studies in this area. Inspired by Hegazy et al. (2000) the study by Tam et al. (2001) and Wongwai and Malaikrisanachalee (2011) considered tiler, bricklayer, screeding layer, terrazzo layer and marble layer as a group of resources which are undertaking repetitive tasks as a portion of a bigger construction project. Pandey and Maheswari (2015) envisaged multiskilling in repetitive units within a mass housing project and propose constructing three different sets of multiskilling from
the set of skills used by: shuttering worker, carpenter, bar bender, mason and concrete operator. Thomas and Horman (2006) considered building basement walls as another type of project in this regard. Finally, the study by Ahmadian Fard Fini et al. (2016) recognized concrete work in a residential building, including: concrete columns, concrete beams and concrete slabs as different elements of a repetitive construction project.

Applications of multiskilling in different repetitive construction projects have been identified in the literature including: road (Gouda et al. 2017; Manley and Mcfallan 2006), rail (Algaard and Estp 2014), tunnel (Gouda et al. 2017), pipeline installation projects (Gouda et al. 2017), and bridge building (Thomas and Horman 2006; Liu and Wang 2011 & 2012). Liu and Wang (2011 & 2012) determined five different types of repetitive activities in a bridge construction: excavation, foundation, column, beam and slab work. Manley and Mcfallan (2006) and Algaard and Estp (2014) evaluated the application of multiskilling from a social science perspective.

Prefabrication transfers a large proportion of construction activities to factory environments (Arashpour et al. 2015). Here a multiskilled crew is used to balance the production line in modular and panelized prefabrication. Modular production studies include producing customized houses (Moghadam et al. 2014) and constructing kitchen, bathroom and laundry pods (Arashpour et al. 2017). One paper investigated employing a multiskilled crew in panelized prefabrication, including operations related to: steel frames, concrete boards, screw fixing, roof trusses, windows and frames, finished panels, quality control, and load dispatching (Arashpour et al. 2015). A similar study in precast concrete fabrication was conducted by Ballard (2001).

Another stream of social science research explored off-site suppliers, advising of the benefits of using a multiskilled workforce with a medium level of training (Goodier et al. 2007) and
emphasizing the need for a multiskilled workforce in off-site prefabrication (Mcguinness and Bennett 2006).

As can be seen in Table 2-2 multiskilling in on-site construction is a broad area of research. Few researches concentrate on multiskilling pertaining to labor related issues including labor benefits from multiskilling (Burleson et al. 1998; Carley et al. 2003; Florez et al. 2012; Florez et al. 2013) and workforce attitudes towards multiskilling (Carley et al. 2003).

Several studies focus on satisfying employers’ interests by minimizing construction project duration (Srour et al. 2006) or minimizing the number of workers in the construction site for different reasons including safety reasons (Hyatt et al. 2004). In this regard, different strategies for multiskilled workforce recruiting, training and planning are used to satisfy a broad range of employer interests (Hegazy et al. 2000; Gomar et al. 2002; Hyatt et al. 2004; Ejohwomu et al. 2006; Ejohwomu et al. 2008; Lill 2008; Lill 2009).

Skill shortage is a crucial challenge for construction contractors in developed economies and multiskilling of a workforce is an appropriate solution to fill the skill gap (Ho 2016). Consequently, numerous studies investigate alleviating skill scarcity using multiskilling (Burleson et al. 1998; Mcguinness and Bennett 2006; Lobo and Wilkinson 2008; Haas et al. 2001).

Seven studies consider a combination of aspects of multiskilling by evaluating both betterment of employees through higher salary and duration of employment and increased prosperity of employers through achieving and greater project productivity (Gomar et al. 2002; Lill 2008; Lill 2009; Florez et al. 2012; Florez et al. 2013; Florez et al. 2017; Ahmadian Fard Fini et al. 2017).

Several papers evaluate the structure of multiskilling. Burleson et al. (1998), Michael et al. (2017), and Wang et al. (2009) suggested potential crafts to be multiskilled to satisfy a range of diverse purposes. (MOM 2016) and (BCA 2016) identified seventy-three different skills in the project
context and do not suggest any combination of multiskilling, leaving the workforce to choose an appropriate combination of skills by themselves. Innovative multiskilling structures are suggested by Castaneda et al. (2003) and Castaneda et al. (2005) expanding multiskilling boundaries to soft skills and Teizer et al. (2013), MOM (2016), and BCA (2016) expanded it to include safety.

2.4.4. Multiskilling Strategies

This section presents a categorization of publications in cross-training with consideration of possible strategies. Decision-making about cross-training strategy identifies which workers should be cross-trained in how many and for what tasks. Reviewing the literature revealed that there are three general strategies used: partial cross-training, full cross-training, and cross-trained teams (see Table 2-3).

No cross-training is the traditional way of working in which no worker performs more than one task. In the cross-training literature, it is usually used as a benchmark to help measure the benefits of other cross-training strategies (Burleson et al. 1998; Arashpour et al. 2015).

In partial cross-training, the workforce is cross-trained to undertake a few tasks in addition to their primary task. In this strategy, full cross-training is avoided due to a large number of aggregated tasks required to be completed or because of specific human resource policies (Burleson et al. 1998).

The configuration of partial cross-training in a project context is a controversial matter and is mainly dependent upon one-off characteristics of projects and the purpose of cross-training (Haas et al. 2001). The structure of cross-training could be unique and the number of tasks performed by a multiskilled workforce could range from two (Burleson et al. 1998) up to eight (Hyatt et al. 2004). However, there are some common configurations in manufacturing and service contexts (Hopp and Oyen 2004; Aksin et al. 2007). For example, Qin et al. (2015) categorized chaining and
direct capacity balancing as famous forms of partial cross-training in operational research, which are also applicable to prefabricated construction (Arashpour et al. 2015).

Table 2-3. Multiskilling strategies

<table>
<thead>
<tr>
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<th>Partial Cross-training</th>
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NC= No cross-training, DS= Dual-skill, CH= Chaining, UP= Upstream, DO= Downstream, CC=Customized cross-training, DCB= Direct capacity balancing, FSH= Four-skills helpers, FS= Four-skills, FC= Full cross-training, CT= Cross-trained teams

In repetitive construction projects, there are studies which suggest a combination of two skills (Pandey and Maheswari 2015). However, other studies showcase the potential for incorporating extra skills or even full multiskilling due to common features which are shared between different crafts, which makes learning cost and time effective (Ahmadian Fard Fini et al. 2016). Accordingly, Liu and Wang (2012), Liu and Wang (2011), Tam et al. (2001), Hyari et al. (2010),
and Wongwai and Malaikrisanachalee (2011) integrated two or three skills depending on the situation.

Hegazy et al. (2000) incorporated two different multiskilling strategies. In the first multiskilling configuration, there is just one type of multiskilled workforce capable of performing one additional task. In another strategy, there are five substitution rules for multiskilling. Some workers are specialists and others are capable of performing two or three tasks.

Chaining is a cross-training strategy in which workers are enabled to undertake operations in their original workstation and also subsequent workstation. It is considered as an appropriate cross-training strategy when there is a functional proximity between different job locations and the level of work in progress is low (Qin et al. 2015). This cross-training configuration was initiated in manufacturing (Hopp and Oyen 2004) and then developed in off-site prefabrication contexts (Arashpour et al. 2015; Arashpour et al. 2017).

A dual-skilling strategy aims to enhance the performance of workers in projects based on identifying complementary workloads (Burleson et al. 1998). For example, an idle ironworker in a project can assist overloaded painters. The main complexity with this specific type of cross-training strategy is that skill demands are project specific and also significantly diverse. Therefore, the structure of this strategy varies in different projects.

A four-skills labor strategy is suggested by Burleson et al. (1998) and is based upon the principle that craft workers can be categorized into four general classifications including civil/structural, general support, mechanical and electrical, reflecting different stages in a construction project. Four-skills-helpers strategy has the same structure as four-skills strategy, however, training is limited to helper level.
Full cross-training means every worker can perform all required tasks. Obviously, this strategy provides the most flexibility; however, the corresponding costs of training, salary and transfer expenditures are high (Burleson et al., 1998). Although this strategy is sometimes applicable to off-site construction, it should be noted that in the literature the number of workstations incorporating a full cross-trained workforce usually does not exceed four or five (Daniels et al. 2004). This reflects cross-training costs and potential learning and forgetting effects.

There is no study investigating full cross-training in construction projects as the number of extra tasks is significant (Ejohwomu et al. 2008). Burleson et al. (1998) recognized this strategy as economically inefficient and impractical in the construction project context. However, in theory, this strategy can be used as an upper bound to evaluate related benefits achieved by other multiskilling strategies. Gomar et al. (2002) showed, the benefits of multiskilling become marginal after obtaining competency in two or three trades.

The other area allowing application of full cross-training is repetitive construction projects because of the limited number of tasks and similarity between different jobs. This reduces the time and cost for the workforce to master other skills and also alleviates learning and forgetting effects (Ahmadian Fard Fini et al. 2016). In this context, Gouda et al. (2017) tested the applicability of full cross-training in a pipeline construction with nine repetitive activities.

Cross-trained teams can be formed by grouping a number of multiskilled individuals or by combining differently skilled individuals (Koch 2002). Size of the teams (Thomas and Horman 2006), similarity of skills (Koch and Marton 2002) and ability of working in parallel (Wang et al. 2009) are important factors in configuring multiskilled teams.

Multiskilled teams attract some attention in the site construction context (Koch, 2002; Koch and Marton 2002; Sacks and Goldin 2007) and in repetitive construction (Thomas and Horman 2006).
However, this strategy is absent in off-site construction contexts and this provides opportunity for future research. Sacks and Goldin (2007) proposed the use of multiskilled teams along with other initiatives to minimize production makespan. The benefit of using multiskilled teams arises mainly from having an increased number of work teams that can operate in parallel instead of working in series. This is analogous to having two different machines in a production line working in parallel to reduce queuing time (Sacks and Goldin 2007). Thomas and Horman (2006) measured how using multiskilled teams influence performance measures in concrete work in a residential building and bridge construction.

2.4.5. Multiskilling Collateral Effects

Implementing multiskilling is associated with several benefits including enhancement in productivity (Arashpour et al. 2015), enhancement in social sustainability (Lill 2008), and increased employment duration for the workforce (Burleson et al. 1998). However, these benefits are coming with a number of side effects. Seven prevalent side effects of cross-training that are identified in the literature and listed in Table 2-4 include: reduced efficiency, transfer costs, training costs, increased salary, learning and forgetting effects, psychological effects and retention costs.

Reduced efficiency occurs when workers are more efficient in their primary task compared with their secondary task (Hegazy et al. 2000). Transfer costs are associated with cross-trained workforce movement, machine setting, and obtaining needed information, which add no value to the final product (Lill 2009). Training costs are related to education of the workforce and include mentoring costs and obtaining certificates or other expenses associated with training (Ahmadian Fard Fini et al. 2016a). Increase in wage is attributed to additional compensation for the workforce with extra skills in a skill-based financial structure (Hyari et al. 2010). Learning and forgetting
effects consider the need of the workforce to receive training to develop their full potential, but if cross-trained workers fail to periodically practise a skill, it will be lost (Ahmadian Fard Fini et al. 2017). Retention costs arise from expenditures which will be lost if cross-trained workers leave a company (Pollitt 2009).

Table 2-4. Collateral effects of multiskilling

<table>
<thead>
<tr>
<th>Reference</th>
<th>RC</th>
<th>RE</th>
<th>TRC</th>
<th>TGC</th>
<th>ES</th>
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RC= Retention costs, RE= Reduced efficiency, TRC= Transfer costs, TGC= Training costs, ES= Enhancement in salary, LFE= Learning and forgetting effects, PE= Psychological effects

In addition to the above cross-training side effects, there are additional collateral effects which are known as psychological effects, including but not limited to, less social identity and less moral and high responsibility confusion (Qin et al. 2015). Other effects include increasing confusion with regard to what exactly is the overlap between different trades and whether they can be transparently distinguished (Clarke and Wall 2000). Despite existence of the aforementioned collateral effects, they are not discussed in cross-training studies due to difficulties associated with investigating and analyzing (Qin et al. 2015).

2.4.6. Multiskilling Mainstream Research
Mainstream research in the area of multiskilling can be classified into three streams. The first stream evaluates different multiskilling configurations. The second stream concerned with exploiting different scheduling and planning techniques, tries to find the extent to which different objectives can be achieved by one or more multiskilling configurations. The last stream focuses on other applications of multiskilling such as the relationship between multiskilling and innovation (Manley and Mcfallan 2006).

In the first stream, decision-making about a multiskilling configuration is analyzed using a wide range of techniques (see Table 2-5). A number of studies consider multiskilling as a combination of different trades (Burleson et al. 1998; Haas et al. 2001; Wang et al. 2009; Arashpour et al. 2017). Other studies suggest that multiskilling is a mixture of one craft and one or some soft skills (Castañeda et al. 2003; Castañeda et al. 2005; Pagano and Heathcote 2003; Dainty et al. 2005; Detsimas et al. 2016). Some studies suggest that multiskilling is a mixture of a craft and one or more safety skills (BCA 2016; MOM 2016; Teizer et al. 2013).

In the first research stream, the process of establishing multiskilling practice at the individual (Pollitt 2009 & 2010) and team level (Koch 2002; Koch and Marton 2002) is investigated. Limitations of multiskilling have been identified as labor behavior (Carley et al. 2003; Michael et al. 2017) and regulatory limitations including licensing (Lobo and Wilkinson 2012). The common methodology used in this stream is to investigate the market and industry using social science research techniques.
<table>
<thead>
<tr>
<th>Reference</th>
<th>Objective</th>
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<th>MSA</th>
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MC=Multiskilling with craft, MSO=Multiskilling with soft skills, MSA=Multiskilling with safety, CE=Configuration establishment, LC=Limitation of configuration.

In the second stream, three different objectives are identified encompassing minimizing cost, minimizing time and maximizing social sustainability (see Table 2-6).
A stream of research tries to decrease project completion time. For minimizing the project delay, Hegazy et al. (2000) incorporated a heuristic algorithm that analyses information about resources which can be substituted, in case there is a need for a less utilized workforce to be substituted in over-utilized locations, taking into account productivity loss. Cost considerations in this study presented as opportunities for future research. Wongwai and Malaikrisanachalee (2011) developed a heuristic algorithm supplementing the study of Hegazy et al. (2000) by covering pre-emptive operations for which a required number of resources is not totally fulfilled. However, minimization of project cost is not guaranteed since there is a possibility for an available expensive resource to be substituted for a cheaper resource to finish the projects sooner. Liu and Wang (2012) proposed a constraint programming which minimizes the duration of a bridge execution project. In addition to a single-skilled workforce, a multi-skilled workforce who are capable of assisting with different
operations are subcontracted to help with specialist manpower. The developed scheduling technique was investigated in a repetitive construction project in two different scenarios, including minimum total interruptions and no interruption. In this study, even though the cost corresponded to the optimized value of time presented, cost optimization is not incorporated in the objective function of the mathematical model. In the concrete work of a residential building, Ahmadian Fard Fini et al. (2016) incorporated multiskilling and learning effects to minimize the duration of construction projects. A hybrid methodology encompassing constraint programming, statistical analyses, and a genetic algorithm, is used to demonstrate optimal crew compositions for different tasks included in the project.

A stream of papers concentrates on reducing the labor cost of a project. The study by Tam et al. (2001) presented a genetic algorithm with the objective of maximizing the usage level of the workforce to encourage contractors to employ labor directly, while dealing with a shortage of skilled craft workers. The findings of this study highlight that although implementing multiskilling strategies leads to extra costs, the consequent enhancement in performance measures outweighs the additional expenses of multiskilling. Srour et al. (2006) developed a linear programming approach to help strategic decision-making for training the available workforce, and for hiring additional workers to match supply and demand of construction labor in a petro-chemical construction project. The objective function of the mathematical model is to minimize labor costs by considering labor demand satisfaction and considering the skill shortage situation in the construction industry. The developed model was applied in five different scenarios corresponding to different situations in the real world, in which there are one or more limitations to hiring or training multi-skilled or single-skilled workforce. The model results suggest appropriate resource management strategy relevant to existing situations in the real world. Gouda et al. (2017)
incorporated a line of balance technique for optimizing resource allocation in the context of a sewage pipeline project. It is found that using this model can decrease the manpower required to finish the project from 20 to 9.

A stream of publications considers both enhancement in performance measures of the project in terms of cost or time, and labor well-being. Gomar et al. (2002) developed a linear programming model to investigate the allocation of cross-trained crew to optimize the multi-skilled workforce assignment and allocation process in a construction project, or between the projects of one company, taking into account a minimization of hiring and firing and also project productivity measures. Later, multiskilling of labor with the objective of minimizing hiring and firing was considered as a measure of social sustainability and investigated by mixed integer programming (Florez et al. 2013; Florez 2017) and simulation (Lill 2009).

The third research stream which includes 10 papers investigates relevance of multiskilling to lean production (Gao and Low 2015; de Miranda Filho et al. 2007; Seppänen and Kenley 2005; Mostafa et al. 2016), knowledge-based economy (Ofori 2002), innovation (Manley and Mcfallan 2006), prevalence of off-site construction (Goodier et al. 2007), flexibility (Ofori and Debrah 1998), workforce strategy (Brandenburg et al. 2003), and benchmarking (Algaard and Estp 2014).

2.4.7. Interaction between different components of multiskilling

Twelve different forms of cross-training strategies, their context, benefits and collateral effects identified in this literature review are summarized in Table 2-7 to provide an appropriate basis for discussion. The table indicates whether an advantage in a specific context can be achieved from a cross-training strategy. Collateral effects are categorized as of low, medium and high effect.

All cross-training strategies have potential to increase the productivity of construction. For example, chaining, direct capacity balancing, upstream, downstream, and in some cases full cross-
training can be used to even out production flow by targeting bottleneck processes and feeding
enough resource to over utilized locations, leading to reductions in production time and cost.

Mastering more skills results in better employability and employment prospects (Detsimas et al. 2016). Dual-skill, four-skills-helpers and four-skills cross-training can be used to enhance employment duration because these workers have skill sets constructed to meet the needs of different stages of construction projects (Haas et al. 2001). Though the literature shows that dual-skill, four-skills-helpers and four-skills reduce the cost and time of a project (Burleson et al. 1998), they will not to be as efficient as chaining, direct capacity balancing, upstream, and downstream multiskilling strategies in dealing with bottlenecks. Customized multiskilling and cross-trained teams are pragmatic strategies to deal with both bottlenecks and social sustainability, according to the way the skill set is tailored.

Safety is negatively affected by an increase in worker turnover rates as most accidents involve newly hired workers, unfamiliar with site conditions (Haas et al. 2001). Therefore, since a

Table 2-7. Multiskilling comparison table

<table>
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<tr>
<th>Cross-training strategy</th>
<th>Collateral effects</th>
<th>Advantage</th>
<th>Context</th>
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L=Low effect, M=Medium effect, H=High effect, MSO=Multiskilling with soft skills, MSA=Multiskilling with safety, DS= Dual-skill, CH=Chaining, UP= Upstream, DO= Downstream, CC=Customized cross-training, DCB= Direct capacity balancing, FSH= Four-skills-helpers, FS= Four-skills, FC= Full cross-training, CT= Cross-trained teams, PE= Psychological effects, LFE= Learning and forgetting effects, RC= Reduced efficiency, TRC= Transfer costs, TGC= Training costs, ES= Enhancement in salary, MC= Minimizing cost, MT= Minimizing time, SS= Social sustainability, RC=Repetitive construction, OffC=Off-site construction, OnC=On-site construction.
multiskilled workforce is able to perform several tasks, it is expected to stay for longer periods of time at the construction site and become familiar with site conditions and hence decrease the rate of accidents occurring (CII 1998). Therefore, dual-skilling, four-skills-helpers and four-skills strategies, which enhance employment duration, lead to a safer workplace. Additionally, a stream of literature considers labor with one primary skill and one or more safety skills as multiskilled labor (BCA 2016; MOM 2016; Teizer et al. 2013).

Cross-training labor in extra skills leads to additional productivity, social sustainability, and collateral effects. Therefore, attention should be paid to choosing cross-training strategies to find the best compromise between advantages and collateral effects.

Training costs and enhancement in salary have a direct relationship with the number of extra skills to be trained in (Qin et al. 2015). Therefore, full cross-training should have the highest enhancement in salary and training costs followed by four-skills and four-skills-helpers. Costs associated with four-skills-helpers are less than four-skills because helpers are trained to a lower level. Dual-skill, chaining and direct capacity balancing have the lowest training costs and associated salary change since they involve learning just one extra skill. Depending on the number of extra skills to be learned, the costs of upstream, downstream, customized cross-training, and cross-trained teams vary between the costs of the strategies above. Psychological effects, reduced efficiency and learning and forgetting effects are expected to be similar to training and salary costs, having a direct relationship with the number of extra skills to be acquired (Qin et al. 2015).

Dual-skill, Four-skills-helpers and four-skills strategies are associated with minimum transfer costs because movement of labor corresponds to alteration in four stages of construction including civil/structural, general support, mechanical, and electrical (Burleson et al. 1998). Meanwhile, chaining, upstream, downstream and direct capacity balancing are associated with higher transfer
costs because they are designed to deal with bottlenecks, which can demand for hourly or daily substitutions (Arashpour et al. 2015). Transfer costs for customized cross-training, full cross-training, and cross-trained teams depend on the aim of multiskilling, which affects the combination of skills required (De Bruecker et al. 2015). Generally, all multiskilling strategies, except full cross-training, can be advantageous in on-site construction. Full cross-training is not appropriate for on-site construction considering the high number of skills needed (Burleson et al. 1998). Dual-skill, four-skills and four-skills-helper training can be modified for repetitive and off-site construction (Arashpour et al. 2017). Customized cross-training is the most promising multiskilling strategy in all contexts, considering that each construction project is of a one-off nature with unique features (Haas et al. 2001). An important limitation on the expansion of customized cross-training is the lack of appropriate models which calibrate the skill configuration pertaining to the features of every project.

2.4.8. Multiskilling studies keyword investigation

Keywords represent principal areas of research in a specific investigation (Su and Lee 2010). Illustrating keywords and their relationships in a network will provide appropriate scientific knowledge about patterns, relationships and intellectual organization of investigated areas of science (Van Eck and Waltman 2007). Fruchterman Reingold is an algorithm for visualizing interactions of keywords in scientific publications (Hosseini et al. 2018). This algorithm is frequently used in literature review studies in the construction management area (Hosseini et al. 2018).

Fig. 2-3 includes 27 nodes and 103 edges and is derived by forming a pool of keywords used in papers which are identified in this literature review. To produce this figure, two considerations were taken into account. Firstly, the terms with similar implications such as
labor, workforce and craft were merged to cover all. Secondly, a number of general terms such as country names are omitted to obtain meaningful results. Each node represents a keyword and the size of each node reflects the number of repetitions in the literature. The thickness of each edge (or link) indicates the number of publications considering two keywords simultaneously.

As can be seen in Fig 2-3, nodes relating to programming, optimization and simulation have attracted considerable attention. However, the human resource node is relatively small which provides a potential area for future research. Even though training has been investigated intensively in the literature (Burleson et al. 1998; Srour et al. 2006; Wang et al. 2009; Castañeda et al. 2005; Ejohwomu et al. 2008), the learning remains a less covered area of research (Ahmadian Fard Fini et al. 2016a).
Fig. 2-3. Fruchterman Reingold presentation of keyword
2.5. Summary

This chapter is a comprehensive literature review trying to classify multiskilling literature into appropriate categories to provide an in-depth knowledge about cross-training in construction and to facilitate future studies. To this end, a framework is established enabling cross-training literature to be classified into four different classes of context, strategy, collateral effects, and mainstream research. The cross-training context considers the effects of off-site prefabrication, on-site construction and repetitive construction projects in examining cross-training feasibility and configuration. Cross-training strategy outlines a wide range of multiskilling strategies and their applications. Collateral effects included cross-training disadvantages in terms of financial and psychological consequences. Mainstream research often pertains to cross-training advantages and different methodologies to obtain them.

This classification is insightful by alerting decision makers regarding i) whether the nature of a specific construction tasks allows a given multiskilling policy to be operationally expedient by referring to cross-training context; ii) a range of multiskilling configurations from which a desirable one can be selected by consulting cross-training strategy; iii) whether a cross-training strategy is suitable for fulfilling decision makers’ goal and the extent to which operational and financial benefits of a multiskilling strategy is attainable by getting advice from mainstream research iv) what is quantitative and qualitative cost of incorporating an specific strategy by investigating cross-training collateral effects.
Chapter 3

3. Scheduling platform development

Multiskilling allows for dynamic reallocation of workers from one stage of production to another in response to bottleneck configurations, and therefore, has been advocated as a potential strategy to improve productivity in off-site construction. The aim of this chapter is to investigate the extent to which operational benefits associated with different resource management policies pertaining to bottleneck configurations can be achieved in off-site construction based on an optimization-based scheduling platform. To this end, the flowshop environment is recognized as an appropriate operational framework for modelling production dynamics. A quadratic scheduling model for resource allocation is developed to expose different operational performances corresponding to different resource management strategies. Different resource management policies include no cross-training, hiring single-skilled crew, direct capacity balancing, chaining, and hiring multi-skilled crew. Operational performance encompasses makespan and labor costs. Production data from a prefabrication factory based in Melbourne, Australia, was fed to the model, providing the basis for comparison of different resource management policies. Research findings contribute to resource planning and management in off-site construction.

3.1. Introduction

Despite the extensive literature on multiskilling in construction projects, a majority of previous studies are focused on multiskilling in on-site construction projects (Burleson et al. 1998; Florez 2017; Gomar et al. 2002; Hegazy et al. 2000; Lill 2009; Sacks et al. 2015); and little effort has been made to investigate the potential benefits of multiskilling in off-site construction by

recruiting a flexible workforce. In particular, the existing literature on multiskilling in prefabricated construction is limited to: i) qualitative studies on the need for multiskilling in off-site construction and its potential benefits (Goodier et al. 2007; Mcguinness and Bennett 2006); and ii) simulation based and multi-criteria decision making methods to identify the appropriate cross-training configuration in the prefabricated construction (Arashpour et al. 2015, 2018b).

There is currently a lack of a systematic method to implement multiskilling strategies in prefabricated construction through optimizing the jobs assignment to a combination of multi-skilled and single-skilled workers (See Chapter 2). The ability to allocate appropriate workers to the relevant tasks by considering the aim of multiskilling (Haas et al. 2001) is crucial to ensuring the benefits of multiskilling are fully realized (Gomar et al. 2002). Identifying the optimal job assignment in prefabricated construction projects involving multi-skilled workers is, however, challenging, due to the large number of alternative ways in which workers can be allocated to tasks, as well as the large number of constraints pertaining to production sequence and layout (Arashpour et al. 2018b). In this chapter, a mathematical optimization model is proposed for assigning construction activities in a prefabricated project to multi-skilled workers, with the objective of minimizing the makespan in off-site construction projects, while considering the constraints of typical prefabricated construction projects. The proposed method is applied to an illustrative case study to highlight its applications and benefits in practice.

3.2. Problem context
The cross-trained resource scheduling problem is a subset of the resource allocation problem in which all or some human resources are multi-skilled, providing the flexibility to allocate them to different tasks to improve utilization of resources. The aim is to optimize the use and allocation of resources to maximize or minimize certain functions related to performance and productivity (Bouajaja and Dridi 2016). Optimizing the allocation of multi-skilled workers has been broadly
investigated in the on-site construction literature to achieve several important objectives (See Chapter 2).

So far, multiskilling in off-site construction specifically, optimization of prefabrication performance measures by incorporating cross-trained resources attracted little attention (Arashpour et al. 2015). To this end, this chapter presents an optimization-based scheduling framework for single-skilled and multi-skilled workforce allocation in the context of off-site construction. A quadratic mathematical model was developed to incorporate features of prefabricated construction. The developed model linearized to solve the problem in a reasonable timeframe. The objective function of the model is minimizing project duration by taking into account labor costs pertaining to different compositions of single-skilled and multi-skilled crews.

The literature of cross-training in on-site construction is mainly based on the critical path method, which does not work properly in precast production (Benjaoran et al. 2005). Production layout, flow and operations routines in prefabricated construction (Chan and Hu 2002), plus optimization of production performance such as makespan (Benjaoran et al. 2005), shift the resource allocation problem in prefabricated construction towards operational research techniques (Arashpour et al. 2015). There is a wide range of studies in the operations research literature investigating the optimization of performance measures by efficient scheduling of multi-skilled resources. For example, Stewart et al. (1994) and Campbell (2011) used mathematical programming to minimize cost and time of training and to minimize the number of cross-trained workers, respectively. Campbell and Diaby (2002) and Azizi and Liang (2013) applied heuristic approaches to maximize service level and to minimize training costs of multi-skilled manpower. Brusco (2008) utilized a branch and bound algorithm to minimize labor shortage. Easton (2011) employed a mixed integer
programming to solve cross-trained manpower problem with objective of minimizing labor costs and maximizing service levels.

The extent and way in which flexibility can be implemented in a specific sector is a highly context-specific matter (Easton 2011). Therefore, even though there are several techniques in operations research literature for multi-task resource allocation, all of them are not applicable to off-site construction, and modifications should be applied to them by reviewing construction literature (Arashpour et al. 2018b). Yang et al. (2016) and Rogalska et al. (2008) argued that flowshop principles are an appropriate framework to effectively formulate resource scheduling problems in precast construction. Although flowshop literature in off-site construction is focused on single-skilled crews (Leu and Hwang 2002), optimization of flowshop makespan via full (Daniels and Mazzola 1993, 1994) and partial cross-training of crews (Daniels et al. 2004) is intensively investigated in the manufacturing literature, which provides an appropriate basis for this chapter.

3.3. Problem description and Model formulation

A classic flowshop problem is defined as a problem which consists of two main elements: a group of $m$ machines and a set of $n$ jobs or products which should be processed in these machines (Hejazi and Saghafian 2005). There are four basic assumptions for a classic flowshop problem: the jobs should be processed in all machines, job splitting is not allowed, operations are non-pre-emptive, and set up times are included in the processing time. Extra assumptions to a classic flowshop problem which has makespan minimization as an objective function include permutation (Hejazi and Saghafian 2005), zero buffering (Allahverdi et al. 1999), blocking (Abadi et al. 2000), no wait (Aldowaisan and Allahverdi 1998), no intermediate queue (Abadi et al. 2000), and sequence-dependent set-up (Tseng and Stafford 2001). Flowshop problems with and without permutation are the best fit to optimize the off-site construction scheduling problem (Yang et al. 2016).
Consider a set of products $N=\{1,2,\ldots,N\}$ that is going to be processed sequentially and in the same order in a set of workstations $M=\{1,2,\ldots,M\}$ which generates a flowshop problem, where $N$ is the last product and $M$ is the final workstation. Notation $(n, m)$ is an indication of processing product $n$ in workstation $m$ which is referred as procedure $(n, m)$ in this chapter. A limited number of workers from a set of workers $\Omega=\{1,2,\ldots,W\}$ can be allocated to a workstation based on cross-training strategies, where $W$ is the last worker. $\Lambda=\{1,2,\ldots,K\}$ is a set of status which denotes the number of workers who can be engaged in the procedure $(n, m)$, where $K$ is maximum number of workers who can work in the procedure $(n, m)$. $T=\{1,2,\ldots,T\}$ is the set of time periods which encompasses all possible values for starting and completion times of a procedure where $T$ is upper bound on makespan. The objective function of this chapter is to minimize makespan, as presented by equation 2-1.

$$\text{Minimize } C_{\text{Max}} \geq C_{nm} \quad (1) \quad n \in N, \ m \in M$$

$C_{\text{Max}}$ denotes the makespan and $C_{nm}$ indicates the completion time of the procedure $(n, m)$. Let us consider $\theta_{nmkt}$ as a binary variable which is equal to one if procedure $(n, m)$ is processed with $k$ resources and finished at time $t$. The non-pre-emptive condition of the flowshop requires each procedure to have a unique status, which results in a specific corresponding completion time. This requirement is satisfied in equation (2-2).

$$\sum_{k=1}^{K} \sum_{t=1}^{T} \theta_{nmkt} = 1 \quad n \in N, \ m \in M \quad (2-2)$$

Let $D_{nm}$ denote the duration of procedure $(n, m)$. Duration of the procedure $(n, m)$ is a function of a different procedure status. Obviously, allocation of a higher $k$ will result in decreasing the value of $D_{nm}$. Given $d_{nmk}$ is the duration of procedure $(n, m)$ when $k$ workers are assigned to it, the value of $D_{nm}$ can be computed according to equation (2-3).
\[ D_{nm} = \sum_{k=1}^{K} \sum_{t=1}^{T} d_{nmk} \theta_{nmkt} \quad n \in N, m \in M \] (2-3)

Then \( C_{nm} \) is obtained as equation 2-4:

\[ C_{nm} = \sum_{k=1}^{K} \sum_{t=1}^{T} \theta_{nmkt} t \quad n \in N, m \in M \] (2-4)

Equations (2-5) and (2-6) satisfy the requirement for a flowshop problem with permutation. Equation (2-5) limits the start time of processing a product in a workstation to always being more than the completion time in the previous workstation. Equation (2-6) insures permutation exists in the flowshop.

\[ C_{nm} \geq C_{n(m-1)} + D_{nm} \quad n \in N, m \in M \] (2-5)
\[ C_{nm} \geq C_{(n-1)m} + D_{nm} \quad n \in N, m \in M \] (2-6)

Let \( a_{wmt} \) be a binary variable which is equal to 1 if worker \( w \) is allocated to the workstation \( m \) in \( t \). In a similar manner, \( s_{wm} \) is a binary parameter which is equal to 1 if worker \( w \) has received appropriate training to be allocated to workstation \( m \). Accordingly, inequality (2-7) denotes that workers can just be allocated to workstations for which they are cross-trained.

\[ s_{wm} \geq a_{wmt} \quad m \in M, w \in \Omega, t \in T \] (2-7)

Let \( q_{w} \) be daily cost of worker \( a_{wmt} \). Then, total worker cost can be computed by equation (2-8).

\[ \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{w=1}^{W} q_{w}a_{wmt} = Q \] (2-8)

Constraint (2-9) insures that in each interval of time each worker can be allocated to just one workstation.

\[ \sum_{m=1}^{M} a_{wmt} = 1 \quad w \in \Omega, t \in T \] (2-9)
Constraint (2-10) designates the needed sum of workers to a specific procedure according to procedure status by converting values of \( a_{wmt} \) to 1 until their summation satisfies the value of \( k \).

\[
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} \theta_{nmkt} a_{wmt} = \sum_{k=1}^{K} \sum_{t=1}^{T} k \theta_{nmkt} \quad n \in \mathcal{N}, m \in \mathcal{M} \quad (2-10)
\]

Equation (2-11) indicates that when a specific worker is allocated to a specific procedure in its final interval of processing, then the worker should remain in the same procedure for the whole duration, which is determined by a unique procedure status. This means when worker \( w \) is allocated to the procedure \((n, m)\) in \( t_1 \), \( \theta_{nmkt_1} \) becomes 1 and worker \( w \) should be allocated to the same procedure during the interval \([t_1 - d_{nmk} + 1, t_1]\) which is determined by procedure status affecting \( d_{nmk} \) value.

\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{t} \theta_{nmkt} a_{wml} = \sum_{k=1}^{K} \sum_{t=1}^{T} a_{wmt} d_{nmk} \theta_{nmkt} \quad n \in \mathcal{N}, m \in \mathcal{M}, w \in \Omega \quad (2-11)
\]

The presented formulations minimize off-site construction production makespan, subject to constraints which define makespan as the maximum completion time of the last product in the final workstation. These formulations illustrate generating an optimal solution for makespan that involves a simultaneous resolution for two interrelated sub-problems of procedures’ status and procedures’ completion time. Procedure status is an indication of the number of crew to be allocated to procedure, and determines its processing time, which affects the procedure completion time. Completion time is a translation of resource allocation policy to a procedure to minimize makespan while protecting resource feasibility.
3.4. Case study description

This Ph.D. study uses a modular prefabrication factory that produces bathroom pods in Melbourne as its test bed. Different approaches and methodologies, including observation, evaluating financial reports and production data, and interviewing the site manager, were adopted to gather corresponding values for parameters in the mathematical model. Workstation layout and operations flow obtained from direct observation supported the choice of flowshop framework, which was in accordance with assumptions of classical flowshop problem argued in the previous section. A total of twelve workstations in a serial configuration were identified, and their related operations are outlined in Table 3-1.

<table>
<thead>
<tr>
<th>Workstation</th>
<th>Operation</th>
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<tbody>
<tr>
<td>1</td>
<td>Laboring</td>
</tr>
<tr>
<td>2</td>
<td>Caulkering</td>
</tr>
<tr>
<td>3</td>
<td>Mechanical controlling</td>
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<tr>
<td>4</td>
<td>Tiling</td>
</tr>
<tr>
<td>5</td>
<td>Plumbing</td>
</tr>
<tr>
<td>6</td>
<td>Plastering</td>
</tr>
<tr>
<td>7</td>
<td>Carpentry</td>
</tr>
<tr>
<td>8</td>
<td>Electric work</td>
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<tr>
<td>9</td>
<td>Water-proofing</td>
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<tr>
<td>10</td>
<td>Glazing</td>
</tr>
<tr>
<td>11</td>
<td>Joining</td>
</tr>
<tr>
<td>12</td>
<td>Painting</td>
</tr>
</tbody>
</table>

The duration of product completion and of operations in each workstation, bottleneck locations, the set of products, and set of workers, were obtained by evaluating the production data and consulting the site manager. Additionally, the maximum number of workers who can work in a workstation was determined by the advice of the site manager. The binary skill parameter was constructed by reviewing the literature (Arashpour et al. 2015, 2018b; Burleson et al. 1998; Wang et al. 2009), and interviewing the site manager. The effect of using a multi-skilled workforce on
the duration of operations was based on previous literature (Hopp and Oyen 2004; Qin et al. 2015; Qin and Nembhard 2015), and interviews with the site manager. Related data to different resource management policies (RMPs), including the number of workers, the combination of skills, the location, and cost of single-skilled and multi-skilled workforces, are presented in Table 3-2. The cost of labor includes salary, tax, and the superannuation pension fund in the Australian context. Fig. 3-1 visualizes different RMPs investigated in this chapter. Workstations \((m \in \mathcal{M})\) and laborer \((w \in \Omega)\) are presented with the same notations as described in the problem description section. Blue and red arrows indicate initial and secondary skills, respectively. A worker is single-skilled if he/she has only a single blue arrow. Whereas blue and red arrows together indicate a multi-skilled worker who has been also trained for a secondary skill. A worker with red arrows only represents a hired multi-skilled worker.

As shown in Fig. 3-1–a, the prefabrication plant considered in this chapter comprises twelve workstations. The number of workers and the sequence of processes in the production line are based on the actual conditions in the real fabrication layout of the case study factory. At the moment, no cross-trained workers are employed in this production line, representing the no cross-training (NC) policy, in which one single-skilled worker is allocated to each workstation. This originally adopted NC strategy is therefore adopted in this investigation as the benchmark for comparing other multiskilling policies (Qin et al. 2015; Qin and Nembhard 2015).
Table 3-2. Worker number, skill set, and costs in different RMPs

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<tr>
<td>1</td>
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<td>180.16</td>
<td>Laborer</td>
<td>180.16</td>
<td>Laborer</td>
<td>180.16</td>
<td>Laborer &amp; Caulker</td>
<td>228.16</td>
<td>Laborer</td>
<td>180.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
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<td>Caulker</td>
<td>180.16</td>
<td>Caulker &amp; Laborer</td>
<td>196.16</td>
<td>Caulker &amp; Mechanical controller</td>
<td>228.16</td>
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<td>180.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3</td>
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<td>Mechanical controller</td>
<td>219.28</td>
<td>Mechanical controller</td>
<td>219.28</td>
<td>Mechanical controller &amp; Tiler</td>
<td>243.28</td>
<td>Mechanical controller</td>
<td>219.28</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
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<td>Tiler</td>
<td>195.2</td>
<td>Tiler &amp; Laborer</td>
<td>209.6</td>
<td>Tiler &amp; Plumber</td>
<td>243.28</td>
<td>Tiler</td>
<td>195.2</td>
<td></td>
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<td>5</td>
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<td>Plumber</td>
<td>224.96</td>
<td>Plumber &amp; Plasterer</td>
<td>224.96</td>
<td>Plumber &amp; Plasterer</td>
<td>256.96</td>
<td>Plumber</td>
<td>224.96</td>
<td></td>
<td></td>
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<td>7</td>
<td>Carpenter</td>
<td>234.64</td>
<td>Carpenter</td>
<td>234.64</td>
<td>Carpenter &amp; Electrician &amp; Glazer</td>
<td>234.64</td>
<td>Carpenter &amp; Electrician &amp; Glazer</td>
<td>266.64</td>
<td>Carpenter</td>
<td>234.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Electrician</td>
<td>243.52</td>
<td>Electrician</td>
<td>243.52</td>
<td>Electrician &amp; water-proofer</td>
<td>243.52</td>
<td>Electrician &amp; water-proofer</td>
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<td>Electrician</td>
<td>243.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>9</td>
<td>Water-proofer</td>
<td>220.16</td>
<td>Water-proofer</td>
<td>220.16</td>
<td>Water-proofer &amp; Carpenter</td>
<td>236.16</td>
<td>Water-proofer &amp; Carpenter</td>
<td>252.16</td>
<td>Water-proofer</td>
<td>220.16</td>
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<tr>
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<td>Glazer</td>
<td>189.92</td>
<td>Glazer</td>
<td>189.92</td>
<td>Glazer &amp; Carpenter</td>
<td>205.92</td>
<td>Glazer &amp; Joiner</td>
<td>229.92</td>
<td>Glazer</td>
<td>189.92</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Joiner</td>
<td>234.64</td>
<td>Joiner</td>
<td>234.64</td>
<td>Joiner &amp; painter</td>
<td>234.64</td>
<td>Joiner &amp; painter</td>
<td>266.64</td>
<td>Joiner</td>
<td>234.64</td>
<td></td>
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<tr>
<td>12</td>
<td>Painter</td>
<td>205.76</td>
<td>Painter</td>
<td>205.76</td>
<td>Painter &amp; Electrician</td>
<td>231.2</td>
<td>Painter &amp; laborer</td>
<td>229.76</td>
<td>Painter</td>
<td>205.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>-</td>
<td>-</td>
<td>Laborer</td>
<td>180.16</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Laborer, Carpenter &amp; Electrician</td>
<td>248</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>14</td>
<td>-</td>
<td>-</td>
<td>Carpenter</td>
<td>234.64</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>Laborer, Carpenter &amp; Electrician</td>
<td>248</td>
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<tr>
<td>15</td>
<td>-</td>
<td>-</td>
<td>Electrician</td>
<td>243.52</td>
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</tbody>
</table>
Fig. 3-1. RMPs: (a) NC; (b) HSC; (c) DCB; (d) CH; and (e) HMC
The site manager identified the laboring, carpentry, and electrician workstations as the main bottlenecks. Accordingly, the site manager decided to add one more single-skilled worker to each bottleneck workstation to balance the production output in every workstation. At the time of inspecting the production line, the aforementioned workers were still apprenticed and not ready to be engaged in the production process. However, the site manager was unsure about the financial and operational justification of training single-skilled crew in additional skills and allocating them to potential bottleneck workstations. This decision is modelled in this chapter as hiring single-skilled crew (HSC), and is schematically presented in Fig. 3-1-b.

The next strategy considered in this chapter, Fig. 3-1-c, is direct capacity balancing (DCB) which is a well-recognized cross-training policy in the off-site construction context (Arashpour et al. 2015, 2018b). In this strategy, because extra workloads are not compensated in the first workstation, the caulker and tiler are cross-trained to be engaged in the first workstation when needed. The choice of cross-trained workers is informed by their proximity to a bottleneck location (Hopp and Oyen 2004) and skills affinity (Wang et al. 2009). The second bottleneck is the carpentry workstation. Carpentry is a licensed trade in Australia and therefore cross-training for this bottleneck will be in the helper level. The water-proofer and glazer are selected to be cross-trained in this workstation due to their low hourly rates and proximity to the bottleneck. The other reason for this decision is the fact that licensed trades with higher skill levels and higher initial salaries are usually unwilling to be cross-trained in other tasks (Carley et al. 2003). This assumption was confirmed by the site manager’s experience. Following the same reasoning, it was decided to cross-train the painter in the helper level to support the electrician.

The fourth strategy is chaining (CH) which has been previously investigated in manufacturing (Hopp and Oyen 2004; Qin et al. 2015) and off-site construction (Arashpour et al. 2015, 2018b).
As shown in Fig. 3-1-d, in this strategy, each worker is cross-trained to work in his/her current workstation as well as in a secondary adjacent workstation. Since there is no adjacent workstation in the last workstation, worker no. 12's secondary workstation will be the first.

Hiring multi-skilled crew (HMC) which is suggested by Liu and Wang (2012) is illustrated in Fig. 3-1-e. In this strategy, two cross-trained workers who are capable of helping in bottleneck workstations are hired and will provide help across bottlenecks. Given the fact that the number of hired cross-trained workers tends to be less than the number of bottlenecks due to financial considerations (Liu and Wang 2012), 14 workers in total are used in this strategy.

This investigation implements the above strategies in three production cases. In the first case, all bathroom pods have identical specifications with the same operation durations. In the second case, there are small customizations in production, resulting in different procedures. However, the bottleneck spots are same as in the first case. In the third case, the extent of customization is high, and some non-bottleneck workstations are converted to bottlenecks. In this case, seven out of ten modules are highly customized, and three modules have identical production data equal to the first case. Accordingly, case one, two, and three are named as no variability (NV), medium variability (MV), and high variability (HV) cases, respectively.

Incorporating the collected data, the prefabrication assembly line was modeled using the optimization model presented in the methodology section. The production data fed to the model, and different productivity measures including makespan, and the cost associated with implementation of different cross-training strategies, were calculated. The output of computation process is presented in Tables 3-3, 3-4, and 3-5.

3.5. Computational experiments
3.5.1. Performance of all RMPs in each case
Table 3-3 shows the performance of different RMPs after implementing the NV strategy (case one). As can be seen, considering the base case with NC, it takes 44 days to complete 10 bathroom pods with a corresponding labor cost of 73,886 AUD.

<table>
<thead>
<tr>
<th>RMP</th>
<th>Extra skills</th>
<th>Extra single-skilled worker</th>
<th>Extra multi-skilled worker</th>
<th>Cmax</th>
<th>Improvement in Cmax</th>
<th>Cost of labor</th>
<th>Fluctuation in cost of labor</th>
</tr>
</thead>
<tbody>
<tr>
<td>NC</td>
<td>0</td>
<td>3</td>
<td>44</td>
<td>0</td>
<td>73886</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>HSC</td>
<td>3</td>
<td>32</td>
<td>27%</td>
<td>131789</td>
<td>+78%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DCB</td>
<td>5</td>
<td>30</td>
<td>32%</td>
<td>54850</td>
<td>-25%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CH</td>
<td>12</td>
<td>32</td>
<td>27%</td>
<td>93249</td>
<td>+26%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HMC</td>
<td>3</td>
<td>26</td>
<td>41%</td>
<td>91062</td>
<td>+17%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As shown, the results indicate that HMC and DCB lead to the greatest improvements in makespan, with 41% and 32% improvements, respectively. CH and HSC strategies, on the other hand, were found to lead to 27% improvement in makespan. Furthermore, the results highlight DCB as the only strategy leading to cost savings, with an estimated cost reduction of 25%. All other strategies result in extra costs. HSC leads to the greatest extra cost, about 80%, which makes this strategy inefficient. HMC brings the least extra cost, about 17%, which looks justifiable considering its huge contribution to makespan.

Table 3-4 reflects performance measures in the second case. In the base case with NC strategy, makespan is 46 days for producing 10 bathroom pods leading to a labor cost of 132,268 AUD. Similar to the first case, in the MV environment HMC and DCB lead to the most enhancement in makespan, with 37% and 28% improvements, respectively. HSC’s and CH’s performances are the same. However, the situation regarding cost fluctuations is different. HMC is the only strategy which causes extra costs. All other strategies induce a significant cost-saving, equivalent to 58%, 42%, and 38%, corresponding to CH, DCB, and HSC, respectively.
Performance measures of different RMPs in case three are illustrated in Table 3-5. It takes 49 days to produce 10 bathroom pods leading to a labor cost of 150,734 AUD. In the HV environment, CH and HMC generate the best improvement in makespan. Despite being similar to previous cases, HMC brings extra costs, while CH leads to about 50% cost saving, which makes this strategy the best one in a HV environment. Like previous cases, DCB outperforms HSC in terms of improvement in makespan and cost saving.

### Table 3-5. RMPs’ Performance in HV

<table>
<thead>
<tr>
<th>RMP</th>
<th>Extra skills</th>
<th>Extra single-skilled worker</th>
<th>Extra multi-skilled worker</th>
<th>Cmax</th>
<th>Improvement in Cmax</th>
<th>Cost of labor</th>
<th>Fluctuation in cost of labor</th>
</tr>
</thead>
<tbody>
<tr>
<td>NC</td>
<td>0</td>
<td>0</td>
<td></td>
<td>49</td>
<td>0</td>
<td>150734</td>
<td>0</td>
</tr>
<tr>
<td>HSC</td>
<td>3</td>
<td></td>
<td></td>
<td>38</td>
<td>22%</td>
<td>101747</td>
<td>-32%</td>
</tr>
<tr>
<td>DCB</td>
<td>5</td>
<td></td>
<td></td>
<td>35</td>
<td>28%</td>
<td>92682</td>
<td>-38%</td>
</tr>
<tr>
<td>CH</td>
<td>12</td>
<td></td>
<td></td>
<td>34</td>
<td>31%</td>
<td>77405</td>
<td>-49%</td>
</tr>
<tr>
<td>HMC</td>
<td>2</td>
<td></td>
<td></td>
<td>34</td>
<td>31%</td>
<td>111261</td>
<td>+26%</td>
</tr>
</tbody>
</table>

### 3.5.2. Performance of each RMP in all cases

Fig. 3-2 illustrates different productivity measures’ fluctuations with the implementation of different RMPs in different cases. Different RMPs are outlined in the horizontal axis. The vertical axis shows change in performance measures in comparison with NC in terms of percentage.
Fig. 3-2. Performance measures of RMPs: (a) Makespan; and (b) cost

Fig. 3-2-a and Fig 3-2-b expose fluctuations in makespan and labor cost, respectively. As a whole, HMC contributes the most to makespan. DCB and CH have average performance, while HSC has the lowest effect on makespan. On the other hand, HMC always leads to extra costs, since a multi-skilled workforce is expensive to hire. CH leads to extra costs in NV, because except for bottleneck workstations, a multi-skilled workforce on a higher salary perform the same as a single-skilled workforce. In MV and HV cases, CH becomes a cheaper strategy, since a multi-skilled workforce can contribute to procedures. DCB always results in cost-saving, because the workforce is cross-
trained to help in workstations which are always bottlenecked. HSC is expensive in an NV environment; however, it becomes cost-effective in the two other cases. High fluctuations in labor cost in HSC and CH demand extra attention in the choice of these strategies.

3.5.3. Cost-time performance of RMPs

Fig. 3-3 considers the influence of different strategies on performance in terms of both time and cost, which are the most important productivity criteria in the flowshop environment [44]. Equal weights allocated to time and cost in Fig. 3-3-a, Fig. 3-3-b considers the weighting of cost to be twice that of time, and Fig. 3-3-c assumes the weighting of time to be twice that of cost. Although the
distribution of weights between cost and time varies in academic literature and practice, arguing around weight allocation is beyond the scope of this chapter. Interestingly, in all of the above situations, the figures share significant similarity, which is an indication that they are governed by the same rule in the aforementioned priorities for cost and time. In all situations CH and HSC are not appropriate for an NV environment. However, in MV and HV environments, both strategies result in appropriate performance measures. The performance of DCB in all cases is clustered in a close proximity, which makes it a reliable strategy in production environments that include all three cases of variability and different priorities for cost and time. When more weight is allocated to time, HMC gains more credibility. The high costs associated with HMC make this strategy inappropriate when crucial enhancement in makespan is not needed, however, in the case where minimizing makespan is of a significant importance, no strategy can perform as well as HMC.

3.5.4. Sensitivity analysis

Fig. 3-4-a, 3-4-b, and 3-4-c present the results of the sensitivity analysis that was conducted to evaluate and compare the effects of variations in the input variables on the production performance of cases one, two, and three, respectively. In these charts, vertical and horizontal axes represent makespan and the number of bottlenecks, respectively. A scenario considering three bottlenecks was considered to represent the actual situation observed in the case study factory, while five other scenarios with zero, one, two, four, and five bottlenecks were investigated to evaluate the sensitivity of the model to bottlenecks’ configurations. As shown in Fig. 3-4-a, in the NV case and no bottlenecks scenario, the performance of all multiskilling strategies is found to be the same. In the MV and HV case and no bottleneck scenario,
Fig. 3-4-b and 4-c, respectively, due to pre-existing variability in procedures, the makespan in NC is not necessarily the same as for the other strategies.

By adding one extra bottleneck, DCB, HMC, HSC, and CH significantly outperform NC. This trend continues until exceeding three bottlenecks, after which CH exceeds other strategies by far.

The reason for this behaviour can be attributed to the fact that HSC, DCB and HMC are initially
designed to deal with three bottlenecks, and they lose their advantage encountering more bottlenecks, whereas chaining keeps its superiority because it is designed to deal with a range of bottlenecks across the production line.

The significant implication of the preceding argument is that design of HSC, HMC and DCB should be conducted according to the maximum possible number of bottlenecks in the production line, because they became increasingly inefficient in response to even one extra bottleneck, while they are efficient in dealing with fewer bottlenecks. CH showed to be efficient to deal with a wide range of bottlenecks and variability situations.

3.6. Summary

The review of the relevant body of knowledge revealed the need for optimization of scheduling of multi-skilled resource allocation in off-site construction (Arashpour et al. 2016). Solving this problem has the potential to increase throughput and profitability. Firstly, flowshop is recognized as an appropriate framework to represent off-site construction. A mathematical programming approach was employed to provide an optimization-based framework for matching multi-skilled workers to the appropriate spots during the planning horizon by taking into account the planning objective.

The developed scheduling platform suggest that, as Hopp and Oyen (2004) argued, a resource management policy configuration is a highly context-specific issue, as dynamics of bottlenecks and variability should always be considered when it comes to advising a specific configuration. The developed scheduling platform in this chapter evaluate resource management policy’s performance under four different circumstances. Firstly, the performance of every resource management policy in each variability case, secondly, the performance of each resource management policy on all variability cases collectively. Thirdly, the cost-time performance of
resource management policy with different weightings for time and cost and finally, effects of different bottleneck locations in resource management policy’s performance.

Considering the performance of every resource management policy in different variability cases, if the production manager is sure about the variability extent in the production flow, she or he can choose the best strategy depending upon the production objective. For example, if the production manager maintains a prefabrication factory with medium variability, and the objective of the factory is minimizing labor costs, chaining is the best strategy. However, if there is no variability in the production flow with the same objective, direct capacity balancing is the best strategy.

Consideration of each resource management policy in all variability cases is useful if the existence of every variability case is possible. In this regard, if there is high emphasis on makespan, hiring multi-skilled crew is the appropriate strategy. Hiring single-skilled crew and chaining cost performance varies significantly in different cases; therefore, if there is a possibility of experiencing all different cases, these two strategies are not recommended.

Cost time evaluation suggests that direct capacity balancing is an appropriate strategy for all variability cases when both time and cost are determining factors in the decision-making. Again, if the variability extent of production flow is not predetermined, hiring single-skilled crew and chaining should be avoided.

Sensitivity analyses exposed that if there is no guarantee about the number of bottlenecks, chaining is an appropriate choice. Also, direct capacity balancing, hiring multi-skilled crew and hiring single-skilled crew should be designed with consideration of the maximum potential number of bottlenecks.

The developed modelling methodology contributes to the production resourcing theory by optimizing makespan, through increasing the competency of crews. New understanding of
productivity enhancement by quantifying the improvement in performance attributable to the workforce skill set is another contribution of this research. Research results will benefit the prefabrication industry by deepening insights into multi-skilled resource deployment. Additionally, the results help managers allocate workers to the right tasks to reach production objectives.
Chapter 4

4. Staffing strategy by comparative studies

The aim of this chapter is to investigate the extent to which operational benefits can be achieved in off-site construction by using different multiskilled staffing strategies to address bottlenecks in production. A hybrid research method that adopts optimization and multi-criteria decision-making techniques is used to compare staffing strategies pertaining to performance measures associated with different labor skill sets. To this end, multiskilling staffing policies are ranked and the situation under which ranking results can be changed is discussed. The findings of this chapter reveal performance and sensitivity of different multiskilling strategies pertaining to different criteria.

4.1. Overview

In this chapter, process integration is suggested as a way to deal with bottlenecks in prefabricated production environments. In the literature, process integration is also referred to as multiskilling staffing configuration (architecture) or cross-training staffing policy (Arashpour et al. 2015). In this chapter, trade means a skilled human resource who can perform operations in a specific workstation in off-site construction. In a prefabricated environment, operations which need a skilled trade to perform them are called craft. Cross-training or multiskilling of resources refers to training trades in a range of craft sets so that they can be assigned to different workstations when and where they are needed to balance the production flow (Haas et al. 2001).

This chapter provides a method to choose appropriate skill sets for trades to manage bottlenecks resulting from excess work load in off-site construction. Multiskilling staffing strategies transfer excess capacity from underutilized workstations to overutilized locations to even out the production
flow. However, identifying an appropriate multiskilling staffing strategy in prefabricated construction is a controversial task. This is due to: the large number of alternative areas in which a trade can be trained to operate at a specific workstation; considerable differences in the range of skill sets needed to operate different workstations; and the wide range of often conflicting criteria pertaining to costs and benefits relating to various multiskilling strategies (Nasirian et al. 2018a).

Previous literature concentrated on advising appropriate multiskilling strategies by taking into account a very limited number of criteria and using optimization (Liu and Wang 2012) or simulation techniques (Arashpour et al. 2015). A literature review of multiskilling in Chapter 2 identified a gap in research to investigate the wide range of existing criteria, in addition to including several qualitative criteria, which cannot be used in optimization or simulation modellings. To this end, in this chapter multi-criteria decision-making methods, incorporating a wide cluster of qualitative and quantitative criteria, are recognized as an appropriate method to supplement optimization techniques, to provide advice on multi-skilling staffing strategy (Behzadian et al. 2010).

The structure of this chapter is as follows. First, a survey reveals existing process integration alternatives which have been used so far in the construction literature. Also, in the same section the existing criteria to evaluate process integration alternatives are outlined. Next, the methodology for this chapter, is described. It includes a combination of: DELPHI; Analytic Hierarchy Process (AHP); Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE); and optimization. Then, mathematical framework for the optimization and PROMETHEE platform is outlined. In the next section the case study factory is described. Results and discussion are then presented by mainly relying upon different visualization techniques. Finally, conclusions and opportunities for future studies are presented.
4.2. Problem context

A comprehensive survey is conducted to identify all process integration alternatives and the criteria for evaluating their performance.

4.2.1. Process integration alternatives
Decision-making about process integration indicates which trades at what level should be cross-trained for what tasks and in how many of them (Haas et al. 2001). More importantly, it is a question of whether multi-skilled workers should be hired or whether already existing single-skilled crew should be trained in appropriate tasks (Srour et al. 2006). Generally, decision-making regarding an appropriate process integration strategy is a controversial (Hopp and Oyen 2004) and context specific (Haas et al. 2001) matter. As it is outlined in chapter 2 there are five general categories of process integration which can be achieved through managing trade skill sets, including: basecase, training in non-craft, training in craft, hiring workers skilled in many crafts, and multi-skilled teams (see Fig. 4-1).

![Fig. 4-1. Categorization of process integrations policies](image-url)
Fig. 4-2 visualizes different process integration strategies which have so far been investigated and discussed in the construction literature. Each part of the figure represents a modern prefabricated factory with several workstations, shown by $x$, along a production line. Bottleneck workstations are highlighted. Trades skilled in different crafts, shown by $r$, can be engaged to operate in different workstations, based on their skill set. In Fig. 4-2, a trade is single-skilled if he/she has only a single solid arrow. Whereas solid and dotted arrows indicate a multi-skilled trade who has been also trained for a secondary skill. Here, solid and dotted arrows indicate initial and secondary skills, respectively. A worker with only dotted arrows represents a hired resource, skilled in more than one craft.

Basecase, mean there is no cross-training (NC), is the traditional approach in the construction industry (see Fig. 4-2-a). Multiskilling by training trades in non-craft includes cross-training in soft skills or in safety. Since training in non-craft and safety does not affect resource movements in a production line, they are not illustrated in Fig. 4-2 and not investigated in this research. Multiskilling by training existing trades in craft includes: chaining (CH), direct capacity balancing (DCB), downstream (DO), upstream (UP) and full cross-training. Strategies for hiring multi-skilled trades include: hiring dual-skills (HDS), hiring four-skills (HFS), and hiring four-skills-helpers (HFSH). CH, DCB, UP and DO are illustrated in Fig. 4-2-b, Fig. 4-2-c, Fig. 4-2-d, and 4-2-e, respectively. For more information see Chapter 2.
Fig. 4-2. Process integration architecture visualization
Due to financial and operational reasons, it is appropriate to keep the number of additional hired workforce equal or less than the number of bottlenecks (Liu and Wang 2012). Thus, in a system with three bottlenecks hiring one dual-skill (H1DS), hiring two dual-skill (H2DS) and at maximum hiring three dual-skill (H3DS) trades, is a justifiable process integration policy. See Fig. 4-2-f, g and h for illustrations of each of these.

Due to its high training costs, it is not feasible to use a Hiring Four-skill (HFS) strategy in the majority of cases (Nasirian et al. 2018b). Hiring one Four-Skills-Helpers (H1FSH), Hiring two Four-Skills-Helpers (H2FSH) and Hiring three Four-Skills-Helpers (H3FSH) to address three bottlenecks is shown in Fig. 4-2-i, j and k. Full cross-training enables multi-skilled trades to operate across the whole production line. Obviously, this strategy is associated with substantial investment in training and therefore when the number of crafts is more than four or five, it is avoided (Daniels et al. 2004).

4.2.2. Criteria

The most ideal state for solving a decision-making problem is to prepare numerical performance of all the alternatives based on criteria with the same unit. In the real-world scenarios some criteria cannot be expressed in quantitative manner by decision makers otherwise their value and meaning will be lost. Furthermore, possibly appropriate tools and techniques for this translation are not always available or expression of performance in quantitative way is extremely resource consuming (Brans and Mareschal 2005). This chapter approaches three categories of criteria by a qualitative method, and two categories of criteria by a quantitative technique. The MCDM technique that is presented in this chapter can incorporate all criteria which are expressed in qualitative or quantitative terms. This platform is available and can be modified in future in case it is intended to translate qualitative expressions to quantitative ones and vice versa.
The literature review in Chapter 2 revealed that there are eleven criteria in the construction literature which affect the skill set configuration choice for process integration. See Fig. 4-3. Seven out of the eleven criteria are cost criteria. Four cost criteria are quantifiable including transfer costs, training costs, salary costs, and retention costs. There are three cost elements which can be expressed in quantitative terms and yet are qualitative by their nature (See Chapter 2). These include: psychological effects, learning and forgetting effects, and reduced efficiency which commonly investigated under non-monetary cost. There are few approximation methods to allocate a numerical value to non-monetary costs (Qin et al. 2015). Four out of the eleven criteria are benefit criteria including two operational and two social criteria. Minimizing cost and time are two operational advantages of process integration and can be approached quantitatively. Social sustainability which includes increasing employability (Florez 2017) and improving safety (Lill 2009) is considered qualitatively in this chapter. However, in the literature there are approximation approaches or suggestions to quantify benefits of enhanced employability (Burleson et al. 1998) and safety (CII 2018), respectively.

**Fig. 4-3.** Criteria hierarchy
Transfer costs take effect when multi-skilled trades operate across two workstations and spend time to set up machinery and obtain needed information (Lill 2009). Training costs pertain to the training of multi-skilled trades and encompass apprenticeship training, participation in related classes, and other training related expenses to enable them to work in the prefabrication environment (Ahmadian Fard Fini et al. 2016). Salary is an indication of extra wage for the trades with higher skill sets in a skill-based financial structure (Hyari et al. 2010). Retention costs occur when a multi-skilled resource leaves a company and expenses are incurred in hiring a replacement multi-skilled trade or in training an existing single-skilled resource (Pollitt 2010). Retention costs are more associated with additional hired trades since these workers are likely to remain with the company for shorter periods of time than already recruited trades (Haas et al. 2001).

Psychological effects refer to responsibility confusion when a resource encounters several tasks instead of one task (Nasirian et al. 2019a). Learning and forgetting effects are attributed to the fact that trades need to repeat a specific task several times to reach their full potential. In fact, when a cross-trained resource fails to periodically practice a skill due to a high number of substitutions between different machines the skill will be lost (Ahmadian Fard Fini et al. 2017). Reduced efficiency means resources are more efficient in their primary task in comparison with their secondary one (Hegazy et al. 2000).

Decreasing project cost can be achieved through reducing the number of workers (Gouda et al. 2017) or decreasing labor idleness (Wongwai and Malaikrisanachalee 2011). In the construction literature, decreasing time is mainly approached through minimizing makespan. Reducing project time can be interpreted in monetary terms and be compared with costs (Sacks et al. 2015) and vice-versa.

Social sustainability can be enhanced by increasing the employment duration of hired multi-skilled trades (Florez 2017), and by improving worker safety. Although, enhancing workforce employability by multiskilling of crew does not directly relate to corporate financial performance, however, it can
be a concern for companies which pay attention to corporate social responsibility (Lill 2009). Hiring multiskilled crew can be a financial concern when there are levy encouragements for adopting multi-skilled workforce from governmental authorities similar to Singapore authorities’ policies (BCA 2016). In the case study presented in this chapter enhancing workforce employability from corporate social responsibility perspective is considered.

Safety achieved by training the workforce in safety skills (BCA 2016) or by keeping multi-skilled workers at a construction site for longer periods of time, since the majority of accidents are associated with newly hired workers who are not familiar with site conditions (Haas et al. 2001).

Safety actions such as elimination of injuries and damage in the workplace enhance project financial results by reducing compensation costs, avoiding schedule interruptions due to the absence of a damaged worker and enhancing positive perspective of workforce toward their job, and better management and worker relationships (CII 2018).

Quantifying positive effects of safety measures is a challenging task as there are non-similar compensation costs in different states and availability of the required data related to schedule interruptions and indirect delay costs. Due to unavailability of such data safety is approached qualitatively in this chapter, yet, proposed MCDM method is capable of incorporating safety as a numerical input if the related data is available.

4.3. Optimization and MCDM integrated platform

Basically, decision-making regarding process integration is similar to other real-world decision problems which include several conflicting objectives and in which the decision-maker needs to optimize all of them at the same time. For example, economic factors like labor costs should be minimized while social factors like employment duration need to be maximized. Therefore, multi-
criteria decision-making methods are identified as the appropriate methodology for investigating integration processes (Behzadian et al. 2010).

Despite, there are several MCDM techniques in the literature, this chapter adopts PROMETHEE method. The advantage of PROMETHEE method is its simplicity in conception and application when compared with alternative decision making approaches (Kabir and Sumi 2014). There is an increasing trend in application of PROMETHEE from industry and academia which is demonstrated by increasing number of scholarly papers and reports (Behzadian et al. 2010). Application of PROMETHEE method in different areas has been investigated and it is evaluated as an appropriate MCDM approach due to its mathematical properties and user friendliness (Brans and De Smet 2005).

Despite PROMETHEE’s highlighted advantages in complex decision-making problems such as resource management (Behzadian et al. 2010) this method has not been used in addressing multiskilled human resource management in the construction management area (Nasirian et al. 2018b). The novelty of the decision-making approach presented in this chapter originates from hybrid use of the PROMETHEE method, the flowshop based optimization platform and a DELPHI approach which can incorporate both quantitative and qualitative data, respectively. AHP is used for allocating criteria weights.

Mathematical properties of the optimization framework is explained under following section. A flowshop based optimization technique is adopted as it provides an appropriate platform to model quantitative performance measures of off-site construction (See Chapter 3). Optimization formulations are coded in Julia that is a free open access programming interface. Additionally, MCDM framework is also modelled in visual PROMETHEE that is a user-friendly software. Both of developed platforms are available upon request from corresponding author.
DELPHI assists elimination of bias by structuring communication in different rounds that makes it a reliable approach for collecting data from a panel of experts (Dalkey and Helmer 1963). DELPHI has been previously applied to solve a similar skilled based production problem in the construction context (Arashpour et al. 2017). Four participants from academia with industrial experience were included in DELPHI decision making process. Identified alternatives and criteria are circulated to the participants and consensus was reached in the second round providing the results to be fed to the MCDM model. The rationale for integrating PROMETHEE and AHP is that a hybrid of AHP and PROMETHEE produces a suitable match to deal with a multi-criteria decision-making problem (Macharis et al. 2004). In previous literature AHP and PROMETHEE have been used to supplement each other (Behzadian et al. 2010). Mathematical process used in PROMETHEE will be discussed in the following section. For mathematical process in AHP see (Saaty 1990).

4.3.1. PROMETHEE

To complete a PROMETHEE analysis, three crucial pieces of information are required: the performance of each alternative based on different criteria, preference parameters, and the weight for each criterion. The performance of alternatives is obtained via the DELPHI method and an optimization framework. Preference parameters include preference functions, thresholds, and objectives and are determined using a similar approach to that of Podvezko and Podviezko (2010). The weights are gained by the AHP method.

A multi-criteria problem involves set of alternatives \( \Delta = \{a_1, a_2, a_3, \ldots, a_n \} \) and a set of criteria \( \mathbf{V} = \{f_1, f_2, f_3, \ldots, f_j \} \). Given \( f_j \) is a specific criterion and \( a_n \) and \( a_m \) are two different alternatives, then \( f_j(a_n) \) and \( f_j(a_m) \) are the performance of alternatives \( a_n \) and \( a_m \) pertaining to criterion \( f_j \). By definition, \( p(d) = p(a_n, a_m) \) is a preference function which is a non-decreasing function of \( d = f_j(a_n) - f_j(a_m) \) between the evaluation of two alternatives \( a_n \) and \( a_m \). Logically, \( p(d) \) cross ponds
to the degree of preference that is expressed for \( a_n \) over \( a_m \) according to criterion \( f_j \). By definition, \( p(d) \) is a preference function that reflects the preference of decision makers regarding the performance of alternatives pertaining to each criterion. Amplitude of preference function is between 0 and 1. When the value of preference function is 0, there is no preference between alternatives and when the value of preference function is 1, this is an indication of a strict preference. The value of preference function is sensitive to its thresholds which include a lower and upper bound. \( q \) is the lower bound and if the value of \( d \) is less than \( q \) there is no preference between alternatives’ performance on the given criterion of \( f_j \) meaning \( p(d) = 0 \). \( s \) is the upper bound meaning if the value of \( d \) is greater than \( s \) there is a strict preference of one alternative over another one pertaining to criterion \( f_j \) which means \( p(d) = 1 \). The preference objective indicates whether the value corresponding to each alternative should be maximized or minimized to be desirable.

An evaluation outcome depends on both choice of preference function and its parameters (Brans and Mareschal 1994). In this chapter preference functions are depicted by consulting relating literature (Goumas and Lygerou 2000) and preference thresholds are depicted according to the smallest and largest module, as presented in Podvezko and Podviezko (2010).

Consider, \( w_i \) as the weight of criterion \( f_i \) that is already normalized using AHP. More important criteria receive larger weights. If the thresholds and weights are available for a preference function, then the preference index, leaving flow, entering flow, and net flow are all computable. The preference index simply is the weighted summation of the preference functions (equation 3-1). The purpose of flow calculations is to rank an alternative with respect to other ones partially and globally. Leaving flow is a measure of the strength of an alternative in comparison with others, (equation 3-2). Whereas,
entering flow is a measure of the weakness of an alternative with respect to other ones (equation 3-3). Finally, net flow is the balance between leaving flow and entering flow (equation 3-4).

\[ \prod_{i=1}^{l} (a_n, a_m) = \sum_{i=1}^{l} w_i \cdot \{P_i \left( f_i(a_n) - (f_i(a_m)) \right) \} \]  

(3-2)

\[ \phi^+(a_n) = \sum_{m=1, n \neq m}^{N} \prod (a_n, a_m) \]  

(3-3)

\[ \phi^-(a_n) = \sum_{m=1, n \neq m}^{N} \prod (a_m, a_n) \]  

(3-4)

\[ \phi_{net}(a_n) = \phi^+(a_n) + \phi^-(a_n) \]  

(3-5)

To make comparisons between alternatives PROMETHEE I and PROMETHEE II are used. In PROMETHEE I alternative \( a_n \) is preferred to alternative \( a_m \) if strength of an alternative is confirmed by both \( \phi^+ \) and \( \phi^- \) (equation 3-5 and 3-6). If \( \phi^+ \) and \( \phi^- \) are equal for both alternatives there is no difference between them (equation 3-7 and 3-8). If both \( \phi^+ \) and \( \phi^- \) do not support an alternative preference, they are incomparable (equation 3-9 and 3-10) (Brans and Mareschal 2005). In PROMETHEE II the higher the net flow the better the alternative. An advantage of PROMETHEE II over PROMETHEE I is the ability to compare all alternatives; however, it is at the expense of losing some information on differences between entering and leaving flows (Mareschal and Smet 2009).
\[ \phi^+(A_n) > \phi^+(A_m) \& \phi^-(A_n) < \phi^-(A_m) \quad (3-6) \]
\[ \phi^+(A_n) > \phi^+(A_m) \& \phi^-(A_n) = \phi^-(A_m) \quad (3-7) \]
\[ \phi^+(A_n) = \phi^+(A_m) \& \phi^-(A_n) < \phi^-(A_m) \quad (3-8) \]
\[ \phi^+(A_n) = \phi^+(A_m) \& \phi^-(A_n) = \phi^-(A_m) \quad (3-9) \]
\[ \phi^+(A_n) > \phi^+(A_m) \& \phi^-(A_n) > \phi^-(A_m) \quad (3-10) \]
\[ \phi^+(A_n) < \phi^+(A_m) \& \phi^-(A_n) < \phi^-(A_m) \quad (3-11) \]

The Geometrical Analysis for Interactive Aid (GAIA) is based on uni-criterion net flows \((\phi_i)\) and its calculation is close to net flow calculation; however, flow for each criterion is computed separately as in formula 3-11.

\[ \phi_j(a_n) = \sum_{m=1}^{N} \left\{ p_j(a_n, a_m) - p_j(a_m, a_n) \right\} \quad (3-11) \]

4.3.2. Optimization framework

Multiskilling problems with the objective of minimizing makespan in a prefabrication environment in which all elements should be processed in all workstations sequentially, can be modelled as a problem consisting a set of \(x\) workstations \(M = \{1, 2, \ldots, X\}\) and a set of \(y\) elements \(N = \{1, 2, \ldots, Y\}\). The operation \((y, x)\) is an indication of processing the \(y\)th element in the \(x\)th workstation. A multiskilling strategy determines how many trades from the set of trades \(\Omega = \{1, 2, \ldots, R\}\) can be allocated to a workstation based on cross-training strategies. In this regard, \(s_{rx}\) is a binary parameter determining whether the trade \(r\) can be allocated to workstation \(x\). \(\beta_{rxt}\) is a binary variable which is equal to 1 when trade \(r\) is allocated to workstation \(x\) in the time period \(t\). \(\Lambda = \{1, 2, \ldots, K\}\) is a set of statuses which denotes the number of workers who can be engaged in the procedure \((y, x)\). \(\gamma_{yxk}\) is a binary variable.
which is equal to 1 when the status of operation of \((y, x)\) is \(k\). \(\mathcal{T} = \{1, 2, \ldots, T\}\) is the set of time periods which encompasses all possible values for starting and completion times of operation \((y, x)\). \(\lambda_{qpt}\) is a binary variable which is equal to 1 when completion time of the operation \((y, x)\) is \(t\). This optimization procedure is originated from Daniels et al. (2004) work. Same framework is linearized and applied to a real case in Chapter 3.

\[
\text{Minimize } C_{\text{Max}} \geq C_{yx} \quad y \in N, x \in M \tag{3-12}
\]

\[
\sum_{k=1}^{K} \sum_{t=1}^{T} \gamma_{yxk} \lambda_{yxt} = 1 \quad y \in N, x \in M \tag{3-13}
\]

\[
D_{yx} = \sum_{k=1}^{K} d_{ytk} \quad y \in N, x \in M \tag{3-14}
\]

\[
C_{yx} = \sum_{t=1}^{T} \lambda_{yxt} t \quad y \in N, x \in M \tag{3-15}
\]

\[
C_{yx} \geq C_{y(x-1)} + D_{yx} \quad y \in N, x \in M \tag{3-16}
\]

\[
C_{yx} \geq C_{(y-1)x} + D_{yx} \quad y \in N, x \in M \tag{3-17}
\]

\[
s_{rx} \geq \beta_{rxt} \quad y \in N, x \in M, \quad r \in \mathcal{T} \tag{3-18}
\]

\[
\sum_{x=1}^{M} \beta_{rxt} = 1 \quad w \in \Omega, r \in \mathcal{T} \tag{3-20}
\]

\[
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{r=1}^{R} \lambda_{yxt} \beta_{rxt} = \sum_{k=1}^{K} k \gamma_{yxk} \quad y \in N, x \in M \tag{3-21}
\]
\[
\sum_{k=1}^{K} \sum_{t=d_{y,xt}}^{T} \sum_{l=d_{y,xt}+1}^{t} y_{y,xt} \lambda_{y,xt} \beta_{r,xt}
\]
\[
= \sum_{k=1}^{K} \sum_{t=1}^{T} \beta_{r,xt} d_{y,xt}
\]

Constraint 3-12 guarantees minimization of makespan. Equation 3-13 allocates a unique finishing time and status to each operation \((y, x)\). Equation 3-14 indicates the duration of operation \((y, x)\). Equation 3-15 allocates a completion time to each operation. Inequality 3-16 determines the sequence of workstations. Inequality 3-17 determines the sequence of releasing elements to the production environment. Constraint 3-18 limits allocation of trades to workstations for which they are trained. Constraint 3-19 determines the total salary of trades. Constraint 3-20 guarantees each trade in each period of time cannot be allocated to more than one workstation. Equation 3-21 based upon operation status allocates an appropriate number of trades to each operation. Equation 3-22 guarantees that trades stay in the workstation for the duration of the whole operation.

**4.4. Case study in relation with platform**

This chapter investigates the same modular off-site construction factory as what is introduced in Chapter 2 that produces bathroom pods in Melbourne, Australia. Inputs of PROMETHEE parameters are obtained from an optimization model for quantitative criteria and by implementing a DELPHI methodology for qualitative ones. Observations, evaluations of financial reports and production data, and an interview with the site manager produced raw data for optimization and DELPHI.

For information pertaining to collection, factory environment and production line refers to Chapter 2, Case Study subtitle. The site manager identified workstations \(x_1, x_7,\) and \(x_8\) as the main bottlenecks, which are highlighted in Fig. 4-2. The factory management team recruited few single-skilled trades to cover bottlenecks.
Factory executives identified HDS and HFSH as feasible hiring strategies. Also, four different training policies that are recognized in the literature review section above, CH, DO, UP, and DCB, were agreed would be practical in this situation. For details about salary of hired and trained multi-skilled trades refer to Chapter 2.

Three different configurations of the HDS strategy are considered. In H1DS one extra resource is hired \(r_{13}\) who is capable of operating in workstations \(x_1\) and \(x_{10}\). In H2DS in addition to \(r_{13}, r_{14}\) is hired who is capable of contributing in \(x_2\) and \(x_8\). In H3DS three resources of \(r_{13}, r_{14},\) and \(r_{15}\) are hired, with \(r_{15}\) being similarly multi-skilled to \(r_{14}\).

The HFSH strategy includes H1FSH, H2FSH and H3FSH. H1FSH has one additional trade \((r_{13})\) who can work in \(x_1, x_2, x_7\), and \(x_8\). For H2FSH, in addition to \(r_{13}, r_{14}\) is also hired who can be engaged to operate in workstations \(x_3, x_4, x_9,\) and \(x_{10}\). H3FSH has one more resource \((r_{15})\) in addition to \(r_{13}\) and \(r_{14}\) who can be used in \(x_5, x_6, x_{11},\) and \(x_{12}\).

The next four strategies considered in this chapter are training strategies. DCB is a well-recognized process integration policy in the off-site construction context (Arashpour et al. 2016). In this strategy, \(r_1\) and \(r_2\) contribute to the first bottleneck \((x_1)\), \(r_6\) and \(r_{10}\) support operations in \(x_7\), and \(r_{12}\) assists procedures in \(x_8\). Choice of a trades skill set for extra skills training is informed by the worker’s proximity to a bottleneck location and skills affinity (Carley et al. 2003).

In CH each resource is cross-trained to work in his/her current workstation as well as in a secondary adjacent workstation. Since there is no further workstation beyond the last workstation, worker \(r_{12}\)’s secondary workstation will be \(x_1\). In DO trades \(r_1\) to \(r_6\) are cross-trained to be able to help in their adjacent workstation and the rest of the trades are single-skilled. In UP trades \(r_7\) to \(r_{12}\) are multi-skilled to help in their adjacent workstation and other trades are single-skilled.

In the problem context section eleven criteria are recognized which can be used to evaluate process integration policies in the prefabricated environment. Makespan and salary are calculated according
to the optimization-based formulations presented in the methodology section. Retention cost is the total cost of hiring a new worker—including costs for advertising, evaluating different applicants and other administration costs. It is the replacement cost incurred when a hired resource leaves, i.e. is not retained. Therefore, a retention cost is not calculated for existing resources. Similarly, there is no training costs for hired trades because they are already multi-skilled. However, the contractor must invest in training of the existing workforce. Training costs are considered as a function of the number of additional crafts that the existing trade will need to be trained in. In this case study, investments in training of existing single skilled human resources is limited to the amount of 2500 Australian Dollars. Transfer cost is not included in the model because of the layout of the fabrication line with the site manager advising that this cost is negligible in this setting.

Because the psychological effects, learning and forgetting effects and reduced efficiency are correlated, they are considered together under the non-monetary costs category. Consultation with the factory managerial team provided initial insights to determine non-monetary costs as a function of extra skills and recruitment or hiring policy.

Increasing contract duration applies to the hiring of additional resources. It leads to improvements in their well-being and consequently in social sustainability. It is assumed that already recruited staff are permanent employees and cannot increase their hiring period. As, hired resources stay for longer periods of time in the factory they gain more knowledge about the site and accident rates are decreased. Permanent resources are already trained in different aspects of safety or have at least gained some perspectives on safety in the workplace. Social sustainability is a qualitative criterion by essence (Lill 2009).

In decision-making regarding process integration in off-site construction, a range of scenarios should be investigated to avoid bias (Arashpour et al. 2018b). Therefore, five different types of production data from the same factory relating to different product orders are considered and average values used
as inputs for the PROMETHEE model. The results of optimization and DELPHI used as input for the model are presented in Table 4-1.

Table 4-1. Problem hierarchy

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Criteria</th>
<th>NMC</th>
<th>RE</th>
<th>TC</th>
<th>SAL</th>
<th>SUS</th>
<th>MS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>numeric</td>
<td></td>
<td></td>
<td>AUD</td>
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</tr>
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<td></td>
<td>AUD</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>y/n qualitative</td>
<td>Max</td>
<td>Min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>Min</td>
<td>Min</td>
<td>Min</td>
<td>Min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weight</td>
<td>15.9</td>
<td>10.6</td>
<td>10.6</td>
<td>14.1</td>
<td>6.36</td>
<td>42.4</td>
<td></td>
</tr>
<tr>
<td>Preference function</td>
<td>Level</td>
<td>Linear</td>
<td>Linear</td>
<td>Linear</td>
<td>Usual</td>
<td>Linear</td>
<td></td>
</tr>
<tr>
<td>q</td>
<td>5</td>
<td>1000</td>
<td>2000</td>
<td>3000</td>
<td>n/a</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>s</td>
<td>9</td>
<td>2000</td>
<td>5000</td>
<td>8000</td>
<td>n/a</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Basecase</td>
<td>NC</td>
<td>0</td>
<td>0</td>
<td>5100</td>
<td>n</td>
<td>175</td>
<td></td>
</tr>
<tr>
<td>Training</td>
<td>CH</td>
<td>12</td>
<td>0</td>
<td>3000</td>
<td>5600</td>
<td>n</td>
<td>83</td>
</tr>
<tr>
<td></td>
<td>UP</td>
<td>6</td>
<td>0</td>
<td>1500</td>
<td>5400</td>
<td>n</td>
<td>145</td>
</tr>
<tr>
<td></td>
<td>DO</td>
<td>6</td>
<td>0</td>
<td>1500</td>
<td>5300</td>
<td>n</td>
<td>142</td>
</tr>
<tr>
<td></td>
<td>DCB</td>
<td>5</td>
<td>0</td>
<td>1250</td>
<td>5300</td>
<td>n</td>
<td>140</td>
</tr>
<tr>
<td>Hiring</td>
<td>H1DS</td>
<td>1.5</td>
<td>2400</td>
<td>0</td>
<td>5500</td>
<td>y</td>
<td>129</td>
</tr>
<tr>
<td></td>
<td>H2DS</td>
<td>3</td>
<td>4800</td>
<td>0</td>
<td>6000</td>
<td>y</td>
<td>124</td>
</tr>
<tr>
<td></td>
<td>H3DS</td>
<td>4.5</td>
<td>7200</td>
<td>0</td>
<td>6500</td>
<td>y</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td>H1FSH</td>
<td>2.5</td>
<td>2700</td>
<td>0</td>
<td>5800</td>
<td>y</td>
<td>93</td>
</tr>
<tr>
<td></td>
<td>H2FSH</td>
<td>5</td>
<td>5400</td>
<td>0</td>
<td>6400</td>
<td>y</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>H3FSH</td>
<td>7.5</td>
<td>8100</td>
<td>0</td>
<td>7000</td>
<td>y</td>
<td>83</td>
</tr>
</tbody>
</table>

TC=training costs, SAL=salary, RC=retention costs, NMC= non-monetary costs, MS=makespan, SUS=sustainability

4.5. Numerical studies

4.5.1. PROMETHEE ranking and network illustration

The results of partial and complete ranking of alternatives are shown in Table 4-2. Illustrations of PROMETHEE ranking and network can be used to comprehend outranking results (Brans and Mareschal 1994). Fig. 4-4 is a PROMETHEE I ranking presentation. The left side bar shows leaving
flow with better values in the upper part of the bar and worse values in the bottom section. The bottom of the bar corresponds to zero and the top of the bar corresponds to one. Therefore, when an alternative is in a higher position it is an indication of its strength. Entering flow is shown on the right sidebar with better and worse values displayed in bottom and upper sections, respectively. In contrast to leaving flow, the values of entering flow increase from top to bottom. Therefore, a higher location for an alternative in this bar is an indication of weakness. To this end, partial ranking is illustrated by a line corresponding to each alternative showing entering and leaving flows on the left and right-hand side, respectively. In PROMOTHEE I if lines representing different alternatives cut each other, alternatives are incomparable. Incomparable information is useful for decision-makers because it indicates complex and difficult comparisons (Mareschal and Smet 2009). In this figure, different training strategies, HFSH, HDS, and NC are shown by different colors and dashes.

<table>
<thead>
<tr>
<th>Rank</th>
<th>action</th>
<th>( \Phi_{net} )</th>
<th>( \Phi^+ )</th>
<th>( \Phi^- )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>H1FSH</td>
<td>0.2697</td>
<td>0.4633</td>
<td>0.1935</td>
</tr>
<tr>
<td>2</td>
<td>H2FSH</td>
<td>0.2302</td>
<td>0.4368</td>
<td>0.2066</td>
</tr>
<tr>
<td>3</td>
<td>CH</td>
<td>0.2190</td>
<td>0.4662</td>
<td>0.2472</td>
</tr>
<tr>
<td>4</td>
<td>H3FSH</td>
<td>0.1951</td>
<td>0.4316</td>
<td>0.2365</td>
</tr>
<tr>
<td>5</td>
<td>H1DS</td>
<td>0.0621</td>
<td>0.3542</td>
<td>0.2921</td>
</tr>
<tr>
<td>6</td>
<td>H2DS</td>
<td>0.0121</td>
<td>0.3278</td>
<td>0.3157</td>
</tr>
<tr>
<td>7</td>
<td>H3DS</td>
<td>-</td>
<td>0.3200</td>
<td>0.3647</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.0447</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>DCB</td>
<td>-</td>
<td>0.2177</td>
<td>0.4092</td>
</tr>
<tr>
<td>9</td>
<td>DO</td>
<td>-</td>
<td>0.1921</td>
<td>0.4210</td>
</tr>
<tr>
<td>10</td>
<td>NC</td>
<td>-</td>
<td>0.2161</td>
<td>0.4622</td>
</tr>
<tr>
<td>11</td>
<td>UP</td>
<td>-</td>
<td>0.1743</td>
<td>0.4513</td>
</tr>
</tbody>
</table>

As Fig. 4-4 shows regarding both leaving flow and entering flow, HFSH, HDS, and training strategies perform closely together and make separate clusters with considerable distance between them. Two
exceptions are CH and NC. CH performs closely to HFSH strategies instead of training strategies and NC performs closely to training strategies.

Fig. 4-4. PROMETHEE I ranking presentation

As Fig. 4-4 shows the best four alternatives of H1FSH, H2FSH, H3FSH, and CH are incomparable. DO and UP are incomparable with NC, which shows these two training decisions are poor alternatives because all benefits of multiskilling are lost due to collateral effects. The reason for this can be
attributed to the fact that DO and UP are used in a condition in which the site manager knows exactly whether the bottleneck is located in the downstream or upstream of the production line (Hopp and Oyen 2004). In the absence of such knowledge, as in this case study, DO and UP lose their advantage.

4.5.2. GAIA plane

GAIA analysis originates from uni-criterion net flow formulation. It aims to facilitate decision-making (Mareschal and Brans 1988) by presenting preference relations on a two dimensional interface (Brans and Mareschal 1994). In this method, each criterion corresponds to one dimension in a multi-dimensional space and each alternative is a point in that dimension. In practice, visualization of a decision problem with more than three dimensions is difficult since our world is three dimensional. Therefore, a GAIA plane with calculating a principal component reflects the majority of available data on a two-dimensional screen (Brans and Mareschal 1994). This is at the expense of losing some information. The more the number of criteria and alternatives, the less is the quality of information displayed in the GAIA plane (Mareschal and Brans 1991).

Because in the GAIA plane, alternatives and criteria are indicated by nodes and axes, respectively, the position and size of these allows recognition of the following features: differentiation power of criteria, similar criteria, independent criteria and conflicting criteria (Mareschal and Smet 2009). The length of each axis is a measure of differentiating power for each criterion. Increased length of an axis is an indication of boosted differentiation power and vice versa. When the orientation of two axes is approximately the same, this implies that those two criteria express the same preference and named similar criteria. When two criteria are independent their projections on the GAIA plane are nearly orthogonal. Opposite directions for two criteria imply that they are conflicting.
Alternatives make clusters in the same direction of the criteria to which they have the best performance. For example, DCB, UP, and DO have a very tight cluster in the direction of retention costs and salary, which shows that these alternatives have very similar performances based on retention costs and salary. See Fig. 4-5-a. Considering, H1FSH, H2FSH, and H3FSH as a cluster and H1DS, H2DS, and H3DS as another one, the low cluster density of each indicates sharing less degree of similarity in comparison with the denser cluster of DCB, UP, and DO. This can be attributed to the point that in UP, DO, and DCB, even though different sets of workers are trained to be multi-skilled, the number of workers who are multi-skilled is almost the same—5, 6, and 6 for DCB, UP, and DO, respectively. Consequently, it can be proposed that the similarity of multiskilling training strategies is mainly dependent upon the number of workers who are multi-skilled and less related to the position of multi-skilled workers.

Additionally, this chart shows that H1FSH, H2DS, and H3DS can be considered in a denser cluster when compared with clusters of just FSH or DS. This can be attributed to the fact that two or three dual-skilled trades are needed to perform the same work as one four-skills-helpers and provide the same advantages and disadvantages. NC and CH make a cluster by their own showing their unique characteristics.
TC=training costs, SAL=salary, RC=retention costs, NMC= non-monetary costs, MS=makeup, SUS=sustainability

Fig. 4-5. GAIA illustrations
As can be seen from the chart, makespan is the most determining and differentiating criterion, which can be attributed to its high weight. Training costs is the second determining factor; however, it does not have the second highest weight. Despite the weight of training costs being about one fourth of makespan, preference values pertaining to training costs fluctuate within a very big range in comparison with makespan—30000 for the former and 92 for the latter. This is because there are no training costs for hiring methods. This finding illustrates that in decision-making about process integration problems, in addition to weight of criteria, statistical features of alternatives’ performance should also be taken into account. This issue should more specifically be considered when both hiring, and training strategies are available since there are features which are specific to each of them and absent in the other one, resulting in a zero value for the absent one and possibly a high value for the present one. This leads to a considerable range of preference values.

The most similar criteria appeared to be non-monetary cost and training costs. The reason can be linked to the point that by training trades in more crafts, more expenditure should be spent in training. Similarly, by mastering more crafts, learning and forgetting effects and reduced efficiency, which are subcategory of non-monetary costs, both increase leading to enhancement in the value of non-monetary costs. The second most similar criteria are retention costs and salary. This can be explained by the fact that, generally, hiring multi-skilled trades is an expensive strategy, which is associated with higher retention costs. Training the existing workforce is a cheaper strategy since it does not have the same hiring administration costs that enhance retention costs (See Chapter 3).
In this GAIA plane, the lines related to salary and training costs are nearly orthogonal indicating that these criteria are independent. Therefore, it should not be possible to find a reasonable relationship between them. This is confirmed by the fact that there are no training costs for both NC and H3FSH while they have the least and the most salary, respectively. Additionally, CH which has the most training costs is associated with salary which is not too far from NC.

The same graph shows that makespan is independent from retention costs. This can be explained by considering CH and H3FSH which perform the same based upon the criterion of makespan. However, their retention costs are 0 for the former and $8100 for the latter, which are minimum and maximum values for retention costs. This means that high performance on makespan can be achieved with or without administration costs associated with hiring, which in turn indicates that both training and hiring strategies can be appropriate to minimize makespan.

The opposite directions of makespan and labor costs indicates that these criteria are conflicting. This matter originates from the fact that for decreasing makespan, expensive multi-skilled trades have to be used, which consequently results in extra salary. It would be preferable to minimize both criteria, but this is impossible. The same situation can be observed between retention costs and sustainability. Increasing sustainability means increasing the employment duration of recruited resources, instead of relying upon existing resources, which is associated with administration costs for recruitment. Relying upon the existing workforce has no retention cost. Therefore, sustainability and retention costs cannot be minimized at the same time.

The decision axis which is labelled as ‘pi’ is the resultant axis which shows overall direction of criteria taken collectively. See Fig. 4-5-b. All alternatives which are positioned in the same direction as the
decision axis are strong alternatives; otherwise they are weak actions. To this end, H1FSH, H2FSH, H3FSH, and CH are in the same direction as the decision axis and they are also located at the top of the PROMETHEE ranking. Likewise, NC, UDP, DO, and DCB are undesirable actions. HDS strategies are orthogonal to the decision axis indicating a neutral performance, which is supported by their net flow which is close to zero. The proximity of the decision axis to makespan indicates the differentiating power of makespan.

A change in the weight of criteria corresponds to a change in direction of the decision axis. In fact, it is usually better to consider weighting criteria within an interval instead of as an exact number (Mareschal and Smet 2009). The GAIA brain shows different possible orientations of decision axes when there is a slight change in the weighting distribution. The position and size of the GAIA brain indicates the complexity of the decision-making problem. If the GAIA brain includes a wide range of directions, which contradict the initial decision axis, this indicates the possibility of other appropriate rankings, and therefore, more attention should be paid to the decision-making problem. Otherwise, if the GAIA brain is in the same direction as the decision axis, it provides extra confidence to the decision-maker that appropriate alternatives are being chosen.

The GAIA brain is presented in Fig. 4-5-c. In this case study, the orientation of the GAIA brain is almost the same as the orientation of the decision axis. This indicates that H1FSH, H2FSH, H3FSH, and CH remain appropriate process integration strategies in different scenarios of weight distribution. The GAIA brain also shows that NC, H1DS, H2DS, DO, and UP are unlikely to be high priority alternatives in this decision-making problem under different weight allocation scenarios, due to their opposite orientation to the GAIA brain.
However, when there are significant differences in weightings in different scenarios there could be slight or considerable substitution in the ranking of the aforementioned strategies. The interval in which current ranking is a stable and how the result of ranking will be changed by manipulating weights will be discussed in the sensitivity analysis section.

4.5.3. GAIA web

GAIA webs are similar in appearance to radar charts. The position of criteria in radar charts is arbitrary; however, in a GAIA web the position of criteria in the GAIA plane is used as a frame of reference (Brans and Mareschal 1994). Therefore, the criteria which are correlated are located close to each other. Since, GAIA webs are precise and the GAIA plane has a limited quality level, it is thus appropriate to investigate the exact profiles (Brans and Mareschal 1994).

In GAIA webs, for each dimension (individual criterion), the radial distance corresponds to the net flow score (see Table 4-3). Values of -1 are at the center of the circle while +1 values are on the outer boundaries of the circle. Again, the decision axis is shown by a ‘pi’ sign. A dotted circle indicates the multi-criteria net flow score of the specific action.

In Fig. 4-6, cost criteria including retention cost, salary, nonmonetary cost, and training cost are navigated toward right and bottom of the chart. Benefit criteria encompassing makespan and sustainability are oriented toward up and left of the GAIA web.

Geometrically, if a GAIA web is more extended toward benefit criteria and less extended toward costs criteria that is more desirable. when GAIA web related to a specific alternative is more oriented toward top and left and less extended toward right and bottom indicating that the action is more desirable. If GAIA web of a specific alternative is less expanded toward top and left and more extended toward right and bottom means it is a less desirable action.
Based on this analogy, for example, H1FSH is a more desirable alternative whereas NC and UP are less desirable actions, refer to Fig. 4-6-i for H1FSH, Fig. 4-6-a for NC, and Fig. 4-6-c for UP. H1FSH high performance on makespan and sustainability and low performance on cost criteria makes it left and top aligned while, NC and UP performance on benefit criteria is negligible and their performance on cost criteria is quite high making their GAIA web right and bottom aligned.

Generally, hiring strategies are left aligned which shows their high performance on benefit criteria, and training strategies are right aligned which shows their high-performance on the two cost criteria of retention costs and salary. Despite DCB, DO, and UP having significantly different multiskilling configurations, (refer to Fig. 4-2), their GAIA web shapes are quite similar indicating their poor ability to enhance makespan and sustainability. CH is extended in the same direction as makespan and taking this with its high differentiating power, suggests that this strategy should be at the top of the ranking.

Fig. 6-f, g, h and Fig. 6-i, j, k represent different HDS and HFSH strategies, respectively. Considering these strategies, increasing the number of recruited trades has a significant negative effect on the two cost criteria of retention costs and salary while having a negligibly positive effect on benefits criteria including makespan and sustainability. Increasing the number of hired trades does not influence their performance on the two criteria of sustainability and training costs. That is why the net flow decreases as the number of recruited trades increases. Therefore, it can be argued that in this case study, benefits including makespan reduction and increased sustainability resulting from increasing the number of hired multi-skilled trades cannot compensate for their costs in terms of retention costs and salary. Indeed, retention costs and salary are quite sensitive to the number of recruited trades. A second conclusion is that alterations in the performance of FSH is more sensitive than DS in responding to increasing the number of hired workers, in terms of makespan, retention costs, salary, and non-monetary costs.
Table 4-3. Uni-criterion net flow

<table>
<thead>
<tr>
<th>Alternative</th>
<th>NMC</th>
<th>RC</th>
<th>TC</th>
<th>SAL</th>
<th>SUS</th>
<th>MS</th>
</tr>
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<td>NC</td>
<td>0.212</td>
<td>0.600</td>
<td>0.400</td>
<td>0.540</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.600</td>
<td>10.00</td>
</tr>
<tr>
<td>CH</td>
<td>-</td>
<td>0.600</td>
<td>-</td>
<td>0.280</td>
<td>-</td>
<td>0.842</td>
</tr>
<tr>
<td></td>
<td>0.612</td>
<td>0</td>
<td>10.00</td>
<td>0</td>
<td>0.600</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
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<td>UP</td>
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<td>0.380</td>
<td>-</td>
<td>-</td>
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<td>0</td>
<td>0</td>
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<td>DO</td>
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<td>0.420</td>
<td>-</td>
<td>-</td>
</tr>
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<td>H1DS</td>
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<td>-</td>
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<td>-</td>
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<td>0.014</td>
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</tr>
<tr>
<td>H3DS</td>
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<td>-</td>
<td>0.500</td>
<td>0.142</td>
</tr>
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<td>0.680</td>
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<td>0</td>
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</tr>
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<td>0.060</td>
<td>0.500</td>
<td>0.428</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.428</td>
</tr>
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<td>H2FSH</td>
<td>0.050</td>
<td>-</td>
<td>0.400</td>
<td>-</td>
<td>0.500</td>
<td>0.685</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.520</td>
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<td>0.620</td>
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<tr>
<td></td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.685</td>
</tr>
<tr>
<td>H3FSH</td>
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<td>-</td>
<td>0.400</td>
<td>-</td>
<td>0.500</td>
<td>0.842</td>
</tr>
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<td>0.900</td>
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<td>9</td>
</tr>
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<td></td>
<td>5</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0.842</td>
</tr>
</tbody>
</table>

NMC = non-monetary costs, RC=retention costs, TC=training costs, SAL=salary, SUS=sustainability, MS=makespan
TC=training costs, SAL=salary, RC=retention costs, NMC= non-monetary costs, MS=make span, SUS=sustainability

Fig. 4-6. Unicriterion net flow GAIA web
4.5.4. Sensitivity analyses

Decision-making models are sensitive to different assumptions which enables them to analyze decision problem (Podvezko and Podviezko 2010). PROMOTHEE methodology is specifically sensitive to the choice of criteria weight (Mareschal 1988). The weighting of criteria, in particular when criteria are highly conflicting, significantly influences the results of an analysis and consequently performing a sensitivity analysis provides useful insights for decision-makers (Mareschal 1988).

Table 4-4 shows values of criteria weight for which ranking results remains intact. In this table, the lower bound and upper bound are the lowest and highest values in which the current ranking is correct; if these boundaries are violated the ranking will be changed. Range is the distance between the upper bound and the lower bound.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Range</th>
<th>Current Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMC</td>
<td>14.46</td>
<td>19.56</td>
<td>5.1</td>
<td>15.9</td>
</tr>
<tr>
<td>RC</td>
<td>9.15</td>
<td>11.48</td>
<td>2.33</td>
<td>10.6</td>
</tr>
<tr>
<td>TC</td>
<td>9.88</td>
<td>12.08</td>
<td>2.2</td>
<td>10.6</td>
</tr>
<tr>
<td>SAL</td>
<td>12.36</td>
<td>15.19</td>
<td>2.83</td>
<td>14.13</td>
</tr>
<tr>
<td>SUS</td>
<td>5.4</td>
<td>8.35</td>
<td>2.95</td>
<td>6.36</td>
</tr>
<tr>
<td>MS</td>
<td>39.46</td>
<td>46.23</td>
<td>6.77</td>
<td>42.4</td>
</tr>
</tbody>
</table>

NMC= non-monetary costs, RC=retention costs, TC=training costs, SAL=salary, SUS=sustainability, MS=makespan

The model is very sensitive to the weights of retention costs, training costs, salary, and sustainability since they have the smallest range, less than 3. Makespan and non-monetary costs have a quite significant range of 6.77 and 5.1, respectively. Despite this table showing the area in which the current outranking is consistent, it does not give any information about how the ranking result will be changed if weighting boundaries are exceeded. This matter will be discussed in the following section.
Fig. 4-7 illustrates how net flow value varies as a function of weight allocation. The horizontal axis shows alteration of weights and the vertical axis shows net flow value. At the righthand side of the weights axis, the weight allocated to the criterion is equal to 100 per cent meaning that there is a single criterion. The left-hand side of the axis has a criteria weight equal to 0 per cent meaning the alternative does not exist in practice. Each alternative is illustrated by a line in which every given dot corresponds to a value of net flow as a function of a specific criterion weight allocation. The intersection of the solid vertical bar in the horizontal axis is equal to the current weight of criteria. The reflection of the intersection of this bar and alternatives’ lines in the vertical axis corresponds to PROMOTHEE II ranking. The thicker line in the horizontal axis indicates the interval in which alteration of that specific criterion weight does not affect PROMETHEE II outranking results.

Even though in Table 4-4 the range in which the PROMETHEE II outranking results remains the same is rather small, after violating ranking results by changing the weights considerably, the best alternatives ranking involves changes between H1FSH, H2FSH, H3FSH, and CH, which remained incomparable in PROMETHEE I ranking. The sensitivity analysis shows in the majority of cases that if the current weighting of criteria is changed considerably the clustering results remain the same and just members of a cluster, which remined incomparable in PROMETHEE I, have their ranking changed. HFSH policies and CH constitute a cluster, HDS strategies form another cluster and training strategies except CH and plus NC make the last cluster.

Fig. 4-7-a shows that CH is very sensitive to non-monetary costs. With increasing weight of non-monetary costs, all alternatives except CH are close to each other, which shows a similar performance to non-monetary costs. Fig. 4-7-b shows increasing weight of retention costs give more advantage to training strategies since they are not associated with retention costs. Fig. 4-7-c indicates high sensitivity of CH to training costs as CH multiskilling involves the most number of trades. Different
weight allocations for training costs shows the ranking of all training and hiring strategies remain the same except for CH, suggesting the importance of considering training cost in CH.

Fig. 4-7-d shows that H2FSH, H3FSH, and H3DS have a sharp slope and sensitive to alterations in weight of salary. To this end, if the weight of salary increased more than 14.3 per cent, the aforementioned strategies would lose their advantages significantly. This shows that when the number of hired multi-skilled workers is increased, special attention should be paid to labor cost to avoid economic loss. Fig. 4-7-e shows that, except for CH, with alterations in the weight of sustainability no change appears in outranking results. However, slight manipulation which exceed the range of 2.95 can result in CH gaining or losing advantage over HFSH strategies. From Fig. 4-7-f it is clear that increasing the weight of makespan separates different hiring and training strategies considerably and in particular enhances Hiring FSH strategies. Decreasing the weight of makespan supports training strategies and increasing the weight of it gives
**Fig. 4-7.** Criteria weight sensitivity analyses on PROMTHEE II ranking
advantage to Hiring FSH strategies, while Hiring DS strategies are not particularly sensitive to alteration of weights of this criterion.

Sensitivity analysis indicates the range in which alterations in decision-makers’ weight allocation confirms current ranking results as well as illustrating how ranking results can be predicted after violating ranking stability range. This information is crucial by showing how alteration in ranking results can be predicted when weight allocation is changed because of different reasons, such as alterations in decision makers’ priorities or due to application of the same model in another case study. Current sensitivity analysis demonstrates that best multiskilling strategy can be selected in the cluster of CH, H1FSH, H2FSH, and H3FSH in different weight allocation scenarios.

Considering hiring configurations, HFS demonstrates much less sensitivity in comparison with HFSH pertaining to all criteria. HFSH strategies are the most sensitive to makespan, salary, and retention costs. Meanwhile, training strategies except CH show less sensitivity to different components of the decision-making model. CH is highly sensitive to sustainability, training cost, and non-monetary costs.

4.6. Summary

Although off-site construction can enhance several performance measures of traditional on-site construction, production in the prefabricated environment can lead to heterogeneity. Appropriate decision making in staffing of multi-skilled workers is presented as an applicable way to level the production workflow. This chapter presents a model that investigates the performance of different multi-skilled staffing strategies.

In contrast to optimization-based studies, which include a limited number of criteria as the objective function, this chapter takes into account values pertaining to a comprehensive set of qualitative and
quantitative criteria, using DELPHI and optimization, respectively. The model which is presented here can be used as a base model that can be easily customized by practitioners by manipulating the weight of each criterion or by choosing an appropriate set of criteria to suit the needs of a particular situation.

The computation results show that preference values for training strategies are, to a high extent, a function of the number of workers who are multi-skilled and less related to the location of multi-skilled workers in the prefabricated environment. With regard to hiring policies, two or three DS trades are needed to obtain a similar preference value as one FSH in terms of both advantages and disadvantages.

Another finding of this investigation is that, in addition to weight of criteria, statistical features of alternatives influence the differentiating power of criteria to push alternatives toward the top of the ranking list. The most similar criteria are non-monetary costs and training costs. The second most similar criteria are retention costs and salary. Independent criteria are identified as salary and training costs plus makespan and retention costs. The most, conflicting criteria are shown to be makespan and labor salary, while the second conflicting criteria are retention costs and sustainability.

When there are several conflicting criteria in a decision making problem it is difficult to choose the best alternative. Because, there are several alternatives which are performing positively pertaining to some criteria and negatively in relation with other criteria. Therefore, potentially the decision-maker cannot compare alternatives or find it extremely difficult to make a comparison. However, such criteria do provide insights into complex decision areas and why they are so intricate. PROMETHEE analysis reveals that H1FSH, H2FSH, CH, and H3SFH are the best process integration policies and incomparable based on partial ranking. Sensitivity analysis shows that with changing the weight allocation, within a considerable range these four cross-training strategies still remain the best ones,
and just their order in the ranking list is changed. Additionally, sensitivity analysis implies that CH is highly sensitive to weight of non-monetary cost, training costs, and sustainability. HFSH policies are the most sensitive to weight of retention costs, salary, and makespan. Other multiskilling strategies do not demonstrate any specific sensitivity to the weight of any criterion.
Chapter 5a

5. Staffing strategy by an optimization platform

This chapter presents a mathematical framework to optimize a multiskilling staffing strategy. The optimization platform explores every possible multiskilling strategy and the corresponding consequences including monetary benefits and costs. The computational experiments suggest that small alterations in the production characteristics can lead to significant changes in the optimal cross-training policy necessitating development of an optimal multiskilling staffing platform. The optimal multiskilling staffing strategy which is developed in this chapter has a superior performance in comparison with well-regarded existing multiskilling strategies such as chaining and direct capacity balancing, in terms of both makespan reduction and contribution to profit. Subjective decision-making regarding a multiskilling staffing strategy, which does not direct the workforce to the most appropriate workstations, can lead to a significant productivity loss. The matrix metrics which are presented in this chapter contribute to the existing body of knowledge by presenting characteristics of an optimal staffing strategy in terms of skill acquisition and distribution.

5.1. Introduction

Scheduling of a multiskilled workforce determines the sequence in which members of the existing workforce should be allocated to different tasks during the production horizon based on their skill set, to optimize system performance as determined by the different measures specified by the decision maker (De Bruecker et al. 2015). Multiskilled workforce scheduling has already been intensively investigated in the literature (Qin et al. 2015). The staffing strategy or configuration of a Multiskilled workforce determines how many new workers, with what specific skill set and level, should be
recruited or hired or, alternatively, in how many tasks and at what level existing single-skilled workforce members should be cross-trained to fill the required skill set and level pool (De Bruecker et al. 2015).

Previous studies often adopt a comparative approach to advise on appropriate multiskilled workforce configurations. In the comparative approach, the performance of several existing multiskilling configurations are compared, based upon a scheduling framework which incorporates scheduling objectives and constraints set by the specific employer. There are a few multiskilling configurations such as chaining and direct capacity balancing (DCB) that are commonly used strategies in these kinds of studies (Yang 2007). For example, Daniels et al. (2004) compared full multiskilling and chaining based upon a non-preemptive flow shop scheduling framework. As an another example, Nasirian et al. (2019b) developed a hybrid optimization and multi-criteria decision-making method to compare the performance of six different multiskilling configurations based upon eleven criteria and advise the best possible alternative.

While a scheduling platform can indicate the best possible multiskilling configuration among existing ones, it cannot create a new multiskilling strategy which gives optimal performance in a specific context. To bridge this gap, this chapter presents a decision-support tool for facilitating optimal multiskilled workforce staffing with a methodologically novel strategy. The experimental results in this chapter indicate that there can be a significant difference between the performance of a new optimal strategy and the best strategy among existing ones. Fig.5-1 illustrates how investigations in this chapter differ from existing literature and hence contribute to the body of knowledge.

The next section describes the problem context. In the third section a mathematical framework is presented. Afterward, Skill matrix metrics are explored. Numerical experiments including the case study from the construction sector are then outlined. The results section summarizes the output from 106
the decision support system pertaining to the case studies and this is followed by discussion and recommendations.

5.2. Problem context

The performance of cross-training configurations depends upon a wide range of technical and managerial factors. Choosing the most appropriate configuration is the most significant technical step in designing a multiskilled system (See Chapter 2). In the cross-training literature, the most common way to propose use of a particular multiskilling configuration is through a comparative study. This means evaluating the system performance, mainly by a scheduling platform, where cross-training is implemented, and then selecting a cross-training configuration associated with the best productivity measures in terms of time and or cost (De Bruecker et al. 2015).

A major stream of literature uses simulation for comparative study purposes. Yang et al. (2002), by adjusting the length of workdays, developed a scheduling method to transfer crosstrained workers
between machines with the objective of maximizing the flexibility and responsiveness in a job shop environment. The developed scheduling platform achieved significant gains in performance over a fixed schedule of eight hours per day. Agnihothri & Mishra (2004), in an environment with three operations requiring three skills, made a trade-off between the cost of multiskilling a crew and the high expenses of having a machine not operating. They used a queueing and simulation framework to study three multiskilling staffing decisions: the number of servers that are multiskilled, the number of skill sets needed for every server to be multiskilled, and efficiency in the cross-trained skills. Yang (2007) carried out a simulation-based comparative study by comparing performance measures for different multiskilling structures. Different multiskilling configurations had variations in the numbers of cross-trained workers, the number of skills that a cross-trained workforce acquired, and the number of additional machines available for use. Performance measures evaluated were based upon: efficiency losses, the extent to which the human resource was utilized, operations processing time, and responses to worker absenteeism. Iravani et al. (2007) investigated using cross-trained labor with flexible machinery and factories simultaneously. Simulation techniques were applied on different production lines for the purpose of scheduling flexible resources and revealed how different alternatives for resource flexibility can be ranked to respond to variability. Bokhorst (2011) conducted a simulation study of a cross-trained crew in a job shop context to investigate how a more balanced use of the extra skills is feasible by reducing the amount of work in process. Colen & Lambrecht (2012), with the objective of evaluating field services in a maintenance service, developed a simulation study to compare performance of technicians conducting preventive maintenance and fully multiskilled technicians. The results of the comparative study in this paper revealed an optimal cross-training policy and how the policy is affected by fluctuation in demand. Another stream of research uses optimization models to make comparative studies to identify an
optimal multiskilling configuration among existing ones. Ebeling & Lee (1994) developed an integer linear program to schedule multiskilled crew to be allocated to different work stations over the production horizons. The developed model generated insights into cross-trained crew assignment by examining the profitability of different assignment strategies. Daniels et al. (2004) developed a scheduling method along with several metrics to explore skill matrix. The presented metrics are used to evaluate the extent to which operational benefits of crew multiskilling can be achieved in comparison with the two benchmarks of no cross-training and full cross-training. Bokhorst et al. (2004) developed an integer goal programming model for scheduling, applying alternative cross-training policies. They argued about the influence of adopting human resource management or operations management targets. Azizi & Liang (2013), with the aim of minimizing training cost, and decreasing efficiency and flexibility costs, developed a scheduling approach that allocates crew to different operations, rotates crew between the operations, and determines the training schedule. Nasirian et al. (2019a) developed a resource constraint scheduling model to facilitate allocation of a multiskilled crew to different operations to minimize production makespan with consideration of production and resource cost. Different cross-training policies which were considered in this study include no cross-training, hiring a single-skilled crew, direct capacity balancing, chaining, and hiring a multiskilled crew.

This chapter proposes that since using comparative studies is based upon selecting a best strategy among a set of existing multiskilling configurations, it is inadequate and represents a gap in the existing literature. Instead, an optimization-based platform is developed to find a new optimal multiskilling configuration which does not exist in the existing literature. This development considers managerial aspects of multiskilling a workforce, as well as training expenses, enhancement in salary and reduced efficiency, which are all applicable costs in this chapter. Maximization of profit is
considered as the objective function.

5.3. Problem description

Consider $\mathcal{N}$ to be the set of independent jobs that are planned to be processed in the set of workstations ($\mathcal{M}$). Let $t$ be an integer number presenting a specific time belonging to the set of time horizons $\mathcal{T}$. It is assumed that every job is available from the beginning of time ($t = 0$) and requires exactly one operation in every workstation. Processing element $i$ in workstation $j$ is represented as operation $(i, j)$. The last job, workstation and time period are denoted by $N, M$, and $T$, respectively. Also, it is assumed that the direction of operations in the production environment is unidirectional, which means that machines can be numbered so that if processing in machine $j$ has to precede $j'$ then $j < j'$.

The duration of every operation is a function of the number of workers allocated to that operation, which is referred as operation mode. Consider $\Omega$ to be the set of workers with $h$ and $W$ being a specific worker inside the set and the last worker, respectively. Consider $\mathcal{K}$ as set of operation modes. Operation modes which are used for problem formulation in this chapter include: workstation operation mode, feasible operation mode, and practical operation mode. $K$ denotes workstation operation mode (WOM), which is the number of workers who can be located in a workstation based on the physical constraints existing in every workstation such as space. Consider $\varphi_j$ as a non-negative integer variable representing feasible operation mode (FOM) by indicating the maximum number of workers which can be allocated to the specific workstation of $j$, based on management strategic decision-making. This will be determined at the beginning of the project and will remain the same until its end. Usually, cost of training is the most important contributor to the magnitude of FOM. Consider $\Pi_{ij}$ as a non-negative integer variable illustrating practical operation mode (POM); it is
the mode with which the operation \((i,j)\) is conducted in reality in every specific workstation \(j\). Determining POM is an operational decision, meaning it can be changed during the production makespan, depending on different operational justifications such as availability of workforce and queuing of products.

Let us define \(r_{hj}\) as feasible worker allocation (FWA) representing a binary variable which is equal to one if worker \(h\) is trained to be allocated to workstation \(j\) and otherwise is equal to zero. Consider that even though worker \(h\) can be trained for allocation to several workstations during production makespan, in practice they cannot be allocated to more than one workstation \(j\) in any specific time interval \(t\). Therefore, practical worker allocation (PWA) \(a_{hjt}\) is a binary variable which is equal to 1 if worker \(h\) is allocated to station \(j\) in time \(t\), in practice. Obviously, multiskilling of crews will come at a cost. Let, \(b_{hj}^1\) and \(b_{hj}^2\) describe corresponding training and salary costs for every worker \(h\) to be multiskilled to enable them to contribute in workstation \(j\). Correspondingly, \(B^1\) and \(B^2\) are considered as total training and salary costs. The other cost which is considered in this chapter is the fixed cost \((B^3)\) which is a function of makespan and daily costs \((l_t)\). Finally, given \(q_i\) as the revenue corresponding to selling the product \(i\), total revenue \(Q\) is computed as a function of makespan and \(q_i\).

Considering the above description of the problem, a model can be formulated as follows.

\[
\text{Maximize } P^T \\
P^T = Q - B^1 - B^2 - B^3 \\
Q = \sum_{i=1}^{N} q_i \quad (4-2) \\
B^1 = \sum_{h=1}^{W} \sum_{j=1}^{M} r_{hj} b_{hj} \quad (4-3)
\]
\[ B^2 = \sum_{h=1}^{W} B_h^2 + \sum_{h=1}^{W} \sum_{j=1}^{M} r_{hj} b_{hj} \quad (4-4) \]

\[ B^3 = \sum_{k=1}^{K} \sum_{t=1}^{T} t x_{Mkt} l_t \quad (4-5) \]

\[ \sum_{f=1}^{K} y_{jff} = 1 \quad j \in M \quad (4-6) \]

\[ \varphi_f = \sum_{f=1}^{K} y_{jff} f \quad j \in M \quad (4-7) \]

\[ \sum_{t=1}^{T} \sum_{k=1}^{K} x_{ijkt} = 1 \quad j \in M, i \in N \quad (4-8) \]

\[ \Pi_{ij} = \sum_{t=1}^{T} \sum_{k=1}^{K} x_{ijkt} k \quad j \in M, i \in N \quad (4-9) \]

\[ \sum_{f=1}^{W} y_{jff} f = \sum_{h=1}^{W} r_{hj} \quad j \in M \quad (4-10) \]

\[ \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{h=1}^{W} x_{ijkt} a_{hjt} = \sum_{t=1}^{T} \sum_{k=1}^{K} x_{ijkt} k \quad j \in M, i \in N \quad (4-11) \]

\[ \sum_{k=1}^{K} \sum_{t=1}^{T} x_{ijkt} k \leq \sum_{f=1}^{W} y_{jff} f \quad j \in M, i \in N \quad (4-12) \]

\[ a_{hjt} \leq r_{hj} \quad j \in M, h \in \Omega, t \in T \quad (4-13) \]

\[ \sum_{j=1}^{M} a_{hjt} \leq 1 \quad h \in \Omega, t \in T \quad (4-14) \]

\[ p_{ij} = \sum_{k=1}^{K} \sum_{t=1}^{T} x_{ijkt} d_{ijk} \quad j \in M, i \in N \quad (4-15) \]

\[ C_{ij} = \sum_{k=1}^{K} \sum_{t=1}^{T} x_{ijkt} t \quad j \in M, i \in N \quad (4-16) \]
\[ M^s = \sum_{k=1}^{K} \sum_{t=1}^{T} x_{NMkt} t \]  \hfill (4-17)

\[ C_{ij} - p_{ij} \geq C_{i(j-1)} \quad j \in M, i \in N \]  \hfill (4-18)

\[ C_{ij} \geq C_{i(i-1)j} + p_{ij} \quad j \in M, i \in N \]  \hfill (4-19)

\[ \sum_{k=1}^{K} \sum_{t=p_{ijk}}^{T} \sum_{l=t-p_{ijk}+1}^{t} x_{ijkt} a_{hjl} \]  \hfill (4-20)

\[ = \sum_{k=1}^{K} \sum_{t=1}^{T} X_{ijkt} a_{hjt} d_{ijk} \]  \hfill (4-21)

\[ x_{ijkt}, a_{hjt}, r_{hj}, y_{jf} \in \{0,1\} \]

\[ j \in M, i \in N, h \in \Omega, t \in T, f \in \Omega \]

The objective function is to maximize the profit. The constraint 4-1 calculates the total profit shown by \( P^T \) based on \( Q, B^1, B^2, \) and \( B^3 \). Equation 4-2 illustrates how \( q_i \) gives rise to \( Q \).

Equation 4-3 defines \( B^1 \) as the cross-training cost, which is dependent on the workstation for which the worker is cross-trained \((r_{hj})\) and the corresponding cost of cross-training. Consider that it is decided to cross-train worker \( h_1 \in \Omega \) to work in workstation \( j_1 \in M \) then \( r_{h_1j_1} \) leading to the statement \( r_{h_1j_1} b_{h_1j_1} = b_{h_1j_1} \). For every other workstations such as \( j_2 \neq j_1 \in M \) since \( r_{h_1j_2} = 0 \) the statement \( r_{h_1j_2} b_{h_1j_2} = 0 \).

Equation 4-4 ensures that depending on the workstations for which a worker is cross-trained, corresponding salary costs are considered. A coefficient of salary is defined as \( b^2_{hj} \) which indicates that when worker \( h_1 \in \Omega \) is trained to be allocated to the workstation \( j_1 \in M \) then \( b^2_{h_1j_1} \) the basic salary of the workforce, should be added. The basic salary of the worker \( h \) is shown by \( B^2_h \).
4-5 calculates the total fixed cost $B^3$ as a function of makespan obtained from the term $x_{NMkt}$ and daily costs $l_t$, which can change during the production horizon.

Consider $y_{jf}$ as a binary variable which is equal to 1 when the FOM for the workstation $j$ is equal to $f$. Formula 4-6 allocates a unique FOM to every workstation according to WOM. In other words, for every workstation $j \in M$ this formula enumerates every possible operational mode and adds them together. To satisfy the right-hand side of the equation, just one $y_{jf}$ can be equal to 1, which is the unique operation mode of $j$.

The value of FOM for every workstation $j \in M$ is denoted by $\varphi_j$. Since for every $j \in M$ in just one $f$, $y_{jf} = 1$, whenever $y_{jf} = 0$ the statement $y_{jf} f$ will be equal to zero and when $y_{jf} = 1$, the statement $y_{jf} f = f$ would determine the value of $\varphi_j$. See equation 4-7.

Let us define $x_{ijkt}$ as a binary variable which is equal to one when operation $(i, j) \in N \times M$ is conducted in mode $k$ and finished in time period $t$. Constraint 4-8 ensures every operation $(i, j)$ has a unique POM ($k$) and finishing time ($t$). Consider operation $(i_1, j_1) \in N \times M$, and assume that after enumerating every possible combination of $k$ and $t$, $k_1$ and $t_1$ are allocated to the $(i_1, j_1)$. Considering the definition of $x_{ijkt}$ this necessitates $x_{i_1j_1k_1t_1} = 1$. Since the right-hand side of the equation is 1, therefore for every $k_2 \neq k_1 \in K$ and $t_2 \neq t_1 \in T$, $x_{i_1j_1k_2t_2} = 0$.

The value of POM for every operation $(i, j) \in N \times M$ is denoted by $\Pi_{ij}$ which is computable as formula 4-9. For a specific operation such as $(i_1, j_1) \in N \times M$ consider that $k_1 \in K$ and $t_1 \in T$ satisfy equation 4-8. Therefore, $x_{i_1j_1k_1t_1} = 1$, which leads to $x_{i_1j_1k_1t_1} k_1 = k_1 = \Pi_{i_1j_1}$. Meanwhile, for every other $k_2 \neq k_1 \in K$, $x_{i_1j_1k_2t_1} = 0$ and therefore $x_{i_1j_1k_2t_1} k_2 = 0$. 

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Despite FOM determining how many workers can be allocated to workstation $j \in M$, FWA determines which workers from the worker set ($\Omega$) should be trained to be allocable to the workstation $j$. Let $r_{hj}$ represent FWA as being a binary variable which is equal to 1 if worker $h$ can be allocated to workstation $j$. Constraint 4-10, ensures there are a sufficient number of workers who are allocable to workstation $j$ to satisfy FOM. In this regard, if the FOM in workstation $j = j_1$ is supposed to be $\varphi_1 = f_1$, then it should be $f_1$ number of workers from the worker set ($\Omega$) who can be transferred to the workstation $j = j_1$.

Likewise, although, POM determines how many workers are allocable to the operation $(i, j) \in N \times M$, PWA indicates which workers among the already allocable workers are allocated to $(i, j)$. Let $a_{hjt}$ represent PWA as being a binary variable which is equal to one if worker $h$, in practice, is allocated to $j$ in time period $t$. Constraint 4-11 ensures enough workers in practice are allocated to operation $(i, j)$ to satisfy POM. Consider the operation $(i_1, j_1) \in N \times M$ which is performed in mode $k = k_1$ and finished at the time $t = t_1$. Therefore, POM for this operation can be calculated as $\Pi_{i_1j_1} = x_{i_1j_1k_1t_1} k_1$ which results in $\Pi_{i_1j_1} = k_1$. To satisfy the right-hand side of the equation, $k_1$ number of workers from workforce set ($h \in \Omega$) should be allocated to the operation $(i_1, j_1)$ for the time period $t = t_1$. For every workstation $j_1 \in M$, FOM $\varphi_{j_1}$ cannot be less than POM for processing every product $i \in N$ which is processed in the same workstation $j = j_1$ and leads to the operation $(i, j_1)$, meaning that $\Pi_{i_1j_1} \leq \varphi_{j_1}$. This is ensured by the constraint 4-12.

Recall that $r_{hj}$ is a binary variable which is equal to one when worker $h$ is trained to be allocable to the workstation $j$. However, $a_{hjt}$ is a binary variable that is equal to one if worker $h$ is allocated to workstation $j$ in the time period of $t$ during the production makespan. Constraint 4-13 ensures the
workers who are allocated to different workstations during the production horizon are the ones who are trained to be allocable according to the FOM. Therefore, for example, if worker \( h = h_1 \) is trained to be allocable to the workstation \( j=j_1 \) then \( r_{h_1j_1} \) and therefore we have \( a_{h_1j_1t} \leq 1 \). This means that the worker \( h = h_1 \) can be allocated to the workstation \( j=j_1 \) during the production horizon for every \( t \in T \). However, if worker \( h = h_2 \) and \( h_2 \neq h_1 \) is not trained to be allocated to the workstation \( j=j_1 \), then \( r_{h_1j_1} = 0 \) leading to \( a_{h_2j_1t} \leq 0 \). This means the worker \( h = h_2 \) cannot be allocated to the workstation \( j=j_1 \) during any given time interval such as \( t \in T \). Because if \( a_{h_2j_1t} = 1 \) the statement \( 1 \leq 0 \) would be impossible.

Constraint 4-14 ensures that every worker in every period of time can be allocated to a maximum of one workstation. Consider the worker \( h = h_1 \) and the time \( t = t_1 \). If the worker is allocated to more than one workstation, let us say the two workstations of \( j_1, j_2 \in M \) then \( a_{h_1j_1t_1} = 1 \) and \( a_{h_1j_2t_1} = 1 \) leading to \( \sum_{j=1}^{M} a_{hjt} > 1 \) which represents a violation of constraint 4-14.

Constraint 4-15 determines the duration of every operation. Consider \( d_{ijk} \) as the duration of operation \((i, j)\) in mode \( k \). Every operation can be conducted in different modes and it is inversely related to the operation duration. In other words, considering the operation \((i_1, j_1) \in N \times M \) and two different operation modes of \( k_1, k_2 \in K \) in the case of \( k_1 \leq k_2 \), then \( d_{i_1j_1k_1} \geq d_{i_1j_1k_2} \). Recall that constraint 4-8 allocates a unique \( k \) for every given operation \((i_1, j_1) \in N \times M \), using the binary variable \( x_{ijkt} \).

In this regard, considering \( p_{ij} \) as a non-negative integer variable representing the duration of every operation \((i, j) \in N \times M \) if \( x_{i_1j_1k_1t_1} = 1 \) then \( p_{ij} = d_{i_1j_1k_1} \). Because, for every other \( k_1 \neq k_2 \) since \( x_{i_1j_1k_2t_1} = 0 \) thus \( x_{i_1j_1k_2t_1}d_{i_1j_1k_1} = 0 \).

Considering \( C_{ij} \) as a non-negative integer variable presenting the completion time of operation
\((i,j)\), constraint 4-16 determines the value of \(C_{ij}\) according to the unique \(t\) which is obtained by \(x_{ijkt}\) in equation 4-8. If equation 4-8 indicates that the operation \((i_1,j_1) \in N \times M\) should be finished in \(t = t_1\) in mode \(k = k_1\) then \(x_{i_1j_1k_1t_1} = 1\) and for every other \(t_2 \neq t_1 \in T\), \(x_{i_1j_1k_1t_2} = 0\). This leads to, determining completion time of operation \((i,j)\) as \(C_{i_1j_1} = x_{i_1j_1k_1t_1}t_1 = t_1\).

Let us define makespan as the time period in which the last product is released from the last workstation. Considering that the last product is denoted by \(N\) and the last workstation is denoted by \(M\), then similar to the way in which completion time is calculated, constraint 4-17 determines production makespan as a function of \(x_{NMkt}\). Consider that operation \((N,M)\) is determined to be finished in \(t = t_1\) with operation mode of \(k = k_1\), then \(x_{NMk_1t_1} = 1\) and for every \(k_2 \neq k_1 \in K\) and \(t_2 \neq t_1 \in T\), \(x_{NMk_2t_2} = 0\) leading to determining makespan as \(M^* = x_{NMk_1t_1}t_1 = t_1\).

Constraint 4-18 limits the start time of an operation inside an specific workstation to be no less than completion time of operation of the same product in the previous workstation. Considering operation completion time as \(C_{ij}\) and moving backward equal to operation duration \(p_{ij}\) results in obtaining operation start time as \(C_{ij} - p_{ij}\) which should be not less than \(C_{i,j-1}\). Constraint 4-19 determines queuing in the production line. It indicates that considering \(C_{ij} - p_{ij}\) as the start time of operation \((i,j) \in N \times M\), the start time should be greater than the finishing time of its preceding product \(i = i - 1\) in the same workstation \(j = j\) leading to the operation \((i - 1,j)\).

Constraint 4-20 ensures that when a worker such as \(h = h_1\) is allocated to conduct an operation such as \((i_1,j_1) \in N \times M\) in the last period of operation in which the process for the product will be finished, such as \(t = t_1\), they should stay in the operation for the whole period, which is
determined by the statement \( x_{i_1,j_1,k_1,t_1}d_{i_1,j_1,k_1} \). Therefore, when worker \( h = h_1 \) is allocated to operation \((i_1,j_1)\), they need to stay there during \([t_1 - d_{i_1,j_1,k_1} + 1, t_1]\). Constraint 4-21 illustrates the domain of employed variables.

### 5.4. Skill matrix metrics

The main objective of this research is to investigate how operational advantages are related to the extent to which the skills of a workforce are acquired from a pool of available skills. A skill matrix is an appropriate tool to investigate skill accumulation and distribution. Daniels et al. (2004) identifies three different metrics which can explain accumulation and distribution of skills in a skill matrix.

Recall that \( r_{hj} \) is a binary skill matrix indicating whether worker \( h \) can be allocated to workstation \( j \). Consider a set of workstations for which the worker \( h \) is trained to be allocated as \( M_h^s = \{ j \in M: r_{hj} = 1 \} \). Let us consider \( m_h^s \) as the number of workstations to which workers \( h \) can be allocated. Given the set of workers who are trained to occupy the workstation \( j \) is \( W_j^s = \{ h \in \Omega: r_{hj} = 1 \} \), the number of workers who can be allocated in workstation \( j \) is shown by \( w_j^s \).

Let \( \lambda^1 \) indicate skill accumulation which is obtained by computing the ratio of obtained skills to the pool of available skills as shown in formula 4-22. Enhancement in the skill accumulation corresponds to higher values for \( \lambda^1 \).

\[
\lambda^1 = \frac{\sum_{j=1}^{M} \sum_{h=1}^{W} r_{hj}}{M \times W} \tag{4-22}
\]

Two matrices can share the same values of \( \lambda^1 \); however, the distribution of skills which are
obtained by workers can be significantly different. For example, let us say that for two $4 \times 4$ matrices of $r^1$ and $r^2$, $\lambda^1 = \frac{7}{16}$ which is an indication of the same skill accumulation. In the first matrix $w^1_1 = 4$ and $w^1_2 = w^1_3 = w^1_4 = 1$; however, in the second matrix $w^2_1 = 1$ and $w^2_2 = w^2_3 = w^2_4 = 2$, which shows significant differences in skill distribution across different workstations.

\[
r^1 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{pmatrix}, \quad r^2 = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}
\]

$\lambda^2$ investigates skill distribution across different workstations. $\lambda^2$ quantifies how skill sets possessed by workers are distributed across workstations as shown in the equation 4-23. In plain language, this measure considers the difference between the workstation with the highest number of allocable workers and the workstation with the lowest number of allocable workers. In the above example, if the value of $\lambda^2$ pertaining to $r^1$ and $r^2$ is shown by $\lambda^2_1$ and $\lambda^2_2$, respectively, then the following values can be assumed for skill distribution across workstations: $\lambda^2_1 = 3$ and $\lambda^2_2 = 0$. This means that there should be at least one $j_1$ and $j_2 \in M$ for which skill distribution is discriminated equal to three different skill sets.

\[
\lambda^2 = Max \{w^j_1 - w^j_2\} \quad j \in M, \ j' \in M
\]

(4-23)

Where $b^s_j = \sum_{h=1}^{W} \frac{r_{hj}}{m_h}$, the station worker balance ($\lambda^3$) can be defined as equation 4-24. $\lambda^3$ supplements $\lambda^2$ as it investigates the distribution of skills towards both workstations and workers. When $\lambda^3 \leq 1$ it is considered that there is a balance of skills between stations and workers.

\[
\lambda^3 = Max \{b^s_j - b^s_j'\} \quad j \in M, \ j' \in M
\]

(4-24)
In the same example, if the value of $\lambda^3$ pertaining to $r^1$ and $r^2$ is shown by $\lambda^3_1$ and $\lambda^3_2$, respectively, then the following values can be assumed for investigating skill distribution across workers and workstations: $\lambda^3_1 = 2$ and $\lambda^3_2 = 1$. $\lambda^3_1 = 2$ is an indication of outstanding skill distribution imbalance across workers and workstations. By looking to the corresponding matrix it can be seen that the majority of skills are concentrated in $j = j_1$ and that $h = h_1$ owns one skill while the remaining workers, including $h = h_2$, $h = h_3$ and $h = h_4$, own two skills. One implication of investigating values of $\lambda^3$ is that even though skill distribution across workstations for the matrix $r^2$ was even, skill distribution for the same matrix across workers and workstations is somewhat uneven.

### 5.5. Numerical experiments

The complexity of a large real-world problem makes it difficult to comprehend the interactions between the acquisition and distribution of skills by workers and quantitative performance criteria. The potential complexity can be seen from the following. If we consider the situation where $M = 3, N = 3, K = 3$, and $T = 30$, there are 57 different skill matrices and about 270 binary variables which explain workforce allocation. If instead, $M = 4, N = 4, K = 4$, and $T = 45$, there are 2306 different configurations for the skill matrix and 720 binary variables which explain workforce allocation. For the situation of $M = 5, N = 5, K = 5$, and $T = 65$, there are 270000 possible types for skill matrix and 1625 binary variables indicating workforce location.

Therefore, firstly, two sets of small-size experiments are used to explore how the appropriate configuration for a multiskilled workforce changes in response to alterations in the production environment and how it consequently leads to a specific performance. Secondly, a real-world case study is presented to provide insights into effective multiskilling of a workforce, in practice. Investigating the case study provides several insights into strategies for managers, in terms of how accumulated skills in a skill pool should be spread across the workforce to achieve optimal
productivity.

Each set of experiments includes $N$ tasks, $M$ workstations which lead to $N \times M$ operations, and $W$ workers. The first set of experiments encompasses $N = 8$ products, $M = 4$ stations, $W = 4$ workers, and with $K = 2, K = 3$ and $K = 4$ WOM, while the second set of experiment includes $N = 8$ products, $M = 5$ stations, $W = 5$ workers, and with $K = 2, K = 3$ and $K = 4$ WOM. The first set of experiments assumes that there is already one single-skilled worker in every workstation capable of performing operations without a cost, meaning that if $h = j$ then $b_{hj} = 0$ and when $h \neq j$ then $b_{hj} \neq 0$. However, in the second set of experiments all of the workers are assumed to be trained to be able to allocated to every workstation. In other words, for every $h \in \Omega$ and $j \in M$, $b_{hj} = 0$. The third set of experiments explores a real-case problem which explored in Chapter 2. This experiment includes $N = 10$ products, $M = 12$ workstations, and $W = 12$ single-skilled workers.

5.6. Numerical results

The results of different numerical experiments are presented in this section. For the first subset, in addition to matrix metrics, the matrix itself is presented to facilitate understanding of how metrics are related to the matrix. However, for the other experiments just the matrix metrics are used to interpret the result.

Table 5-1 investigates skill matrix metrics pertaining to different fixed costs and WOM for the first subset. WOM includes $K = 2, K = 3$, and $K = 4$. Fixed costs encompass the interval of [200, 2000] with steps of 200. Since this numerical experiment is small, the skill matrix is presented in the appendix and referenced in the table. Investigating the values of $\lambda^1$ corresponding to variations in $B^1$ indicates that a skill accumulation of $\lambda^1 = 0.38$ leads to optimal multiskilled staffing in the majority of cases.
Investigating the values of $\lambda^2$ and $\lambda^3$ indicates that, in most cases, matrices with the same $\lambda^1$ share the same degree of skill distribution in terms of $\lambda^2$ and $\lambda^3$.

**Table 5-1.** Alterations in skill matrix metrics in terms of skill acquisition and distribution corresponding to the shift in production fixed cost and different WOM pertaining to the first subset.

<table>
<thead>
<tr>
<th></th>
<th>$\lambda^1$</th>
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<th></th>
<th></th>
<th>$\lambda^2$</th>
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<th></th>
<th>$\lambda^3$</th>
<th></th>
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<td>$K = 3$</td>
<td>$K = 4$</td>
<td>$K = 2$</td>
<td>$K = 3$</td>
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<td>$K = 4$</td>
<td></td>
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<tr>
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<td>0.38</td>
<td>0.38</td>
<td>1</td>
<td>2</td>
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<td>0</td>
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<td>1.5</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td></td>
<td></td>
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<td>2000</td>
<td>0.44</td>
<td>0.56</td>
<td>1</td>
<td>1</td>
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<td>13</td>
<td></td>
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</table>

Under the situation of $K = 2$, since two workers can be trained to be allocated in every workstation $j \in M$ and as a whole there are $M = 4$ workstations and $W = 4$ workers, maximum attainable skill accumulation is $\lambda_{Max}^1 = 0.5$. Similarly, when WOM is changed to $K = 3$ and $K = 4$, maximum attainable skill accumulation can be calculated as $\lambda_{Max}^1 = 0.75$ and $\lambda_{Max}^1 = 1$, respectively. There is a significant jump in skill accumulation when fixed costs changes from $B^3 = 1800$ to $B^3 = 2000$. It is interesting that when $K = 4$, skill accumulation reaches its maximum of $\lambda^1 = 1$. However, under the situation of $K = 2$ and $K = 3$, results show $\lambda^1 = 0.44$ and $\lambda^1 = 0.56$, respectively, which is less than maximum skilled accumulation.

Investigating distribution metrics for circumstances where $B^1 = 1800$ and $B^1 = 2000$ can help to shed light on skill matrix behaviour. For the situation of $B^1 = 2000$ and $K = 4$, $\lambda^2 = \lambda^3 = 0$, which indicates total balance in the skill matrix. This follows $\lambda^1 = 1$ since all of the potential attainable
skills are acquired. Investigating matrix behavior by altering $B^1 = 1800$ to $B^1 = 2000$ under a WOM situation of $K = 4$ reveals no difference in distribution metrics as $\lambda^2 = 1$ and $\lambda^3 = 1$ holds true for both of the situations, even though there is a slight increase in the value of $\lambda^1$. This is justifiable considering that the maximum capacity of every workstation $j \in M$ is $K = 2$, and therefore since extra skills cannot be directed to the bottleneck workstation they will be distributed across preceding workstations which increases the balance of worker and skill distribution.

Exploring matrix behaviour by the shift of $B^1 = 1800$ to $B^1 = 2000$ under a WOM situation of $K = 3$ reveals that as $\lambda^2 = 2$ remains true for both of the situations. As, the maximum number of workers who can be allocated to a given workstation $j \in M$ is $K = 3$ and $\lambda^2 = 2$, three workers should be allocated to a bottleneck workstation while there should be a workstation such as $j \in M$ to which just one worker is allocated. Since, by increase of skill accumulation from $\lambda^1 = 0.38$ to $\lambda^1 = 0.56$, still $\lambda^2 = 2$, there should be non-bottleneck workstations to which no multiskilled worker is allocated.

Fig. 5-2 illustrates the result of comparing the performance of the optimal multiskilling configuration, which is calculated using the model presented in this chapter, with two different multiskilling staffing strategies which are presented as the best multiskilling staffing strategies in the literature, namely chaining and direct capacity balancing (DCB), along with several random multiskilling strategies. In this figure, the X-axis is either relative profit or makespan shown by $P^T_{relative}$ and $M^s_{relative}$, respectively. Profit and makespan are presented in terms of their improvement or decrements in relation to a base case in which there is no multiskilled worker. The Y-axis represents different multiskilling matrix metrics including $\lambda^1$, $\lambda^2$, and $\lambda^3$. 

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Obviously, there is no relative improvement associated with the base case in terms of profit and makespan and therefore the corresponding marker for the base case is always located in the y-axis.

Fig. 5-2-a and b indicate optimal solutions with $\lambda^1 = 0.44$, which correspond to about 50 per cent improvement in the profit and makespan, in comparison with the base case. Chaining and direct capacity balancing show $\lambda^1 = 0.4$, which means having one skill less than the optimal scenario and leading to about 20 per cent improvement in the profit and makespan. This does not mean that increasing the value of $\lambda^1$ necessarily corresponds to better performance; Fig. 5-2-a shows a multiskilling staffing strategy with $\lambda^1 = 0.64$, which lead to a 17 per cent change in the profit performance.

Calculations show that when different skill matrices have the same $\lambda^1$, $\lambda^2$, and $\lambda^3$, but with different configurations, their performance is the same. Table 5-2 presents four different skill matrices which can illustrate this situation. In the current experiment, the model identifies $r^1$ as the optimal multiskilling configuration. Despite $r^2$, $r^3$ and $r^4$ having different configurations, their $\lambda^1, \lambda^2$, and $\lambda^3$ are equal and therefore, they result in the same system performance in terms of makespan and profit. Additionally, the results indicate that the random multiskilling configurations, which have skill matrices that are closer to those producing the optimal skill metrics ($\lambda^1 = 0.44, \lambda^2 = 2$, and $\lambda^3 = 1$) are associated with better performance in terms of makespan and profit.

**Table 5-2.** Comparing configuration of skill matrix corresponding to the optimal multiskilling staffing with skill matrices of multiskilling staffing that share the same metrics in terms of skill acquisition and distribution.

<table>
<thead>
<tr>
<th>Matrix name</th>
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<th>$r^3$</th>
<th>$r^4$</th>
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<td>1 0 0 1 0</td>
<td>1 0 0 1 0</td>
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</tr>
<tr>
<td></td>
<td>0 1 0 1 0</td>
<td>0 1 0 1 0</td>
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<tr>
<td></td>
<td>0 1 0 0 1</td>
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<tr>
<td></td>
<td>1 0 1 0 0</td>
<td>0 1 0 0 1</td>
<td>0 1 0 0 1</td>
<td>0 1 0 1 0</td>
</tr>
</tbody>
</table>
Fig. 5-2. Visualization of relative operational benefits as a function of different multiskilling staffing configurations realized by matrix metrics pertaining to the second subset.
Fig. 5-3. Visualization of relative operational benefits as a function of different multiskilling staffing configurations realized by matrix metrics pertaining to the third subset
Using a real world problem shed lights on how acquisition and distribution of skills can lead to a specific performance in practice. Fig. 5-3 illustrates the operational performance of the system recommended by the mathematical model which is developed in this chapter, in addition to, system performance achieved through using chaining and direct capacity balancing strategies plus ten random multiskilling strategies. In Fig. 5-3-a, c and e, the x-axis is the $P_{\text{relative}}^T$, while in Fig. 5-3-b, d and f, the x-axis is the $M_{\text{relative}}^S$. Different skill metrics of accumulation and distribution are presented along the y-axis.

Fig. 5-3-b indicates that the optimal proposed strategy, one random strategy, direct capacity balancing, and chaining all resulted in significant improvement in the makespan. Fig. 5-3-a illustrates that just the optimal multiskilling strategy resulted in increased profit, while the random strategy, direct capacity balancing, and chaining all led to loss of capital. Considering that profit is a function of revenue, fixed cost and multiskilling costs, and assuming that revenue and fixed costs remain almost the same for each scenario, the reason for loss of capital for those multiskilling strategies can be attributed to high multiskilling costs. This means that there are a number of workers who are cross-trained but their extra skills are not used. Interestingly, all of the multiskilling staffing strategies, except the optimal one, result in loss of capital. Increasing the value of $\lambda^1$ for random multiskilling staffing strategies is negatively related to $P^T$. This provides a warning about the potentially significant financial consequences of subjective staffing strategies such as ensuring that staff acquire extra skills, in the mistaken belief that extra skill accumulation will necessarily lead to higher profit.

Fig. 5-3-d indicates that the optimal multiskilling configuration has the skill distribution character of $\lambda^2 = 2$. When $\lambda^2 = 2$ for a given multiskilling strategy, it can lead to improvement of makespan but there is no guarantee of it since there are multiskilling strategies with $\lambda^2 = 2$ which perform the same as the base case in relation to improvements in makespan. Note that
direct capacity balancing and chaining strategies have $\lambda^2 = 2$ and $\lambda^2 = 0.2$, respectively, and both lead to similar improvements in makespan. However, chaining leads to high cost. This shows the importance of an appropriate labor allocation to bottleneck workstations and avoiding allocation to non-bottleneck workstations. Fig. 5-3 reveals that the optimal staffing strategy, direct capacity balancing and one of the random strategies have almost the same $\lambda^1$ and exactly the same $\lambda^2$. However, their $\lambda^3$ values are considerably different. This indicates the importance of considering $\lambda^3$. While different values of $\lambda^3$ do not lead to significant change in the makespan, they crucially affect total profit.

5.7. Summary

The review of the multiskilling literature exposed the need for an appropriate way to optimize multiskilled crew staffing. The conventional method for choosing a multiskilling structure for a system is based upon comparative studies, meaning that different existing multiskilling strategies are investigated through a scheduling platform and the strategy which corresponds to the highest enhancement in performance measures is selected as the best option. However, the optimal multiskilling staffing strategy for a system could potentially be much more complex and significantly different from the existing simple multiskilling structures commonly used. In this regard, a mathematical programming approach is developed to provide an optimal multiskilling staffing strategy which is mathematically represented in the form of a matrix.

Since comparing and investigating different matrices, especially large-size matrices, is complicated, three different measures are presented which can represent a matrix corresponding to every multiskilling staffing strategy. The first measure deals with the extent to which skills are gained by an existing workforce in relation to all of the skills which can be obtained from the skill pool. The second metric investigates the extent to which skill acquisition is concentrated at a specific workstation with the highest number of workers in comparison with
another given workstation with the lowest number of workers who are skilled to contribute to the operations of that workstation. The third measure evaluates the extent to which the distribution of skills is balanced across workstations and workers.

The experiments demonstrate that the multiskilling strategies which share the same matrix metrics as the optimal multiskilling strategy, have the same performance in terms of contribution to makespan and enhancement of profit. This is an important finding indicating that there can be a number of different multiskilling staffing strategies which are optimal strategies. Production management teams can explore existing optimal staffing strategies and choose the one which is easier to implement, given their available resources and production circumstances.

Part of this investigation explores how the optimal multiskilling strategy changes with alterations in the production circumstances. More specifically, it indicates how much skill should be obtained from the skill pool and how it should be distributed across workers and workstations to meet a specific objective. Alterations in the capacity of workstations in terms of the number of people who can be engaged to contribute to the operations of that workstation has a significant effect on how acquired skills should be distributed. When the capacity of a bottleneck workstation is higher, skill acquisition is lower in comparison with lower capacity bottleneck workstation. Lower workstation capacity forces the model to obtain skills from the other workstations preceding the bottleneck workstation to facilitate production flow. The results indicate that workers are multiskilled in a maximum two workstations before the bottleneck workstation to compensate lack of capacity in the bottleneck workstation. An implication of this result is that in some cases, investments in a workstation to allow more workers to collaborate with each other can lead to cost savings.

The findings of this investigation indicate, as Hopp and Oyen (2004) suggested, that
multiskilling of a workforce is a highly context-specific issue. In other words, a small manipulation in a given level of a bottleneck situation or any other attributes of production such as fixed cost or revenue can lead to significantly different optimal multiskilling structure. Cross-training costs encompassing training costs and enhancement in salary are the main barriers to multiskilling a workforce, while on the other hand, fixed costs are the main motivation for multiskilling a crew. Fixed costs can include motivation of receiving cash flow sooner or cutting operational costs such as electricity. Therefore, the developed model makes a compromise between different cost elements and presents a unique optimal multiskilling staffing strategy considering the context.

Several experiments confirm that enhancing skill acquisition without paying attention to an optimal multiskilling structure and multiskilling collateral effects could have crucial destructive effects. The results confirm that even when a very large amount of capital is invested to multiskill a considerable number in a workforce, if the distribution of skills across workstations and workers is not appropriate, it not only results in capital loss but also possibly in no contribution to makespan reduction, in comparison with a no multiskilling strategy.

Experiments in this investigation explore how the optimal strategy differs from existing well-known strategies such as chaining and direct capacity balancing. The findings indicate that even though well-known strategies have a very similar performance to the optimal strategy in terms of improving the makespan, they are associated with high costs. These high costs can be potentially significant and outweigh the benefits arising from a lower makespan and result in loss. This matter is an important finding indicating the potential destructive consequence of making subjective decisions about the multiskilling of a workforce.
Chapter 6

6. Thesis Restatement and Conclusions

This thesis investigated the concept and application of multiskilling in the construction industry by different operational research methods. The objectives for this research are three-fold: i) To present a multiskilling framework which facilitates understanding of the cross-training concept and its application under different situations; ii) To present a scheduling strategy to facilitate appropriate allocation of human resources for different operations, to achieve a specific aim of production; and iii) To present a multiskilling staffing strategy to choose appropriate labor with an appropriate skill set. Different chapters of this study explored these research objectives.

6.1. Multiskilling framework

In Chapter 2, a comprehensive literature review is conducted investigating how different studies evaluated the conception and application of a multiskilling approach. To facilitate comprehension of the multiskilling concept, a multiskilling framework is developed, which classifies multiskilling into four different categories: context, strategy, collateral effects, and mainstream research. The cross-training context deals with the environment in which multiskilled labor is trained or recruited and examines cross-training feasibility and configurations under different environments. The multiskilling context encompasses off-site prefabrication, on-site construction, and repetitive construction projects. Decision-making regarding multiskilling strategies addresses which workers should be cross-trained for how many and for what tasks. Three different main multiskilling strategies are recognized along with several ramifications. Investigation of cross-training collateral effects mainly includes the extent to which these effects occur under a specific context and strategy. Multiskilling mainstream research identifies cross-training financial and non-financial advantages. Then it
evaluates how different methodologies are used to evaluate benefits of multiskilling pertaining to collateral effects, context, and strategy.

Investigating the relationship of different components of multiskilling framework can be insightful for practitioners and academics. It can reveal whether a specific advantage is achievable in a specific context or not. For example, full crosstraining of workforce is not achievable in on-site projects however it is an effective strategy in repetitive construction projects with small number of tasks. Exploring interaction of different elements of multiskilling framework, can also help the practitioners regarding the trade-off between crosstraining collateral effects and its advantages. For instance, four-skills-helpers and dual-skilling cross-training strategies are not associated with high transfer costs, therefore, they can be highly recommended in a project in which the distance between workstations are considerable.

6.2. Multiskilling scheduling strategy

Since reviewing the existing body of knowledge exposed the need for developing a multiskilling scheduling framework to address the objectives of production in terms of throughput, productivity or every other measurable measure, the matter of developing a scheduling framework is addressed in Chapter 3. Production in the off-site construction environment is modeled, based upon a flow-shop framework. The inputs of the optimization platform are multiskilling configuration and cost. Multiskilling configurations which are investigated in this chapter include: no cross-training, hiring single-skilled crew, direct capacity balancing, chaining, and hiring multi-skilled crew. Information about the labor cost is obtained from pay scale websites and interviewing site managers. The multiskilling context, which is prefabricated construction, is embedded in the formulations of flow-shop. The output of the model presents how different workers should be allocated or reallocated to different places
during the production makespan, to meet the planning objective. Consequently, the production makespan and associated labor cost are revealed. The limitation of this scheduling approach is incorporating just one objective (production makespan) and one collateral effect (labor cost). One important contribution of this scheduling platform is paving the way for comparative studies.

This scheduling platform explores labor allocation and reallocation pertaining to different multiskilling configurations associated with three different production scenarios. The difference between different production scenarios arises from variability in the duration of operations in different workstations leading to bottlenecks of different magnitude. In considering bottleneck magnitude, different variability scenarios are named as no variability, medium variability and high variability. The results of resource allocation in terms of labor costs and makespan are investigated under four different circumstances: (1) the performance of multiskilling strategy in each variability case; (2) the performance of every multiskilling strategy on all variability cases collectively; (3) a combination of cost-time consequences of applying a cross-training strategy with different weightings for time and cost; and (4) the effects of different bottleneck locations on cross-training strategy performance.

The contribution of this scheduling platform to comparative studies is in presenting a method to advise on the most suitable of the existing multiskilling strategies in relation to each makespan and cost, with consideration of the extent to which variability exists in the production flow. The results of implementing this scheduling platform obviously declares that under different variability scenarios with the same objective, different multiskilling strategies can be associated with an optimal scheduling output such as makespan. For example, the results revealed that chaining can be the best strategy in the medium variability environment when the objective of production is minimization of cost and time. By contrast, direct capacity balancing can be the best multiskilling strategy for the same objective in a no variability environment.
The other contribution of this scheduling platform is that it indicates that with all of the variability scenarios possible in an off-site production environment, hiring a multiskilled crew leads to an optimal schedule associated with the lowest makespan; however, it is an expensive strategy. On the other hand, with the same variability scenarios, scheduling of a multi-skilled workforce under chaining can lead to a second-best makespan, but with considerably lower cost in comparison with hiring a multiskilled crew. Again, if the variability in production flow is not predetermined, hiring a single-skilled crew and chaining should be avoided as they can lead to significantly different results in terms of makespan and cost under different variability scenarios.

The most important implication of this section is that uncertainty regarding the bottlenecks variability can significantly outweigh benefits of a given multiskilling configuration. Another important implication is that in case there is a possibility for non-bottleneck workstations to turn into bottleneck workstations, chaining has a significant advantage over other multiskilling strategies which are investigated in the same chapter. This is because chaining does not focus in any specific task area along the production line. Since, multiskilling strategies such as direct capacity balancing or hiring multi-skilled crew losing advantage significantly when there is a small increase in the number of bottleneck workstations, it makes sense to design them based upon maximum potential number of bottleneck workstations. The trade-off between training costs and hiring cost could be significantly important as well. Obviously, high training costs discourage multiskilling and motivate managers for hiring short-term labor. In case hiring short-term labor is not possible because of union regulations, for example, investment in enhancing skills of workforce would be the only resort to deal with underutilization deficiencies.
6.3. Multiskilling staffing strategy

In the Chapter 3 a scheduling platform, originating from optimization-based approaches, is developed for multiskilled labor allocation and reallocation. Plus, it is shown how a scheduling platform can be used for comparative studies to select the best existing cross-training strategy. Despite optimization-based research allocating a precise value to an outcome, it is unable to incorporate qualitative criteria. The literature review showed that there is a wide range of quantitative criteria which should be considered in multiskilling modelling. There is no specific method for quantifying these qualitative criteria in the literature and quantification of them with existing methods is expensive and complicated. Chapter 4 of this thesis attempts to incorporate all existing qualitative and quantitative criteria to propose the best alternative strategy, by using a multi-criteria decision-making approach. The PROMETHEE method is recognized as an appropriate multi-criteria decision-making technique which is applicable in this chapter. The inputs for the PROMETHEE method are gathered by using an optimization-based platform and Delphi approach for quantitative and qualitative criteria, respectively.

Alternative strategies which are investigated in this chapter of the thesis encompass: no cross-training, chaining, upstream cross-training, downstream cross-training, direct capacity balancing, hiring dual-skilled crew, hiring four-skills helpers crew, and hiring four-skills labor. These alternatives are outranked based upon criteria retrieved from the literature, including: multiskilling cost, multiskilling time and social sustainability. The latter includes safety and employability. Multiskilling cost encompass transfer costs, training costs, enhancement in salary, retention costs and non-monetary costs including psychological effects, learning and forgetting effects and reduced efficiency.

The results of this investigation indicate that the factors that significantly influence the preferability of a cross-training strategy are different, depending upon whether the multiskilled workforce is trained or hired. If trained, the preferability of a given cross-training strategy is
determined, to a high extent, by the number of workers who are cross-trained and is only marginally influenced by the tasks in which the multiskilled crew are cross-trained. When cross-trained crew are hired, the preferability of a multiskilling strategy is mainly influenced by the number of hired crews and only slightly affected by their skill set.

Another finding of this investigation is that it illustrates similar, conflicting and independent criteria. The most similar criteria are identified as non-monetary costs and training costs. The second highest similarity in criteria is shown in retention costs and salary. Four independent criteria are identified as: salary, makespan, training costs, and retention costs. The highest degree of conflict is observed in the two criteria of makespan and salary. The next highest degree of conflict between criteria is identified in retention costs and sustainability.

The existence of several similar, conflicting and independent criteria complicates decision-making process, which can lead to incomparability of alternative strategies. However, this can be informative by providing insights into complex decision areas and into why they are so intricate. In the case study which is investigated in this chapter of the thesis, chaining, hiring one-skillHelpers, hiring two-skills-helpers and hiring three-skills-helpers are identified as the best multiskilling alternatives based on existing criteria; however, they remain incomparable in relation to partial PROMETHEE outranking.

Sensitivity analysis illustrates the point that with alterations in the weight allocation, any of the best incomparable multiskilling strategies can have an advantage over the others. However, in every different weight allocation scenario there is no other cross-training strategy which can outrank those four strategies. This is an important finding showing how different scenarios can give rise to the best multiskilling strategy, but the number of most effective strategies is limited.

Additionally, sensitivity analysis was used to investigate the extent to which a given cross-training strategy is sensitive to the weight allocation of different criteria. A high sensitivity to
non-monetary costs, training costs, and sustainability is observed in chaining. Different subcategories of the hiring four-skills -helpers strategy are highly sensitive to weight alterations of salary, retention costs, and makespan. Other cross-training configurations do not show significant sensitivity to changes in the weight of different criteria.

Using comparative studies is the conventional method of choosing a multiskilling strategy. Chapter 5 of this study identifies that such comparative studies are an appropriate, however insufficient, method for choosing a multiskilling strategy. In comparative studies different existing multiskilling strategies are investigated in relation to their performance, based mainly on a scheduling platform. The output of this scheduling platform reveals the performance of different strategies and the strategy with the highest performance measure is considered as the best strategy. In the literature, this comparative method is criticized using the argument that finding an optimal multiskilling strategy for a system can be much more complex and needs to be significantly different. Using a comparative study can produce a strategy which is not optimal and can lead to crucial differences in system performance. To address this gap an optimization-based technique is used to develop a new optimal multiskilling staffing strategy.

The optimal multiskilling strategy as the output of the model is presented in the form of a binary matrix. Optimal multiskilling matrices pertaining to real-world problems are usually large-sized, making comparison and investigation intricate. To solve this problem, three different measures are formulated which can illustrate features of the binary matrices and their corresponding multiskilling strategy in terms of skill acquisition and distribution. The first measure evaluates skill acquisition defined as the extent to which skills are gained by an existing human resource in relation to the whole of existing acquirable skills. The second metric deals with skill distribution across different workstations. It simply compares the workstation with the highest number of workers who are multiskilled to work in it, with the workstation with the lowest number of workers who are multiskilled to work in it. The last metric
investigates the extent to which skill distribution is balanced along with workstations and workers.

The experiments demonstrate that when different multiskilling strategies which are manifested in the form of a binary matrix share the same skill metrics, they have the same performance. Additionally, investigating the skill measures pertaining to the optimal skill matrix and comparing them with other matrices with the same skill measures illustrates they have the same performance. This is an important finding indicating that there can be few different optimal multiskilling matrices in the same context. Production management teams can explore existing optimal staffing strategies and choose the one which is easier to implement, given their available resources and production circumstances.

Defining the capacity of a workstation as the number of workers who can be allocated to that workstation, has a significant effect on skill acquisition and distribution. In some cases, when the capacity of bottleneck workstation is lower than what is needed the model suggests allocating multiskilled labor to the non-bottleneck workstations preceding the bottleneck workstation. Although this does not have a direct effect on the bottleneck, it facilitates the flow helping to decrease idle time. The results of experiments illustrate that in the current case study, a maximum of two workstations before the bottleneck workstation can absorb extra skills to compensate for a lack in bottleneck capacity. An important implication of this matter is that in some cases, investments to enhance the capacity of workstation can be more profitable in comparison with investment in extra skill acquisition.

The presented model in this investigation advises on the optimal multiskilling strategy by making a compromise between cross-training collateral effects and benefits. In this chapter, collateral effects considered are cross-training costs and enhancement in salary, while cross-training benefit is considered as minimizing fixed costs. Several experiments confirm that
making subjective or random decisions about skill acquisition and distribution, without considering their collateral effects, can be associated with crucial destructive consequences.

Few experiments in the existing literature expose the point that a considerable amount of investment in workforce multiskilling, without considering appropriate skill acquisition and distribution, can result in no monetary benefit or even capital loss.

Experiments in this chapter explore how the optimal strategy differs from existing well-known strategies such as chaining and direct capacity balancing. The findings indicate that even though well-known strategies have a very similar performance to the optimal strategy in terms of improving the makespan, they are associated with high costs. These high costs can be potentially significant and outweigh the benefits arising from a lower makespan and result in loss. This matter is an important finding, indicating the potential destructive consequence of making subjective decisions about the multiskilling of a workforce.

To sum up, an optimization-based approach which includes staffing strategy as the output of the mathematical model is the most precise method to propose a multiskilling staffing strategy. Optimization-based approaches cannot incorporate qualitative factors, therefore, if investigating qualitative criteria is of crucial importance comparative techniques can be substituted by the optimization technique. It should be noted that there can be a significant difference between the multiskilling strategy proposed by a comparative and an optimization approach. An implication of this matter can be to develop methods for translating qualitative criteria into quantitative measures. Proposed framework in Chapter 2 of this study can be an appropriate starting point for this investigation.

6.4. Recommendations for Future Research

First, the time which is needed for an operation to be done by one or a group of single-skilled workers is predictable for practitioners and academics. However, determination of the duration
of different construction processes conducted by a group of workers is a function of crew skill set and skill level and is an area which has not been considered so far. Considering that the preciseness of every model is dependent upon the preciseness of its parameters, developing a scientific approach for value allocation to the duration of operations as a function of combination of crew skill set and level would be an innovative and interesting area of research.

Second, considering that the aim of all research in the academy is to facilitate a solution to a problem in practice, developing programming code for the existing model, which can be converted to software to be used by practitioners in the construction industry, would be valuable. The importance of such software is twofold. First, the developed model can be used by practitioners and its shortcomings would be exposed in the real situation, which in turn can be used to understand the complexities of real-world situations and lead to opportunities for developing the existing model. Secondly, since solving problems of this nature using optimization leads to a wide range of outputs, investigating them by the researcher and illustrating the research outputs to others are difficult. However, by developing a scientific code which can be visualized, the researcher’s task would be simplified and sharing the research output with others would be feasible.

Third, an interesting future research area would be to investigate upskilling of a workforce along with multiskilling of a crew. Even though, the literature of multiskilling is expanding and there is an incremental increase in the literature of upskilling, yet investigating these two innovative labor management strategies as a new mixed strategy has attracted negligible attention. The main reason behind using a multiskilled workforce is to manage heterogeneity inside the production line. The main motivation for using an upskilled crew is enhancement in digitalization and automation in the production environment. Since, both heterogeneity and digitalization are increasingly part of the off-site construction sector, there is a crucial need to explore labor strategies relating to both multiskilling and multiskilling of a crew.
7. References


Appendices

Appendix 1

The following procedure explains how two quadratic constraints of (2-10) and (2-11) are linearized.

The product of two binary variables of $x_i$ and $y_i$ can be linearized by introducing a new binary variable of $z_i$, and adding the following constraints:

\[
\begin{align*}
x_i y_i &= z_i \quad (A.1) \\
x_i & \geq z_i \quad (A.2) \\
y_i & \geq z_i \quad (A.3) \\
x_i + y_i - 1 & \leq z_i \quad (A.4)
\end{align*}
\]

Therefore, nonlinearity, which is exposed as a result of the product of two binary variables of $\theta_{nmkt}$ and $a_{wmt}$ in constraints (2-10) and (2-11) can be linearized with the same method with some modifications in variable indices as follows.

\[
\begin{align*}
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} \theta_{nmkt} + a_{wmt} &= \lambda_{nmwkt}^{1} \quad n \in N, m \in M \\
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} \theta_{nmkt} & \geq \lambda_{nmwkt}^{1} \quad n \in N, m \in M \\
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} a_{wmt} & \geq \lambda_{nmwkt}^{1} \quad n \in N, m \in M \\
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} \theta_{nmkt} + a_{wmt} - \lambda_{nmwkt}^{1} & \leq 1 \quad n \in N, m \in M
\end{align*}
\]

Nonlinearity, which is exposed as a result of the product of two binary variables of $\theta_{nmkt}$ and $a_{wmt}$ in constraint (2-11) can be linearized as follows.
\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{W} \theta_{nmkt} a_{wml} = \lambda_{nmwkl}^2 \quad n \in N, m \in M \quad (A.9)
\]

\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{W} \theta_{nmkt} \geq \lambda_{nmwkl}^2 \quad n \in N, m \in M \quad (A.10)
\]

\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{W} a_{wml} \geq \lambda_{nmwkl}^2 \quad n \in N, m \in M \quad (A.11)
\]

\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{W} \theta_{nmkt} + a_{wml} - \lambda_{nmwkl}^2 \quad n \in N, m \in M \quad (A.12)
\]
\[\leq 1\]

Consequently, constraint (2-10) and (2-11) in a linearized form can be written as expression (A.13), and (A.14), respectively.

\[
\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{w=1}^{W} \lambda_{nmwkt}^1 = \sum_{k=1}^{K} \sum_{t=1}^{T} k \theta_{nmkt} \quad n \in N, m \in M \quad (A.13)
\]

\[
\sum_{k=1}^{K} \sum_{t=d_{nmk}}^{T} \sum_{l=t-d_{nmk}+1}^{W} \lambda_{nmwkl}^2 = \sum_{k=1}^{K} \sum_{t=1}^{T} \lambda_{nmwkt}^1 d_{nmk} \quad n \in N, m \in M, \quad w \in \Omega \quad (A.14)
\]
Appendix 2

Table A1: Skill matrix configuration and corresponding skill matrix metrics illustrating optimal multiskilling staffing configuration under different scenarios of fixed cost and WOM pertaining to the first subset.

<table>
<thead>
<tr>
<th>N</th>
<th>Matrix</th>
<th>$\lambda^1$</th>
<th>$\lambda^2$</th>
<th>$\lambda^3$</th>
<th>N</th>
<th>Matrix</th>
<th>$\lambda^1$</th>
<th>$\lambda^2$</th>
<th>$\lambda^3$</th>
</tr>
</thead>
</table>
| 1  | \[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{pmatrix}
\] $\frac{4}{16}$ | 0 | 0 | 5 | \[
\begin{pmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
0 & 0 & 1 & 1 \\
\end{pmatrix}
\] $\frac{7}{16}$ | 1 | 0 |
| 2  | \[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
\end{pmatrix}
\] $\frac{5}{16}$ | 1 | 1 | 6 | \[
\begin{pmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 1 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
\end{pmatrix}
\] $\frac{9}{16}$ | 2 | 1.17 |
| 3  | \[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
\end{pmatrix}
\] $\frac{6}{16}$ | 2 | . | 7 | \[
\begin{pmatrix}
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
\end{pmatrix}
\] | 1 | 0 | 0 |
| 4  | \[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
\end{pmatrix}
\] $\frac{6}{16}$ | 1 | 0 |