Workforce planning for SMEs under stochastic labour turnover

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Abstract

Workforce planning for SMEs under stochastic labour turnover

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In today's rapidly changing manufacturing industry, even minor uncertainties can cause significant disruptions for small and medium-sized enterprises (SMEs). Although previous studies on operational supply chain networks have focused primarily on addressing uncertainties related to demand fluctuations, machine breakdowns, and unpredictable events such as natural disasters and geopolitical disruptions, this paper specifically addresses workforce uncertainty due to stochastic turnover rates. As an extension of the multistage workforce capacity planning problem with turnover proposed by Song and Huang (2008), this study builds on their workforce planning network, which incorporates decisions around transferring, hiring, and firing, by introducing a proficiency ranking system. This system classifies the workforce into three proficiency levels, each with a specific production rate according to the worker's status. Integrating this proficiency ranking system into the planning network allows a more comprehensive evaluation of workforce capabilities to meet the required demand. Results from numerical experiments demonstrate that the modified model offers an optimized workforce planning solution, balancing cost and time effectively, to help SMEs achieve their demand targets under conditions of uncertain workforce turnover.

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Chapter 1

Introduction

The manufacturing industry in China is currently experiencing significant and rapid transformations, driven by a variety of external factors. Beginning with the disruptions caused by the COVID-19 pandemic, the industry continues to face challenges in the post-pandemic era, including slack global demand, uncertainty in labour availability, and energy shortages exacerbated by natural events such as extreme heatwaves and droughts. These factors have placed unprecedented pressure on the industry, leading to the closure of more than 460,000 small and medium-sized enterprises (SMEs) in China during the first quarter of 2022 alone. This situation highlights the fragile state of the manufacturing landscape, where environmental and economic disruptions create profound challenges to the continuity and viability of business operations.

Uncertainty plays a pivotal role in supply chain management, with far-reaching impacts not only on day-to-day operations but also on the broader industrial framework. From a practical perspective, even minor uncertainties can significantly influence the outcomes predicted by deterministic models, making previously feasible solutions impractical or far more costly than anticipated(Techawiboonwong & Yenradee, 2004). The impact of uncertainty manifests not only immediate but also long-term effects ranging from direct impacts, such as unexpected energy supply disruptions, to indirect ones, such as ripple effects that propagate through the supply chain. For instance, a sudden energy shortage in the upstream supply chain can cause cascading disruptions throughout the network. Similarly, market demand fluctuations can give rise to the bullwhip effect, where small changes in demand are amplified as they move up the supply chain.

Some previous studies have also examined the nature of stochastic fluctuations in demand, with many categorizing them as part of broader business cycles or shifts in market share (Oliva, 1996;G & Anderson, 2001). However, macroeconomic studies suggest that these fluctuations may not follow a regular, periodic pattern but rather reflect a non-stationary stochastic process. This distinction is important for accurately modelling and managing demand uncertainty, as the assumption of cyclical behaviour may not adequately capture the true variability present in market demand.

Numerous studies have sought to address the challenges posed by uncertainties in the supply chain. For example, Liu, Zhao, Huang, and Zhao (2015) developed a two-stage non-linear programming model aimed at creating a production line capacity plan to cope with the uncertain demand in manufacturing systems that handle multiple products. This model is particularly relevant for industries that must balance fluctuating demand with the complexities of multi-product production. Similarly, Sereshti, Adulyasak, and Jans (2020) explored a stochastic lot-sizing problem, utilizing aggregate service levels to determine optimal time-dependent lot sizes and buffer stock levels in scenarios characterized by multi-item demand uncertainty. These approaches reflect the growing need for flexible and robust decision-making frameworks capable of handling unpredictable conditions. Alvarez, Cordeau, Jans, Munari, and Morabito (2020) tackled a different aspect of uncertainty in their study of a stochastic inventory routing problem. Their work addresses situations where both product supply and customer demand are uncertain, proposing a two-stage stochastic programming model to determine optimal routing decisions, delivery quantities, inventory levels, and contingency actions. This comprehensive approach underscores the complexity of managing uncertainty at multiple levels of the supply chain.

In prior research on supply chain networks, uncertainty has been categorized into three primary domains: supply uncertainty in the upstream, operational uncertainty in production, and demand uncertainty in the downstream (Tsan Ming Choi, 2011). While earlier studies primarily focused on supply and demand uncertainties, operational uncertainties have received comparatively less attention. This is despite the fact that production uncertainty, often tied to factors such as random machine breakdowns, operational disruptions due to natural disasters, or geopolitical instability, can have significant effects on supply chain performance. The literature has generally concentrated on strategies to mitigate the impacts of supply and demand fluctuations, with relatively fewer studies addressing the challenges posed by daily operational uncertainties.

The uncertainty in production, particularly on a day-to-day basis, remains a critical but underexplored area. While much of the prior literature has focused on addressing the effects of uncertainty in the upstream supply chain and downstream demand, production-related uncertainties, particularly those occurring on a daily operational level, have remained relatively under-represented in academic discourse. Most studies on production and operational uncertainties tend to focus on significant disruptions, such as machine failures or supply chain interruptions caused by external events, rather than the smaller-scale, daily uncertainties that also impact production efficiency. Much of the existing research has examined the effects of demand uncertainty, such as the bullwhip effect, or disruptions in production processes caused by rare and unpredictable events. However, these studies often overlook the operational uncertainties that arise from routine disruptions in the manufacturing environment, such as workforce availability, equipment reliability, or minor variations in production efficiency. Such daily uncertainties, though less dramatic than large-scale disruptions, can accumulate over time and significantly impact the efficiency and cost-effectiveness of manufacturing operations.

This paper aims to address this gap by focusing on the operational uncertainties that impact manufacturing on a daily basis. By addressing these often overlooked but highly impactful factors, this study seeks to provide solutions to how manufacturers can better manage routine disruptions and maintain smooth operations in a rapidly changing environment. Understanding and mitigating these operational challenges is critical for improving the resilience and adaptability of manufacturing systems, especially in an environment where disruptions are becoming increasingly frequent and severe.

The remainder of this manuscript is organized as follows. We first review the recently published literature closely related to the topic of this thesis in the literature review section. The network structure of the problem with the detailed context is presented in section 3. Section 4, focuses on the mathematical formulation of the problem. Finally, the numerical study and analysis is presented in section 5. Finally, we conclude the research of this paper and indicate some possible future research directions in Section 6.

Chapter 2

Literature Review

In labour-intensive manufacturing environments, the production capacity can be considered in terms of workforce (M.Fazil Pac & Tan, 2009). The uncertainty in the workforce directly influences the supplier's performance. Unlike disruptions and risks caused by unpredictable events, such as natural disasters, workforce capacity is more predictable and manageable. Human resource planning becomes more critical for manufacturing enterprises to survive the fluctuating nature and remain competitive in the market. An agile and robust workforce planning strategy facilitates the company to accomplish the demanded service level while reducing waste in terms of human resources and minimizing the expected cost.

The primary concern for smaller firms is how to achieve a balanced workforce by ensuring an appropriate mix of recruitment, training, and retirement policies (Khoong, 1996). While matching capacity to demand at every moment with hire-up-to/ fire-down-to structure will be considered as the ideal solution intuitively (Hyun-Soo Ahn & Shanthikumar, 2005), changing workforce capacity dynamically is too expensive and hardly realistic. In addition, employee morale also suffers if the job is quickly resigned (G & Anderson, 2001). Previous studies suggested a positive relationship between small firm labour productivity and the application of integrated high-performance work systems (HPWS) practice, including selective hiring, extensive training, employee involvement, and teamwork (Ning Wu & Llusar, 2015).

When there is a shortage of workforce capacity between work groups, a cross-trained workforce is one of the frequently applied methods to counteract the effect caused by uncertainty in demand and manpower capacity. As allowing workforce shifts from one type to another, same or even more throughput can be provided while using fewer workers (Edieal J. Pinker, 2000). A cross-trained workforce helps fulfil the uncertain demand and improve service levels, resulting in greater productivity and/or increased robustness (Easton, 2014). Cross-training methods also mitigate the negative effect of uncertain manpower capacity due to unplanned absences(Robert R Inman 1, 2005). The most common objective of cross-trained workforce allocation is to minimize capacity shortage(Easton, 2014). Hence, in our study, there are no constraints on the upper bound of cross-trained workforce that can be transferred to another department as it provides flexibility in solving workforce shortages.

As classified in Pac, All, and Tan's (2009) study, the workforce that labour-intensive manufacturing enterprises comprise can be classified into two main categories. Permanent and contingent capacity. Permanent capacity refers to a company's own regular workforce, and contingent capacity refers to a workforce that can be acquired temporarily from an external workforce pool, for instance, contractors and temporary workers. Where a 30-day notice of resignation is required for permanent employees who resigned, contingent employees can resign from the position with less than 3-day resignation notice or even quit the job immediately without any notice. Due to the nature of the differences between the types of workforce, it is conceivable that the turnover rate of each workforce varies. With the higher percentage of contractors and temporary workers occupying the workforce capacity, the fluctuating turnover rate results in a volatile workforce. Even though involving a high percentage of contingent capacity results in an unstable or stochastic nature of the workforce capacity, contingent capacity is still a tempting method to most small and medium-sized manufacturing enterprises as the cost of recruiting temporary employees is considered more cost-friendly.

In previous research, the approach used to cope with workforce uncertainty can be categorized into three main streams: the workforce assignment problem using existing labour, labour training to achieve a heterogeneously skilled workforce, and recruitment planning to achieve an optimal workforce under uncertainty.

If highly skilled employees are not fully utilized, they can be a drain on resources(M.Fazil Pac & Tan, 2009). Liu, Liu, and Yang (2019) investigated a workforce assignment problem on the assembly line under uncertain demand to minimize the number of employed workers. Steenweg, Schacht, and Werners (2021) evaluated shift scheduling patterns of heterogeneously skilled labour regarding short-term uncertain workforce availability. Easton (2014) proposed a two-stage stochastic program to make decisions regarding cross-trained workforce scheduling and allocations under uncertain labour attendance and demand. Altendorfer, Schober, Karder, and Beham's (2021) research result shows that cross-trained workers can improve the service level significantly even under workforce uncertainty due to stochastic worker absence. Cavagnini, Hewitt and Maggioni (2020) considered uncertain labour learning rates during cross training and practising and making workforce production, inventory, and outsourcing quantity decisions by solving a two-stage stochastic problem. Jaillet, Loke, and Sim (2022) proposed a strategic workforce planning involving hiring, dismissing, and promoting decisions to achieve the required productivity level with uncertain human resource attrition. Malaki, Izady and Menezes (2023) introduced a framework to make optimal recruitment decisions on a combination of permanent and temporary healthcare workers to cope with the highly uncertain demand period in the healthcare sectors.

Song and Huang (2008) categorized the two essential tasks for human resource management as identifying the workforce plan required for the business and future development and determining a workforce plan based on present workforce capacity to match the future requirements. Their study focused on the second task and identified a workforce capacity development plan that involved transferring, hiring, and firing labourers. Techawiboonwong and Yenradee (2004) developed an aggregate production planning tool with a workforce transferring plan for manufacturing companies producing multiple product types, in which workers' resources can be transferred among the production lines to reduce cost.

The most popular modelling technique for solving manpower planning problems is certainly linear programming (Martel & Price, 1981). By including constraints such as upper and lower bounds of the numbers hired, budgetary limitations, and the desired number of manpower, the decision variable, which is the relationship between manpower stock and flows, including transfers, promotions, hiring, and releases, can be determined.

Alvarez et al.(2020) present a sophisticated two-stage stochastic programming model designed to address the complexities inherent in the inventory routing problem (IRP). The first stage focuses on managing lost sales and backlogging by incorporating these risks directly into the decision-making process. The second stage introduces a capacity reservation contract aimed at mitigating uncertainties in both product supply and customer demand. This innovative approach allows for more robust decision-making under uncertain conditions. In order to solve this complex formulation effectively, the authors introduce a progressive hedging-based heuristic algorithm. This algorithm not only offers a practical solution with reasonable computation times but is particularly suited for scenarios with large data sets, thus enhancing its applicability in real-world logistics and supply chain management.

The study conducted by Andrew, Stephen, and Geoffrey(2005) delves into the crisis of labour skills within the construction industry, focusing specifically on the challenges faced by small- and medium-sized enterprises (SMEs). The research identifies several critical factors contributing to the skills shortage, most notably the rise of self-employment, which has fundamentally reshaped the labour market. Additional factors include the changing quality of available skills, the rapid introduction of new technologies that are altering skill requirements, and sector-specific recruitment challenges. These challenges are often exacerbated by the public perception of construction jobs, which negatively impacts recruitment efforts. The authors also note the importance of labour market regulations that, while maintaining industry standards, encourage training and development initiatives. However, smaller firms, constrained by limited financial and human resources, are frequently forced to hire under-trained or less experienced workers, further aggravating the skills gap in the sector.

Wu, Hoque, Bacon, and Llusar's research (2015) offers valuable insights into the relationship between high-performance work systems (HPWS) and organizational productivity in small firms. Their findings suggest that HPWS, which include comprehensive practices such as selective hiring, continuous training, and performance-based compensation, are positively associated with labour productivity. However, the study also reveals a notable discrepancy: while these practices enhance operational efficiency and workforce output, they do not translate directly into improved financial performance. This highlights a potential misalignment between productivity-focused HR strategies and profitability goals in smaller organizations, emphasizing the need for a more holistic approach to workforce management in order to drive both productivity and financial success.

Pac, Alp, and Tan's (2009) examination of integrated capacity and inventory management under uncertain demand and capacity offers an insightful exploration of the relationship between production capacity and workforce management. Capacity, defined as the maximum potential output of a manufacturing system, is closely intertwined with the availability and capability of the workforce, especially in labour-intensive environments. The authors suggest that leveraging a flexible workforce offers a strategic advantage, enabling organizations to adapt more fluidly to fluctuating demand without incurring the high costs associated with hiring and firing permanent staff. This flexibility is particularly valuable in dynamic markets where demand variability is a significant challenge, as it allows firms to optimize both their labour and production resources in response to changing conditions.

In their work, Steenweg, Schacht, and Werner (2021) introduce an evaluation framework aimed at improving shift pattern planning and workforce assignment under conditions of uncertainty. Their framework assesses the effectiveness of various shift patterns by examining three key factors: workforce availability, quality of task assignment, and workload balance. The framework's ability to account for daily fluctuations in workforce availability makes it a valuable tool for organizations seeking to optimize their labour allocation and operational efficiency. By ensuring that all necessary functions are covered and workloads are evenly distributed, the framework helps mitigate operational risks that arise from unpredictable workforce attendance, enhancing overall productivity.

Liu, Zhao, Huang, and Zhao (2015) contribute to the field of production line capacity planning by addressing the complexities of manufacturing systems that handle multiple product lines. Their study highlights the importance of accurately determining production rates, which defined as the number of products produced per unit of time, in the face of demand uncertainty. The authors discuss how variations in production processes and machine configurations can lead to differences in production rates across product types, making it crucial for firms to consider these variations when developing capacity plans. This nuanced approach enables manufacturing firms to better align their production capabilities with demand forecasts, ensuring efficient use of resources.

Techawiboonwong and Yenradee's (2004) study on aggregate production planning (APP) presents two contrasting approaches: a separated APP approach, which treats each product line as an independent entity, and an integrated APP approach, which allows for resource sharing across multiple product lines. The latter approach is particularly advantageous in environments where workforce flexibility is the key factor, as it enables firms to transfer labour resources between production lines to meet varying demand levels. However, the study also highlights the potential downside of such transfers, notably the decreased production rate that occurs when workers are reassigned to new tasks. The authors introduce the concept of transfer costs, which account for the loss of productivity during the required training period when employees are shifted to new departments. This is particularly pronounced when workers are transferred from lower-skill to higher-skill departments, where the training period is longer and the associated costs are higher. Furthermore, the study introduces the distinction between formal training periods and on-the-job training, providing a more granular understanding of the impacts of workforce transfers on production efficiency.

Cavagnini, Hewitt, and Maggioni (2020) addressed the issue of learning curves and forgetting rates in their two-stage stochastic programming model for production planning. Their model incorporates both the learning rate, which reflects the speed at which employees gain proficiency in a given task, and the forgetting rate, which accounts for the decline in proficiency when employees are not consistently engaged in the same task. By considering these two factors, the authors offer a comprehensive framework for managing workforce proficiency in dynamic production environments. In our adaptation of this model, we simplify the concept of the forgetting rate to better suit the needs of small and medium-sized enterprises (SMEs), allowing these firms to plan their workforce more effectively. Our assumption is that when employees are transferred between departments, they are treated as though they are new to the task, regardless of any previous experience in that department. This allows SMEs to account for potential losses in proficiency following transfers, ensuring that workforce planning remains both realistic and efficient.

Employee scheduling and allocation decisions are typically made 1 to 6 weeks in advance of the actual operational period (Easton, 2014). However, in environments where workforce capacity fluctuates frequently, it becomes necessary to conduct workforce planning on a more regular basis. For small and medium-sized enterprises (SMEs), this presents a significant challenge, as they must respond quickly to unpredictable changes in labour availability. As such, the efficiency and feasibility of any workforce planning model are critical to ensuring timely and effective decision-making. In our study, we trade off some actuality against efficiency. By simplifying certain aspects of workforce dynamics, we are able to maintain a highly efficient model that is still sufficiently detailed to account for the complexities of workforce capacity uncertainty. This trade-off allows SMEs to respond rapidly to workforce changes without compromising the overall accuracy of their planning.

In Liu et al.'s (2019) study on the assembly line workforce assignment problem, the authors addressed the challenge of uncertain order demand in situations where the number of available workers is restricted. Unlike models that consider simultaneous operations across multiple departments, their approach focused on a linear assembly line. In this system, parts move sequentially from one assembly station to the next, with each station completing its assigned process before passing the part along to the subsequent station. The study assumed an inverse relationship between the processing time at each station and the number of workers assigned to it. In other words, assigning more workers to an assembly station reduces the operation time for that station. This insight provides a valuable framework for understanding how workforce allocation can impact production efficiency, especially in environments with limited labour resources and fluctuating demand.

Song and Huang(2008) proposed a multistage stochastic linear program and developed a successive convex approximation method to solve the workforce planning problem of an organization that operates under an environment of uncertain workforce demand and random turnover. Decisions, including transferring, hiring, or firing employees among different departments, were considered to achieve a cost-optimal solution for the workforce capacity planning problem. In this study, we build upon the framework established by Song and Huang, specifically utilizing their time-space network model as the foundation for our analysis.

This paper builds upon Song and Huang's multistage workforce capacity planning model, further developing it to enhance flexibility and applicability to be adapted by small and medium-sized enterprises (SMEs). For a more specific definition of the SMEs considered in this study, the focus of this study is specifically on a production plant specializing in plastic injection moulding and computer numerical control (CNC) metal machining, which served as the primary inspiration for the model. The manufacturing system handles multiple production lines and produces two main categories of products: Original Equipment Manufacturer (OEM) components and branded products. OEM components consist of plastic injection-moulded parts that do not require assembly and are packaged in batches for delivery. In contrast, branded products involve a more complex production process, requiring plastic injection, CNC machining, assembly, and both individual and batch packaging. The key difference between these product categories lies in the manufacturing departments involved. While OEM products only necessitate the plastic injection and packing departments—classified in this paper as ”Low-tech departments”, the production of branded products also requires the CNC machining and assembly departments, which we classified as ”High-tech departments.” The criteria for categorizing departments as ”Low-tech” or ”High-tech,” along with the details of the manufacturing workflow, will be discussed in the subsequent sections to provide a clearer understanding of the distinctions and their implications for workforce planning.

Chapter 3

Network Formulation

3.1 Production workflow

Before formulating the actual workforce network formulation, we first clarify the workflow of a production system, a small and medium-sized manufacturing plant that inspired our study. The production plants incorporates both plastic injection moulding and computer numerical control (CNC) metal machining production lines. The workflow requirements vary depending on the specific nature of the orders, as different products and materials necessitate distinct production steps. A simplified schematic representation of the overall workflow within this production system is illustrated in Figure 3.1.

The production system illustrated in Figure 3.1 handles two types of orders: Original Equipment Manufacturer (OEM) products and branded products. OEM products are those ordered by another company, typically involving simple components that require plastic injection moulding and packing process. After the components are manufactured through the injection moulding process, gates are trimmed by workers, and if specified in the design, the components undergo a pad printing process to produce the finished product. Since OEM products generally do not require individual packaging as they are only a component of the final product, the completed components are organized, packed in batches, and prepared for shipment.

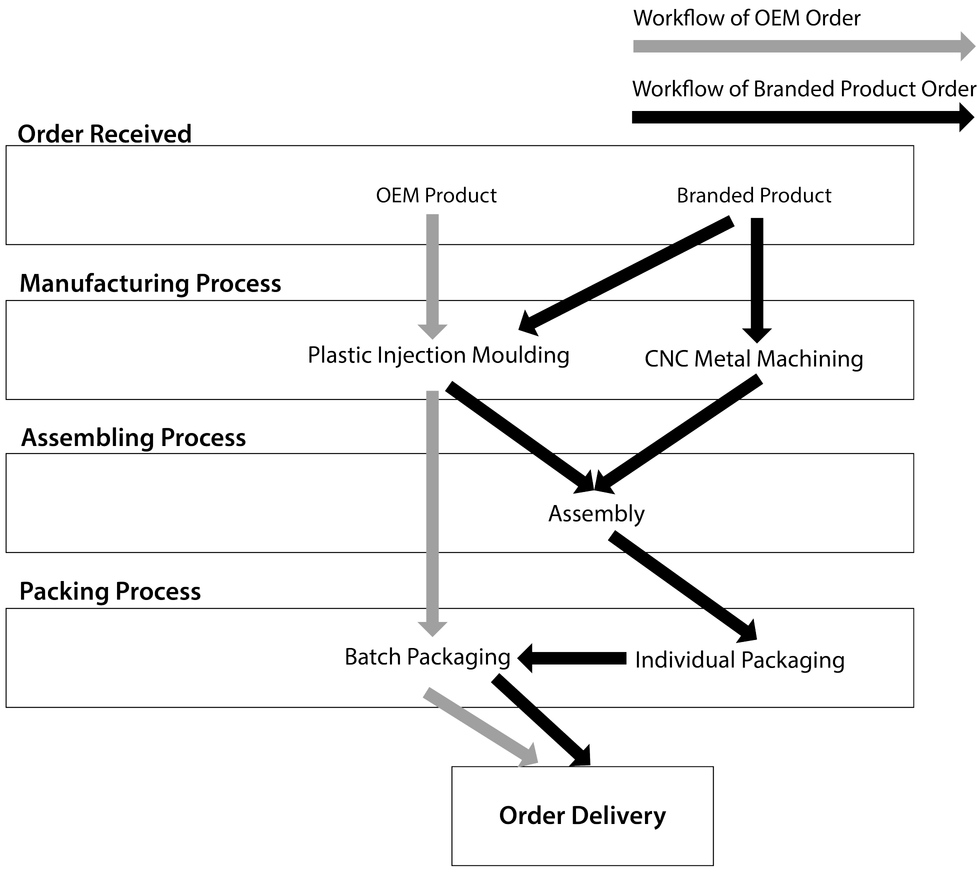

Figure 3.1: Workflow of a small and medium-sized production system

On the other hand, branded products refer to products that have been self-developed in-house by the production system. Unlike OEM products, branded products go through a more complex process, involving not only plastic injection moulding, but also CNC metal machining and assembly. Once the plastic components are produced in the injection moulding department and the metal components are machined in the CNC department, the in-house manufactured parts are transferred to the assembly department. There, along with standard components such as screws and nuts, which are sourced from external suppliers, the components are assembled into the final product following a predefined assembly sequence. Additionally, branded products require both individual packaging and batch packaging before being shipped for order fulfilment, making the overall process more intricate compared to OEM production.

As mentioned in the previous section, this paper categorized production departments into two groups: ”Low-tech department” and ”High-tech department,” based on the level of professional knowledge and technical expertise required to carry out the production tasks. To better define the criteria for these categories, we use the factory setup that inspired this study as an example. In this context, the four main departments in the production network are the CNC department, the injection department, the assembly department, and the packing department. In the injection department and packing department, the production processes demand minimal or limited specialized knowledge of the product’s engineering structure. Once the components are manufactured and ejected by the injection moulding machine, they undergo simply manufacturing process such as gate trimming and surface pad printing before being sent to the final packing process for order delivery. Similarly, the professional knowledge needed for packing process is limited as the packing tasks only required straightforward operations, like placing components into poly bags and boxes. In contrast, the CNC and assembly departments are categorized as ”High-tech departments” due to the specialized expertise required to manage their tasks. These departments demand a thorough understanding of the physical properties of the components and the engineering structure of the final product. Employees in these departments need to apply mechanical knowledge and technical proficiency to perform machining and assembly tasks, unlike ”low-tech departments” which only required more basic operations. As such, in this paper, we classify departments like CNC and assembly departments as ”High-tech department” due to the higher level of technical and engineering skills necessary to complete their operations.

The categorization of departments into ”low-tech” and ”high-tech” departments serves as a foundation for integrating the proficiency ranking criteria, which are used to classify the production rate contributed by transferred employee based on the departments they are transferred from and assigned to. A more detailed explanation of the proficiency ranking criteria will be introduced in the following chapter.

3.2 Time-space network

In alignment with the framework proposed by Song and Huang, the workforce planning problem can be represented as a time-space network, as shown in Figure 3.2. In the schematic diagram network comprised five nodes and five periods, where each node represents a department within the production system. While node 1 to 4 each represent a production department in the system such as plastic injection moulding department and the assembly department, node 0 represents the external human resource pool department 0. The department 0 serves from which the company can recruit new workers into the network; or dismiss the workers from the network if the workforce is no longer needed. In each echelon, the first 4 nodes represent departments, which perform specific tasks and require different skills.

Building upon prior studies that utilize cross-trained workforce to minimize the number of employed workers and improve the service level of the system, this paper allows the movement of workers across departments based on the specific needs of each department. As illustrated in Figure 3.2, there are four types of transfer edge in the workforce planning network: retain transfer, training transfer, recruitment transfer and dismissal transfer. Retain transfer refers to workforce movement where workforce remaining in the same department from one period to the next; training transfer occurs when workers are transferred to a different department in the following period; recruitment transfer refers to recruiting new workforce from department 0 (external workforce pool) into the network; and dismissal transfer occurs when current employees are fired and returned to department 0.

Given that different departments require specialized skills, employees often need to undergo training to perform their tasks proficiently after being transferred to a new department. For example, when transferring an employee who previous worked in the injection or packing department to the CNC or assembly department, training is mandatory; although injection moulding and packing department require limited professional knowledge to perform task, training is required after the workforce being transferred to the ”low-tech” departments ensuring the workforce have enough

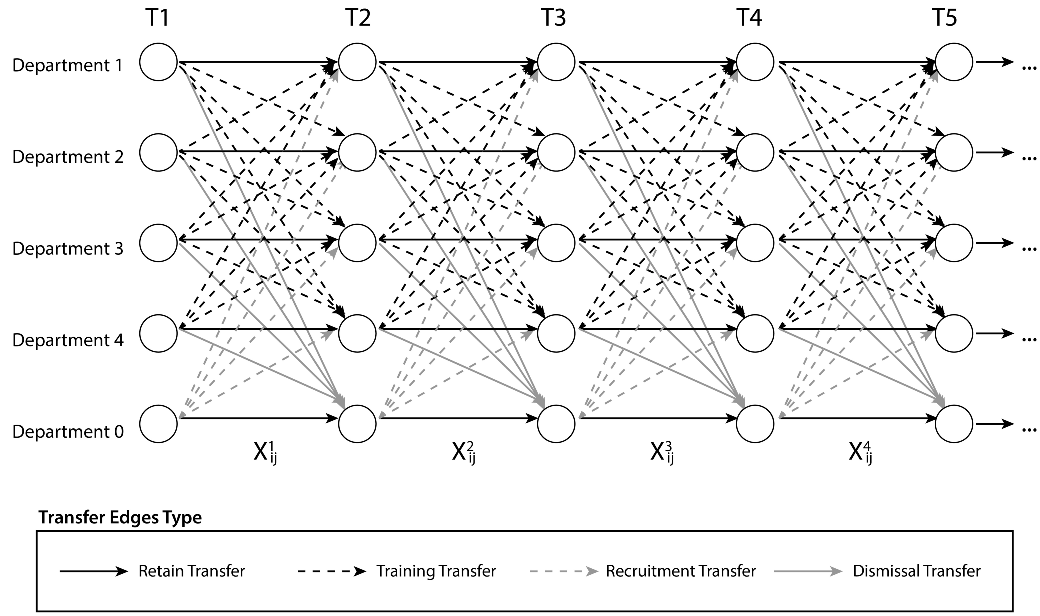

Figure 3.2: A 5 nodes 5 periods time-space network

proficiency to maintain the production rate. Any transfer for an existing employee that requires a training session is defined as training transfer and represented by the black dotted lines shown in figure 3.2.

Retain and dismissal transfer is represented as black and gray solid lines respectively. These two types of transfer do not necessitate a training session before employees moving to the successor department. In the case of a retain transfer, as employee remains in the same department as the previous period, no extra training is required for the employees to continuously perform the same tasks. In the case of dismissal transfer, since the employees are no longer part of the production system in the next period, training is meaningless.

Recruitment transfer edges are presented by gray dotted lines in the diagram. Like training transfer, recruitment transfer also required a training session before the new recruits can begin working. However, we distinguish recruitment transfer from training transfer because, unlike existing workers, who may have varying proficiency based on their previous department (predecessor node) and their new department (successor node), newly recruited employees are assumed to have the same initial proficiency level regardless of the department to which they are assigned.

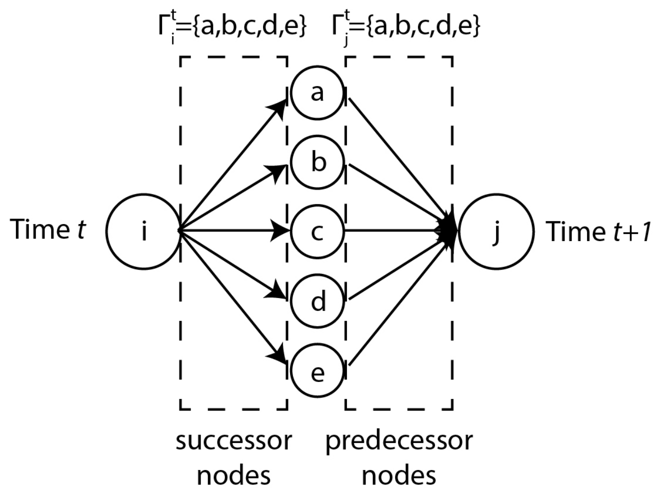

Figure 3.3: Successor nodes and predecessor nodes definition

Following Song and Huang's framework, at the beginning of each time period, the turnover of each period is known due to the policy that voluntarily leaving employees are requried to inform the organization in advance, decisions are then made regarding whether the existing workforce will remain in their current department or be transferred to another department(Including department 0 in the case of discharge). Additionally, new workforce may be recruited into the network depending on the current workforce capacity and the demand for labour in each department. At the end of each time period, the present node of period t connects the successor node of period $t+1$ with one of the four types of transfer edges; retain transfer, training transfer, recruitment transfer or dismissal transfer. These transferring movements are indexed as $\Gamma_i^t$and Γ_j^t. With a to e representing a type of transfer edges, a visual representation of the relationship connecting time t and time $t+1$ is shown in Figure 3.3.

The duration of one time period t can be adjusted based on what is most suitable for the production system to make planning decisions. Although the workforce scheduling and allocation decision are typically made 1 to 6 weeks before the operational period (Easton, 2014), we recommend more frequent planning intervals to allow for dynamic adjustments, ensuring the system can swiftly respond to sudden changes in workforce capacity and other uncertainties.

Chapter 4

Mathematical Formulation

This section begins with a brief overview of the original linear approximation method proposed by Song and Huang for addressing the multistage workforce capacity planning problem. We then present a revised formulation, incorporating newly developed constraints based on the recently introduced employee proficiency ranking criteria.

4.1 Linear approximation method

Workforce capacity planning problem, especially with turnover and multi-periods involved, are usually complex and involve non-linear relationships due to multiple variables and constraints(Albert Corominas & Olivella, 2012). In our model, which originated from Song and Huang's multistage workforce capacity planning problem, involve workforce recruitment, transferring, firing and turnover across the production network. These multiple interacting factors result in a complex non-linear model that required massive computational resource to approximate the whole model directly. As the focus of this paper is to provide workforce planning solution for SMEs to handle the rapid-changing environment with limited resources, the computational efficiency of the model is crucial. Align with Song and Huang's original approach, linear approximation method was applied to simplify the complex, non-linear aspect of the workforce planning model to simplified the complex relationships interacting between different variables and constraints. By applying the linear approximation method, the model can be separate into sub-problems that are easier to solve iteratively, which required minimal computational resources compare to non-linear models, allowing quicker real-time estimations. Moreover, the linear approximating method provide the model with scalability and adaptability that equipped the model for tackling larger, more complex workforce planning scenarios in the future if needed.

Recall the time-space network presented in Figure 3.2, in the workforce planning problem, the T representing the time period is indexed by t, t = 1,2,...,T. Each of the N independent departments involved in the network, represented by a node in the network, is indexed as i, i = 1,2,...,N. A forecast on the workforce demand available for the T periods, can be derived from the workforce data from the past and the business's future development direction. In each time period t, "time t" represents the time at the beginning of the period, where "time $t+1$" represents the time at the end of the period. As employees are supposed to inform the human resources department in advance of their leaving, it is assumed that the turnover is known at time t of each time period. The movement decisions of existing workforce, as well as recruitment and dismissal decision, are made upon knowing the turnover of the time period.

Refer to the definition of successor nodes and predecessor nodes discussed in Figure 3.3 that represent the movement of workforce between departments from one period to another. Along with Song and Huang (2008) multistage workforce capacity planning problem, the aggregate of the possible transferring edges in the network in the previous section network among departments is indexed as $\Theta(t)$. To sum up the original problem, we define the set referring the connection between nodes as follows (based on 2007Successive):

$\Theta(t)$	the possible transferring edges between department at time t, including hiring and firing, t=1,2,..., T
$\Gamma_j^t\{i : (i, j) \in \Theta(t)\}$	the set of the predecessor nodes of j at time t +1, t = 1,2,...,T (see Figure 3.3)
$\Gamma_j^t\{j : (i, j) \in \Theta(t)\}$	the set of the successor nodes of i at time t, t=1,2,...,T (see Figure 3.3)

Table 4.1: Connection node set

The decision variables and parameters are defined as follows:

X_{ij}^t	the number of employees transferred from department i to j at time t, $\forall\, i, j \in \Theta(t)$. i = 1,...,N, t=1,...,T
c_{ij}^t	the transferring cost of employee from department i to j at time t, $\forall\, i, j \in \Theta(t)$. t =1,..., T
u_{ij}^t	the maximum number of transferable employees from department i to j at time $t \in \Theta(t)$. t =1,..., T
D_j^t	the random workforce demand of department j during period t,j=1,...N, t = 1,...T
ζ_i^t	the random turnover rate in department i during period t, i=1,...N t=2,...T
Z_i^t	the number of employees in department i voluntarily leaving during period t,i=1,...N
s_i^t	the initial number of employees at department i at time t, i=1,...N, t=1,...T
b_i^t	the unit turnover cost of employees at department i during period t, i=1,...N, t=1,...T
$Q^t(s^t, \zeta^t)$	objective value of the minimization problem with random turnover rate for period t, t=1,...T

Table 4.2: Decision variables and parameters

The priority of this study is to provide insight for SMEs to achieve a balanced workforce counteracting the rapidly changing workforce capacity due to uncertain labour turnover. To obtain a model that minimizes the cost of meeting demanded workforce capacity and under stochastic turnover rate, aligned with the model proposed by Song and Huang Song and Huang (2008), we provide the formulation of the recursive model (for period t) below:

$$Q^t(s^t, \zeta^t) = min \sum_{(i,j)\in\Theta(t)} c_{ij}^t \cdot X_{ij}^t + \sum_{i=1}^{N} b_i^t \cdot Z_i^t + \sum_{j=1}^{N} E_{D_j^t}[F_j^t(s_j^{t+1}, D_j^t)] + \gamma \cdot E_{\zeta^{t+1}}[Q^{t+1}(s^{t+1}, \zeta^{t+1})]$$

subject to

$$\sum_{j\in\Gamma_0^t} X_{0j}^t = s_0 \tag{1}$$

$$\sum_{j\in\Gamma_i^t} X_{ij}^t + Z_i^t = s_i^t, \quad \forall\, i \in N \tag{2}$$

$$\sum_{i\in\Gamma_j^t} X_{ij}^t = s_j^{t+1}, \quad \forall\, j \in N \tag{3}$$

$$0 \leq X_{ij}^t \leq u_{ij}^t, \quad \forall\, i, j \in \Theta(t), \quad t = 1, ..., T, \tag{4}$$

$$Z_i^t = s_i^t \cdot \zeta_i^t, \quad \forall i \in N, \quad t = 1..., T, \tag{5}$$

During each period t, With c_{ij}^tas the individual transferring cost of employee from department i to j and X_{ij}^t as the numbers of employees transferred from department i to department j , we have $\sum_{(i,j)\in\Theta(t)} c_{ij}^t \cdot X_{ij}^t$, the sum of transfer cost at time t. The transfer cost varies depending on both the successor and predecessor nodes, which represent the departments where an employee was assigned at period $t-1$ and period t respectively. Note that recruitment cost and dismissal cost are also included in the transfer cost, with $c_{0j}^t \cdot X_{0j}^t$ as the cost of hiring employees from department 0 into department j, and $c_{i0}^t \cdot X_{i0}^t$ as the dismissal cost of firing employees from department i at time t. Refer to the transfer cost associates with training transfer, in general speaking, the cost of transferring an employee from a "low-tech" department to a "high-tech" department is generally higher than the reverse, due to the different professional knowledge required to perform tasks. Transferring employees into "high-tech" departments often demands more intensive training before on-job-training due to the necessary expertise required to meet the technical demands in these departments. In contrast, moving workforce from a "high-tech" to a "low-tech" department tends to be less resource-intensive as employees are already equipped with advanced knowledge and skills from "high-tech" department which often exceed the requirement of the new role in "low-tech" department.

For the second component, b_i^t refers to the unit turnover cost refers to the loss of productivity due to turnover and the cost of advertising the position to restore the vacancy; Z_i^t refers to the number of employees in department j voluntarily leaving the network during period t. We have $\sum_{i=1}^N b_i^t \cdot Z_i^t$ be the sum of turnover cost at department i during period t, which refers to the expense occurs when workforce voluntarily leaves the production system. In addition to the direct cost of hiring, turnover also results in operational inefficiencies arise from the gap between the employee leaving the position and the time for refilling the vacancy.

The third component,$\sum_{j=1}^N E_{D_j^t}[F_j^t(s_j^{t+1}, D_j^t)]$, represents total expected operating costs corresponding to the workforce demand of department j, in period t. The term $F_j^t(s_j^{t+1}, D_j^t)$ is the function calculates operations cost when the demand during period t is D_j^t and the available head-count in the department j is s_j^{t+1} . In alignment with the original model, the expected operation cost changes based on the workforce supply and demand, this cost also accounts for the cost of employee underage and overage. When the workforce capacity does not meet the demand, additional expenses such as temporary hires and overtime pay incurred to fulfil the required demand and results in increased underage cost. In contrast, where there is a surplus of employees, under-utilization of labour results in an increase overage cost, as wages are still paid even though the workforce is not fully productive.

Finally, where $Q^t(s^t, \zeta^t)$ is the objective value of the function, by having the γ as the discount factor considering the discounted expected cost in the future, s^{t+1} as the initial workforce capacity at department i at time $t+1$, and ζ^{t+1} as the scenario of the different turnover rate at period $t+1$ which is known at time t, we have $Q^{t+1}(s^{t+1}, \zeta^{t+1})$ defines the objective value of the recursively minimization problem at time $t+1$. As a whole, $E_{\zeta^{t+1}}[Q^{t+1}(s^{t+1}, \zeta^{t+1})]$ is the expected objective value which makes adjustments that optimizes the responses by minimizing the cost to the outcome of the uncertain turnover rate.

In comparison to Song and Huang (2008) original model, we redefined some of the variables and parameters where we found simplification to be feasible. The parameter l_i^1 in the original model defining the number of employees in department i voluntarily leaving during period t was removed as we found it can be replaced by using variable Z_i^t. The objective function minimizes the total transfer cost of workforce movement across the network, including retain transfer, training transfer, recruitment transfer and dismissal transfer. It also minimizes the total turnover cost when workforce leave the network voluntarily, as well as the total operation cost corresponding to the demand.

Moving to the constraints, the constraint(1) is the total recruited workforce constraint which enforces the sum of employees recruited from department 0 to department j at time t will be the available initial workforce s_0. Constraint (2) calculates s_i^t, the total available workforce at time t in department i, is the sum of employee going to remain in the network and the employee going to leave the network voluntarily during period t. Constraint (3) is the workforce transfer balance constraint between the time t and time $t+1$, calculating the sum of employees, including those who remain in the network(retain transfer and Training transfer), newly hired from department 0 (Recruitment Transfer), and being fired(Dismissal Transfer), will be s_j^{t+1}, the available workforce in department j at time $t+1$. Note that the turnover is not considered here in constraint 3. Constraint (4) is the maximum transferable constraint in the network in period t, ensuring that the number of employees transferred does not exceed the maximum transferable employees from department i to department j at time t. Finally, constraint (5) calculates the number of turnover employees constraints in department i during period t, which is the product of the initial number of employees s_i^t and the random turnover rate ζ_i^t during period t.

While the original model provides workforce planning solutions involving employee transfers, hiring, and firing across departments in response to fluctuating turnover rate, our review of the model revealed a key area for improvement: it does not adequately account for variations in productivity rates among transferred employees. Specifically, when employees are reassigned to new departments and tasks, a temporary decline in proficiency occurs due to the lack of consistent engagement in their prior tasks. Over time, transferred employees gradually regain their proficiency through targeted training and experience within their new roles.

We found that addressing this variation in production rate caused by proficiency declines after transfers is crucial for achieving a more accurate and effective workforce planning solution. By refining the model to incorporate proficiency recovery for cross-trained employees, organizations can better manage workforce capacity in environments with turnover uncertainty. This approach ensures that the cross-trained workforce can be employed more effectively as a strategy to mitigate the impacts of fluctuating workforce levels, leading to improved operational resilience and efficiency. In the following section, we introduce modifications that account for the impact of workforce transfers and cross-training across the network to meet required workforce capacity demands.

4.2 Modified network formulation

In this section, we introduced the proficiency ranking criteria in relation to the change in production rate during training transfer and recruitment transfer, which distinct this study from the previous method proposed by Song and Huang. As mentioned in the previous section, there are four types of transfer edges connecting the present node of period t and the successor node of period $t + 1$: retain transfer, training transfer, recruitment transfer and dismissal transfer. The proficiency ranking criteria is applicable for recruitment and training transfer. In the framework of this paper, employees are categorized into three levels of classification: rookie, trainee, and regular. Reflecting the learning rate of employee gaining proficiency during the on-job-training period after transferring to other departments, each rank has different production rates which develop over time.

4.2.1 Proficiency Ranking Criteria

The employee status changes with respect to the type of transfer edge the employee moves along and the type of relationship between the successor node and the predecessor node. New hired employees, regardless of whether they transfer to a low-tech department or a high-tech department, are classified as recruitment transfer and will be ranked as rookie. An employee transferring from a low-tech department to a different low-tech department is ranked as a trainee, where become rookie if transfers to high-tech department. If the employee currently works in high-tech department and ranked as regular workforce with 100% production rate, they will become trainee in the next period if transferred to other departments, regardless low-tech department or high-tech department. A graphical presentation of the change of proficiency ranking during transfer is shown in Figure 4.1.

When cross-level transfers occur, referring to the movement of employees either from a low-tech department to a high-tech department or vice versa, the proficiency ranking of the transferring employee is adjusted to either ”trainee” or ”rookie.” An employee currently working in a low-tech department will be ranked as a trainee when transferred to another low-tech department but will be ranked as a rookie if transferred to a high-tech department. This is because the professional

Department at t+1

Department at t	LOW TECH	HIGH TECH
NEW HIRED	ROOKIE	ROOKIE
LOW TECH	TRAINEE	ROOKIE
HIGH TECH	TRAINEE	TRAINEE

Figure 4.1: Change of Proficiency Ranking during transfer

knowledge and skills required to perform tasks in high-tech departments take more time to understand and practice before reaching a regular production rate. In contrast, since the tasks in low-tech departments are simpler and require less specialized knowledge, an employee transferring from a high-tech department to a low-tech department will be ranked as a trainee, not a rookie.

To further elaborate on our modified model, which integrates the concept of employee proficiency classification, the following underlying assumptions were considered during the development:

(1) The learning rate of transferred employees is assumed to be constant.

(2) The production rate of employees within the same proficiency rank is assumed to be stable.

(3) Employees transferred to other departments, including newly hired employees, are assumed to go through an on-the-job training period reaching the regular production rate. According to their proficiency levels, they are ranked as follows: "rookie" with a 70% production rate, "trainee" with a 85% production rate, and "regular" with a 100% production rate.

(4) Newly hired employees, regardless of whether they enter a low-tech or high-tech department, are ranked as rookies in their first period, develop into trainees in the second period, and become regular employees by the third period (e.g rookie in time t, trainee in time $t + 1$, and regular in time $t + 2$)

(5) Any employees transferred from a low-tech department to another low-tech department will be ranked as a trainee in the first period and develop into an regular workforce in the second period.

(6) Any employees transferring from a low-tech department to a high-tech department will be ranked as rookies in the first period, trainees in the second period, and regular workforce in the third period.

(7) Any employees transferring from a high-tech department to another high-tech department will be ranked as trainees in the first period and develop into regular workforce in the second period.

(8) Any employees transferring from a high-tech department to a low-tech department will be ranked as trainees in the first period and regular workforce from the second period.

(9) There is no inventory in this production system, so no overproduction will be held.

(10) Training transfers and dismissal transfers only apply to employees ranked as regular workforce.

(11) Employees ranked as rookies or trainees are not allowed to leave the production system voluntarily. Only regular employees are permitted to leave voluntarily.

It is important to note that assumption 10 and assumption 11 restrict employees who are undergoing on-the-job training from transferring to other departments or leaving voluntarily. As training employees is a costly process that involves time, resources, and a reduced production rate compared to regular workforce. Training employees without fully utilizing their potential production capacity leads to workforce inefficiencies and increases costs. Moreover, the same principle applies to dismissal transfers, employees ranked as rookies or trainees cannot be dismissed during this period. This ensures that employee to transition into a more productive role, thus maximizing the production rate that the employee contributes.

In the study by Edward and Anderson(2001), the penalty cost of capacity-demand mismatches, relative to the cost of workforce adjustments between experienced and rookie employees, was included in the control policy problem to balance surplus employee costs with capacity shortfalls. In this paper, rather than using a time-oriented penalty cost, we integrate the concept of production rate into the model. Assuming the production rate of regular employees is 100%, rookies have a production rate of 70%, and trainees have a production rate of 85%. By classifying productivity based on employee proficiency, we account for the decline in efficiency during employee transfers to achieve a more accurate evaluation of production rates. Considering the uncertain capacity of the workforce, not only within the company but also among the resource pool (Department 0), this paper focuses on meeting production demand by optimizing the arrangement of the existing workforce and recruiting new employees when the current workforce is insufficient to meet production requirements.

4.2.2 Modified Constraints

To incorporate the proficiency ranking system into the workforce planning problem, we introduced new constraints to ensure that the development of transferred employees' production rate proficiencies, the total production rate, and network turnover are effectively accounted for. While maintaining the objective function outlined in Section 4.1 and preserving constraints [1] through [4], we have integrated these additional constraints into the original framework to enhance its applicability and precision in real-world scenarios. The supplemental decision variables, parameters and constraints are as follows:

S_i^t	the total production capacity in department i during period t
RO_j^t	the number of rookie workforce in department j during period t
T_j^t	the number of trainee workforce in department j during period t
RG_j^t	the number of regular workforce in department j during period t
RG_i^t	the number of regular workforce in department i during period t

Table 4.3: Supplemental Decision variables and parameters

$$RO_j^t \geq X_{oj}^t + X_{ij}^t \tag{6}$$

for $i \in LT$, $\forall j \in$high-tech department.

$$RO_j^t = X_{0j}^t \tag{7}$$

for $\forall j \in$low-tech department.

$$T_j^t = RO_j^{t-1} + \sum_{i \in HT} X_{ij}^{t-1} \tag{8}$$

for $j \in$ high-tech department.

$$T_j^t = RO_j^{t-1} + \sum_{i \in LT} X_{ij}^{t-1} \tag{9}$$

for $j \in$low-tech department.

$$RG_j^t = X_{jj}^{t-1} + T_j^{t-1} \tag{10}$$

$$S_j^t = RG_j^t + 0.7RO_j^t + 0.85T_j^t \tag{11}$$

$$Z_j^t = \zeta_{cj}^t RG_j^t \tag{12}$$

$$RG_i^t = Z_i^t + \sum X_{ij}^t \tag{13}$$

Constraints [6] to [10] are responsible for enforcing the proficiency ranking criteria across the system. Specifically, constraint [6] addresses the rookie constraint for the high-tech department in period t. It ensures that employees who are newly hired from the workforce pool (department 0) to the high-tech department, as well as those who worked in a low-tech department in $t - 1$ and transferred to the high-tech department in period t, are ranked as a rookie for that period. Constraint [7] is the rookie constraint regarding low-tech department in period t, mandating that employees newly recruited from the workforce pool (department 0) into a low-tech department will be ranked as rookies in that period.

Constraint [8] is the trainee constraint for the high-tech department in period t, applied to employees who were previously ranked as rookie in period $t-1$ and who remain in the same high-tech department in period t. Additionally, employees who transferred from one high-tech department to another will elevated to trainee rank in period t. Constraint [9] is the trainee constraint regarding the low-tech department of employees who were rookies in the low-tech department in period $t-1$, and employees who transferred from a low-tech department to a different low-tech department, will become trainee in period t.

Constraint [10] is the regular workforce constraint that enforce employees who were ranked as regular in period $t - 1$ and remain in the same department in period t, and along with employees who were ranked trainees in period $t - 1$ will be promoted as regular rank in period t. Constraint [6] to [10] ensure that, except for workforce that being dismissed, the proficiency ranking criteria functions properly when workforce move along the network between departments over time.

Constraint [11] is the productivity rate constraint, which takes into account the total production capacity of the workforce within the production system. In terms of production output, each regular employee is considered to contribute 100% production rate. Meanwhile, each rookie is considered to contribute 70%, and each trainee is estimated to contribute 85% . Therefore, the total production rate of department j in period t is determined by the sum of the regular employees, 0.7 times the headcount of rookies, and 0.85 times the headcount of trainees in department j during that same period. This constraint ensures that the workforce's varying levels of experience and skill are accurately reflected in the department's overall productivity.

Constraint [12] addresses the turnover rate and reflects the number of employees leaving department j during period t under scenario ζ. Based on the assumption that only regular employees can leave voluntarily, the number of voluntary departures is computed by applying the scenario-specific turnover rate to the headcount of the regular workforce in department j during t, this ensures that the impact of turnover on workforce levels is accurately modelled for each scenario.

Finally, constraint [13] defines the composition of the regular workforce.. The headcounts of regular employees in period t is calculated as the total of both the number of employees voluntarily leaving (due to turnover) and the sum of employees undergoing internal transfers—whether for retention, training, or dismissal during period t. It is important to note that recruitment transfers are not included in this constraint, as newly hired employees are classified as rookies regardless of the department to which they are assigned. This constraint ensures a clear distinction between the different types of workforce transitions while maintaining the integrity of the regular workforce classification.

Note that we have removed the employee turnover constraint [5] from the original model in Section 4.1 and replaced it with constraint [12]. This change is based on assumptions 10 and 11 discussed in Section 4.2.1, which highlight that training employees is a resource-intensive process involving time, costs, and a temporary decline in production output. Failing to fully utilize the production rate of the workforce leads to inefficiencies and increased costs. Consequently, in our revised framework, only employees with standard production rates are allowed to exit voluntarily. While constraint [5] originally accounted for turnover across the network regardless of employee status, constraint [12] specifically considers turnover headcounts under the refined framework.

4.3 Modifications of original model

Our model builds upon the multistage workforce capacity planning problem initially proposed by Song and Huang. However, throughout the course of our development, we have introduced significant modifications and integrated new concepts into the model's network formulation. While the original model considered employee movement solely in terms of transfers with associated costs, we expanded and subdivided the transfer mechanism into four distinct categories: retain transfer, training transfer, recruitment transfer, and dismissal transfer. Each of these categories not only differs in terms of associated costs but also has varying impacts on production rates, depending on the specific type of transfer. By incorporating these distinctions, our model provides a more granular and accurate representation of workforce dynamics, ensuring that both costs and productivity are more precisely aligned with the underlying workforce transitions.

In contrast to the original model, which measured workforce capacity purely based on headcount, our modified approach redefines workforce capacity in terms of total production rate. Instead of assuming that every employee contributes equally to production regardless of department and decide how many headcounts are needed to maintain in the production system to achieve the demand, our model accounts for the difference in production rates among transferred employees. The total workforce capacity is then determined by the number of employees required to meet a specific production target, rather than by headcount alone. Additionally, while the original work generalize the training cost, including both the cost of training resource and time, and the production losses into a single transferring cost, our modified model separates these factors. We consider training cost and production loss separately, with training cost included as a part of transferring cost. The production losses managed independently through the proficient ranking system. This modification also takes the learning rate of transferred employee into account, further develop the model so that the model allow more precise planning decisions based on desired production rate. As a result, although we have retained much of the original model's notation for variables, we have redefined s to represent production rate rather than employee headcounts. These refinements enable more accurate workforce planning by aligning capacity with production efficiency rather than headcounts.

New constraints have been introduced into the model to ensure that the modifications we integrated into the network function as intended. These constraints play a crucial role in maintaining the structural integrity of the model, ensuring that all aspects of the modified network operate smoothly and accurately. In the following section, the performance of the model will be evaluated through a series of numerical experiments to provide insights into its effectiveness and feasibility.

Chapter 5

Numerical experiments

In this section, we evaluate our developed problem to further explore the effectiveness and feasibility of the model. In alignment with Song and Huang's study, we evaluate the model using the successive convex approximation method to ensure that the same method function properly on the simplified model. To start with, firstly we consider the original two-stage workforce problem in Section 4.1 without integrating the constraints [6] to [13] to ensure that the relationships and factors in the model function and interact in a rational manner. After verifying that the successive convex approximation method functions properly, we proceeded by integrating the constraints [6] to [13] into the model and evaluate the model from both cost and time performance aspect.

5.1 Successive convex approximation method

Adopting the approach applied by Song and Huang, we approximate the model using the successive convex approximation method (SCAM). SCAM was chosen over directly approximating the entire model because workforce planning problems involving turnover and multistage decisions typically encompass non-linear components. This is particularly relevant in models with factors such as workforce transfers and stochastic turnover rates, where the entire model's approximation would often be too challenging and computationally demanding to perform accurately. For this reason, using a direct approximation would limit the model's efficiency and applicability, especially for SMEs, which generally have fewer resources and computational capacity compared to large enterprises. SCAM addresses this by breaking down the complex, non-convex problem into a series of convex sub-problems that can be solved iteratively. This iterative approach ensures that the workforce planning model can be computed efficiently, enabling it to provide timely and adaptive responses. SCAM's method of incremental refinement allows for improved accuracy in each sub-problem stage, which makes it well-suited to handle the variations in workforce planning, such as the fluctuation in turnover rates and production needs.

In addition to SCAM, the overall problem can also be formulated as a very large integer program and can be solved using Mixed-Integer Linear Programming (MILP), Dynamic Programming, or special purpose heuristic approaches. Various non-linear solvers can also solve the problem using sophisticated algorithms. However, SCAM is particularly effective for solving models with non-convex components. MILP and Dynamic Programming, while powerful, may struggle with time efficiency and feasibility when addressing highly complex, high-dimensional, and multi-stage problems, especially in cases with numerous variables or constraints (Razaviyayn, 2014). Furthermore, SCAM's iterative framework allows greater flexibility in setting and adjusting constraints and objectives, which is beneficial when dealing with the dynamic nature of workforce planning. This flexibility means that SCAM can easily adapt to changing factors such as turnover rates, workforce transfers, and shift in production capacity compared to traditional methods or heuristic approaches. By breaking down each sub-problem and solving it in stages, SCAM not only enhances computational efficiency but also enables the model to respond adaptively to uncertainties in workforce capacity, providing a robust solution for practical, real-time application.

Aligned with the approach applied by Song and Huang, in this paper, we approximate the cost function by breaking the non-convex problem into piecewise linear segments using the successive convex approximation method (SCAM). Specifically, the cost function is divided into 20 segments and approximated linearly through a deterministic model. This segmentation allows us to address the non-convexity by simplifying the cost function into manageable parts, making it computationally feasible for iterative analysis and refinement.

The approximation was computed using Visual Studio under Microsoft system environment. To test the model's responsiveness and accuracy, we assigned values to overage cost, shortage cost, hiring cost, and transferring cost. This approach allowed us to observe whether the model could generate rational responses to the interactions and trade-off between these costs, capturing the dynamic relationships that exist in real workforce planning scenarios. The values used for these cost parameters are provided in Table 5.1, where each set of parameters was systematically adjusted to evaluate the model's adaptability across different planning conditions. This testing process ensures that the model not only computes realistic responses but also retains flexibility, which is essential for its application in diverse workforce planning environments.

Table 5.1: Parameter values for the rational check

Parameter	Value
Hiring cost	30, 10
Transferring cost	10, 30
Shortage cost	190, 15
Overage cost	15, 190

With all other variables and parameters remaining the same, we first evaluate the scenario where the hiring cost (30) is higher than the transfer cost (10). In cases where the shortage cost (190) is greater than the overage cost (15), the model suggests solution to hire a sufficient amount of employees at the beginning of the time horizon to meet the required workforce demand. Workforce is transferred between departments to fulfil specific capacity needs, and new employees are hired as necessary to replace turnover. Conversely, when the shortage cost (15) is lower than the overage cost (190), fewer employees are initially hired compared to the previous setting. Workforce is transferred among departments, and new employees are recruited periodically to offset turnover. When the shortage and overage costs are set to be equal (15), the results are similar to the scenario where the shortage cost is lower than the overage cost.

We infer that the difference in results between these scenarios stems from the model's inclination to avoid shortage costs when the shortage cost exceeds the overage cost. In this case, the model maintains a higher workforce capacity than demand to avoid penalties. However, when the overage cost is higher than the shortage cost, the model tends to minimize workforce capacity, hiring only when needed to reduce costs while avoiding overage penalties. Since the hiring cost is equal to the transfer cost in this scenario, the model prefers to retain employees within the network and transfer them across departments as needed.

In the scenario where the hiring cost (10) is lower than the transfer cost (30), when the shortage cost (190) exceeds the overage cost (15), the model suggests a solution that a sufficient number of employees is hired at the start of the time horizon. As time progresses, every employees are dismissed from the network, and new employees are hired at the beginning of each period. When the shortage cost (15) is lower than the overage cost (190), fewer employees are initially hired, and employees are dismissed at the end of each period, with new employees hired at the start of the subsequent period. Additionally, the model suggest similar solution for setting when shortage cost and overage cost are the same(15).

Although the model appears to recommend counter-intuitive solutions, such as dismissing the entire workforce and rehiring each period, it is actually offering rational guidance. Since the hiring cost is lower than the transfer cost in this scenario, it is more cost-effective to hire new employees each period rather than transferring existing staff to meet demand.

5.2 Performance

After verifying that the Successive convex approximation method provides planning solutions of the problem in a rational manner, we proceeded by integrating the constraints [6] to [13] into the approximation. To evaluate the performance of the developed model, we conducted a series of numerical experiences with varying problem sizes. Specifically, we made adjustments to the number of departments, the length of time horizons considered and different value of standard deviation. By testing with different parameters, we aim to assess the model's scalability and robustness under different conditions, and to ensure that the model remains computationally feasible.

Table 5.2: Performance Report(part.1)

Mean Demand 500		Time Horizon 6				
SD		Dept 3	Dept 6	Dept 9	Dept 12	Dept 15
50	Cost ($)	247022.3	492400	735377.75	991775.65	1232408
	Time (ms)	877.05	1709.9	2558.35	3418.75	4293
100	Cost ($)	296314.4	598181.9	892585.05	1187573.5	1482983
	Time (ms)	866.6	1712.5	2566	3436.9	4284.2
150	Cost ($)	357587.8	713601.7	1078000	1420055	1805615
	Time (ms)	870	1714.4	2577.85	3423.45	4314.05
200	Cost ($)	423652.75	846026.7	1267596	1698238	2102429.5
	Time (ms)	897.75	1738.6	2588.9	3477.1	4348.9

Table 5.3: Performance Report(part.2)

Mean Demand 500		Time Horizon 10				
SD		Dept 3	Dept 6	Dept 9	Dept 12	Dept 15
50	Cost ($)	346899.8	704714.5	1021931.2	1389248.5	1735087
	Time (ms)	1421.5	2846.6	4314.95	5989.8	7927.4
100	Cost ($)	446860.65	870614.9	1348151	1755242	2231849
	Time (ms)	1416.8	2851.95	4326.35	5943.95	7739.25
150	Cost ($)	547076.35	1106170	1657479	2190212	2731657.5
	Time (ms)	1421.65	2852.4	4422.85	5932.2	7527.95
200	Cost ($)	664453.1	1317232	1975531.5	2651637.5	3310018
	Time (ms)	1438.7	2903.55	4549.3	6026.85	7688.35

Table 5.4: Performance Report(part.3)

Mean Demand 500		Time Horizon 15				
SD		Dept 3	Dept 6	Dept 9	Dept 12	Dept 15
50	Cost ($)	459080.85	936104.15	1394804	1836526	2347225.5
	Time (ms)	2587.6	4420.65	6727.2	9500.35	11969.9
100	Cost ($)	614407.3	1222685	1834711.5	2464537.5	3079198.5
	Time (ms)	2456.55	4368.05	6772.45	9201.2	11951.35
150	Cost ($)	789671.55	1537953.5	2377949	3100918.5	3927575.5
	Time (ms)	2339.65	4389.85	6806.45	9189.7	11921.85
200	Cost ($)	953605.45	1913034.5	2832537.5	3821927	4732218
	Time (ms)	2266.65	4426.9	7052.6	9286.55	12053.9

By applying the linear approximation method to solve the modified problem, twenty performance results were generated for each problem size, with varying parameter values. After normalizing the cost and time performance results for each problem size, a performance report of the model is presented in Tables 5.2, 5.3, and 5.4.

Sensitivity analysis are conducted to have a deeper understanding of the effect of different variables on the cost and the time performance of the model with a fixed mean demand of 500. To observe the effect of the problem size on the performance of the model, the number of departments, the length of time horizon, and the standard deviation are chosen as the control variable, with the number of departments reflecting the size of small and medium-sized enterprises, length of time horizon reflecting the adaptability, and different values of standard deviation evaluating the robustness of the model towards fluctuations. The value of corresponding parameters investigated in the sensitivity analysis are provided in Table 5.5.

Table 5.5: Parameter values for the sensitivity analysis

Parameter	Value
No. of Dept	3, 6, 9, 12, 15
Time Horizon	6, 10, 15
Standard Deviation	50 ,100 ,150 ,200

5.3 Sensitivity Analysis

5.3.1 Cost performance

Figure 5.1 presents the results of a sensitivity analysis of cost performance with a fixed standard deviation. The cost is plotted against the time horizon for various total numbers of departments considered in the model. Specifically, the lines in each graph represent total department counts of 15, 12, 9, 6, and 3, from top to bottom, respectively. All results show a positive correlation between the length of the time horizon and the cost. As the time horizon increases, the cost of generating planning solutions rises exponentially. As the value of standard deviation applied to analyse

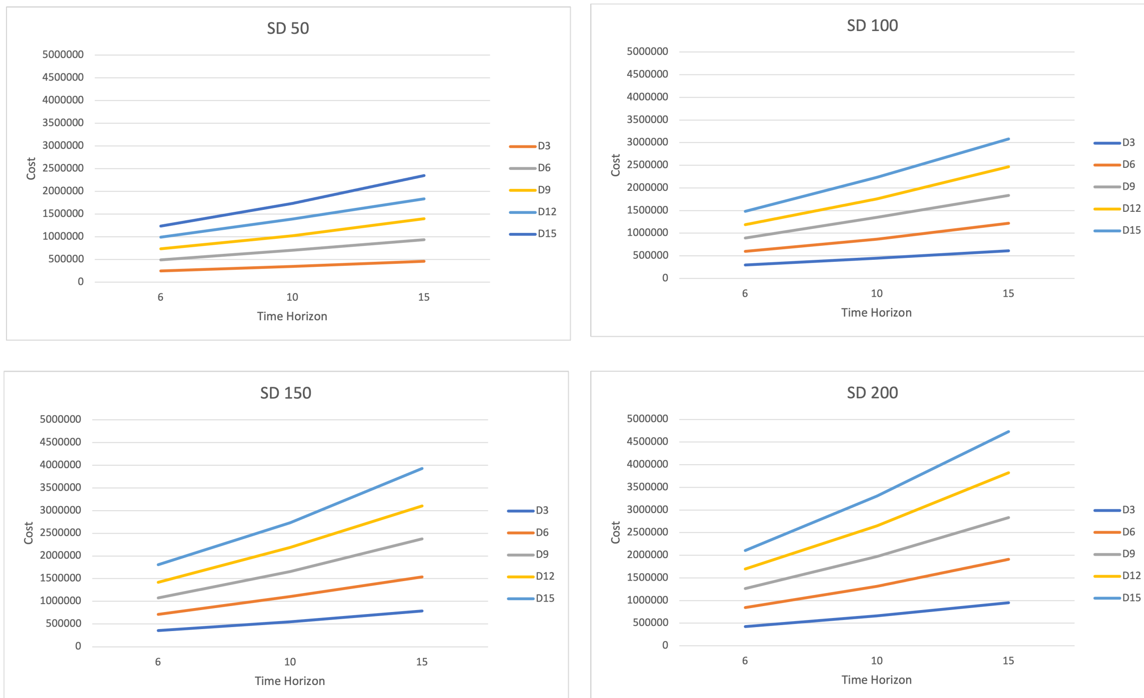

Figure 5.1: Cost performance of time horizons and no. of department under fixed SD

the model increases, the initial cost required to process the model with 6 period of time horizon increases. Moreover, as the divergence between the cost of approximating solutions for different numbers of departments becomes more pronounced depending on the standard deviation, the differences between final cost counts for different numbers of departments elevate as the value of standard deviation increases.

Figure 5.2 illustrates the sensitivity analysis of when the cost performance is plotted against the total number of departments for varying value of standard deviations under fixed length of time horizons. All results indicate positive correlation relationships. As the number of departments increases, the cost rises steadily in a linear fashion. Within each graph, regardless of the standard deviation, the plots begin from closely aligned positions. However, due to varying rates of increase across different standard deviation values, the divergence between the cost performance becomes more pronounced as the number of departments grows. Additionally, when comparing different time horizon lengths, the starting positions of the plots consistently shift upward meaning a larger initial cost and the divergence between different values of standard deviation become larger as the

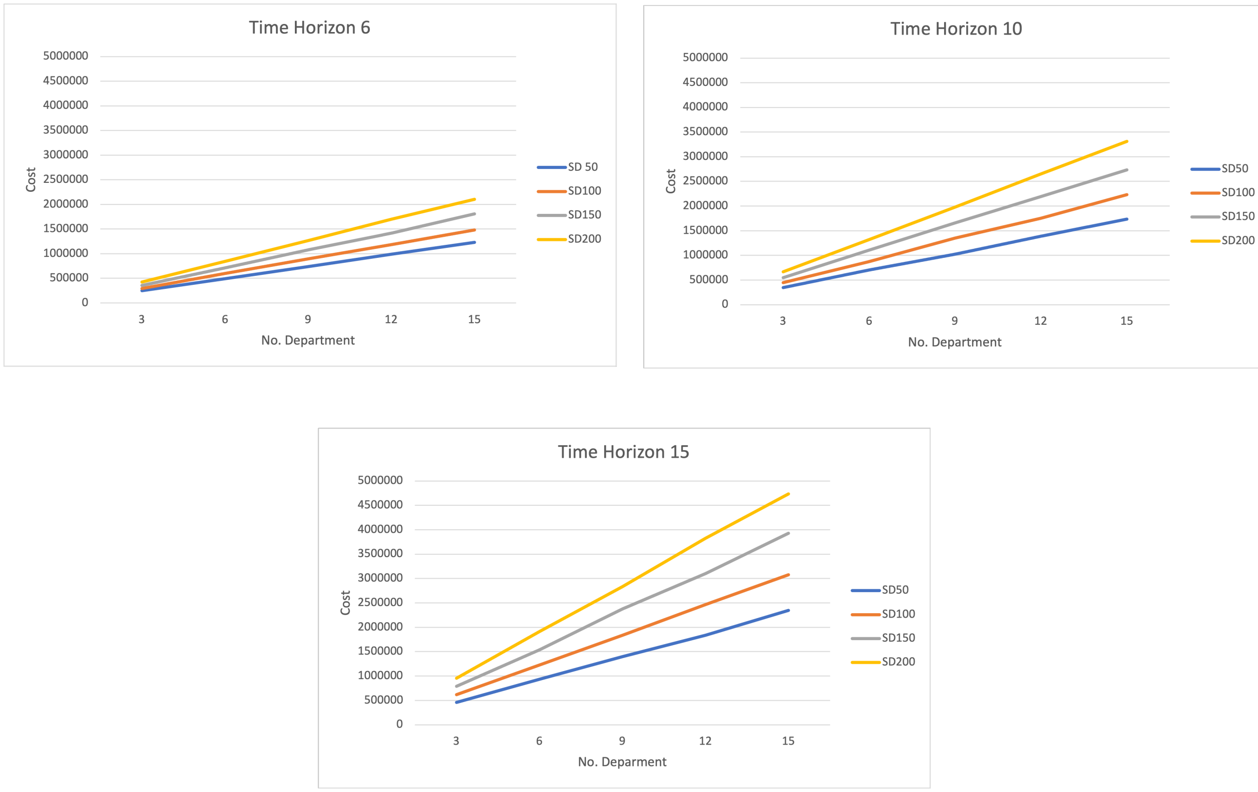

Figure 5.2: Cost performance of no. of department and SD under fixed time horizons

length of time horizon computed increase.

Figure 5.3 illustrates how the time horizon affects the model's cost performance under different standard deviations, with the total number of departments in the network held constant. The results demonstrate a positive correlation between the length of the time horizon and the model's cost performance: as the time horizon increases, the cost rises exponentially. A pattern consistent with Figures 5.1 and 5.2 is observed here as well; the plots start from closely aligned positions, as the number of departments computed increase, the divergence between the cost performance of different values of standard deviation become more pronounced. This phenomenon becomes more noticeable with increased length of time horizon computed.

To summarize the sensitivity analysis of the model's cost performance, positive correlations were observed between the cost and all three parameters tested: the total number of departments,

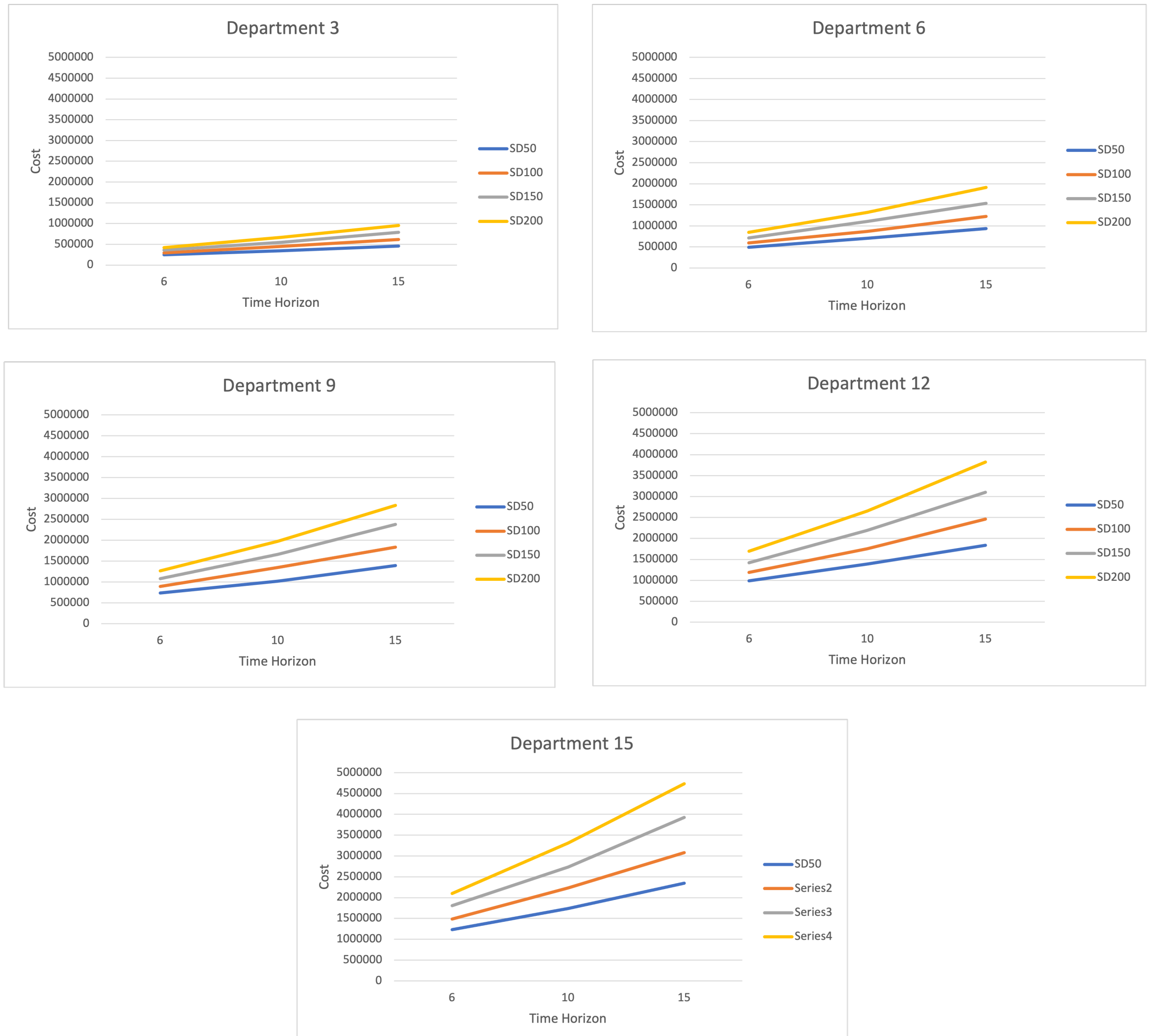

Figure 5.3: Cost performance of time horizon and SD under no. of department

the time horizon, and the standard deviation. In scenarios where the standard deviation or the number of departments was fixed, cost increases occurred exponentially as the other variables grew. In the case where the time horizon was fixed, the cost also showed an upward linear trend, though at varying rates depending on the other parameters. Across all scenarios, the cost displayed a non-parallel growth pattern, meaning that the divergence between cost curves became more pronounced as the values of the variables increased. This behaviour underscores the sensitivity of the model, indicating that as the complexity of the problem grows—whether through the inclusion of more departments, longer time horizons, or larger standard deviations—the cost rises at an accelerating rate, highlighting the importance of careful parameter management in optimizing cost efficiency.

5.3.2 Time performance

Moving to the time performance of the model, Figure 5.4 illustrates the sensitivity analysis regarding how the length of time horizon affects the model's time performance while maintaining a fixed standard deviation. With time performance plotted against time horizon for different numbers of departments under a fixed value of standard deviation, all graphs indicate a positive correlation. As the length of time horizons included in the model increases, the associated costs rise exponentially, and the divergences among the different department counts become more pronounced towards the end of the plots. Notably, regardless of the value of the standard deviation and the length of time horizon, the plots begin from similar positions and end at similar endpoints. This observation suggests that the value of the standard deviation and length of time horizon has a minimal influence on the model's time performance.

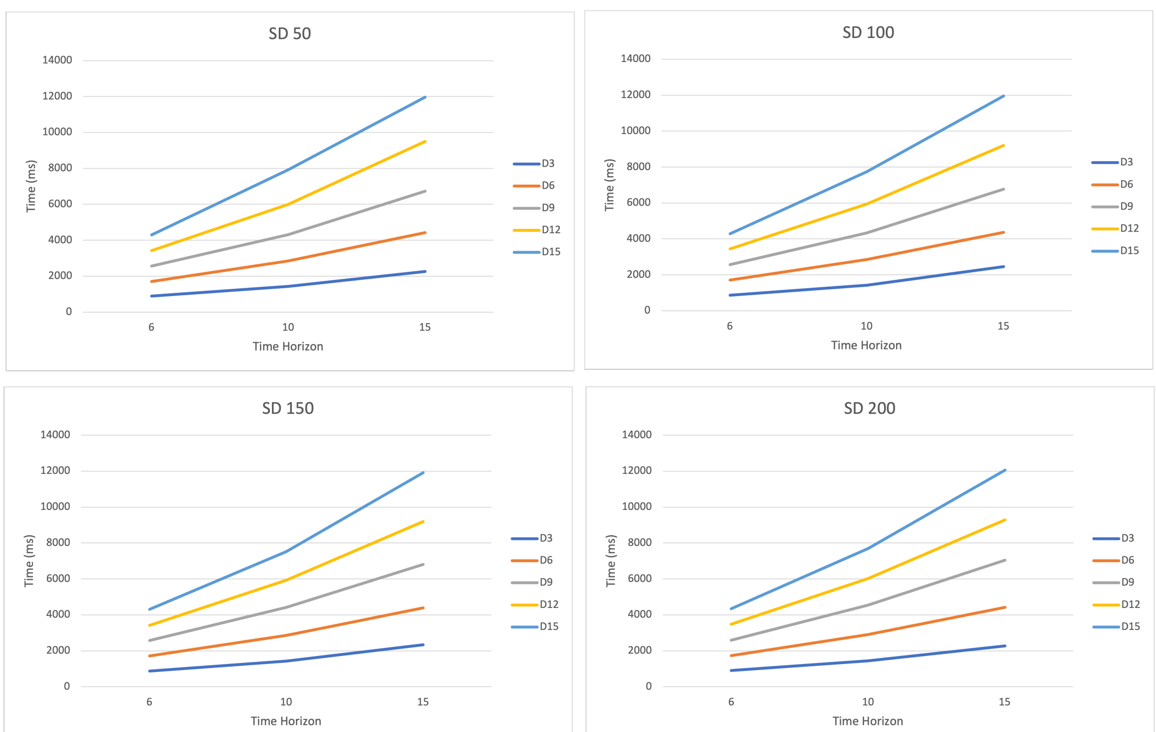

Figure 5.4: Time performance of time horizons and no. of department under fixed SD

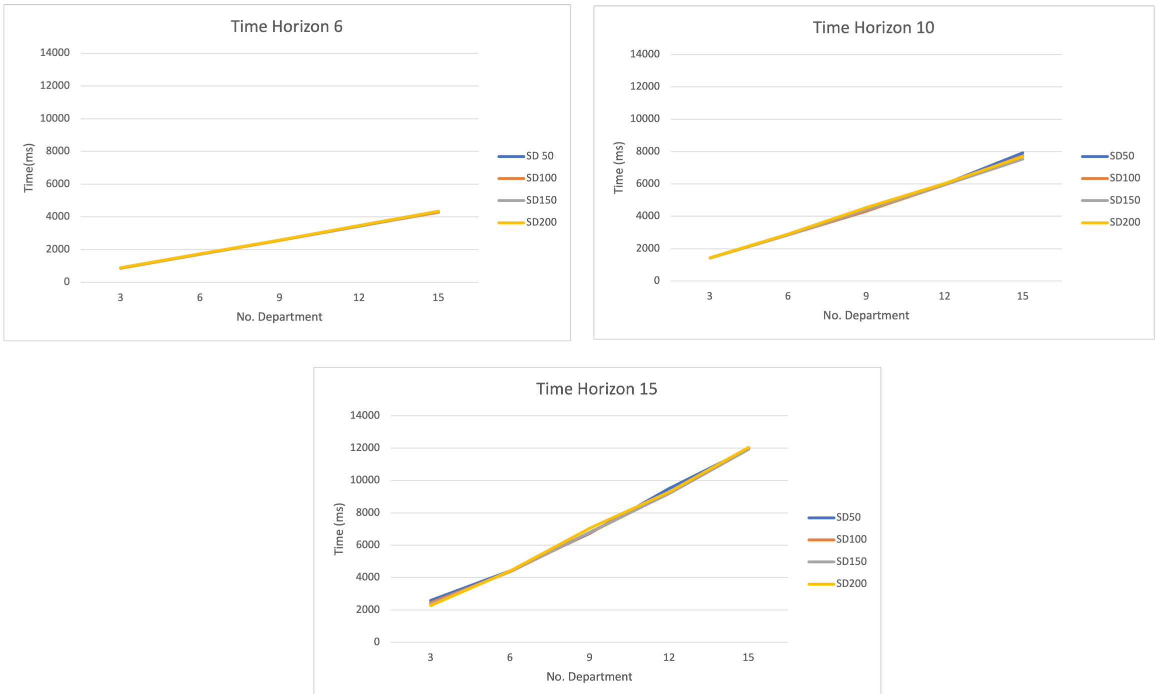

Figure 5.5: Time performance of no. of department and SD under fixed time horizons

Figure 5.5 demonstrates the results of the time performance plotted against the number of departments, approximated with different standard deviations under a fixed time horizon. The time performance of the model exhibits a positive correlation with the number of departments in an obscure exponential fashion; as the total number of departments considered in the model increases, the time required for the model to generate planning decisions also rises. However, contrary to cost performance sensitivity analysis under the same setting in 5.3.1, the plotted lines representing varying values of standard deviation nearly overlap, exhibiting nearby starting points, similar growth magnitudes, and close endpoints. Although these results may appear atypical, they align with findings of Figure 5.4, where the value of the standard deviation was shown to have an insignificant impact on the model's time performance. When comparing scenarios with different fixed time horizons, it is observed that as a longer time horizon is considered in the model, the starting point of the plot shifts upward, resulting in a higher endpoint. This indicates that a longer processing time is required to compute planning solutions for time horizons that comprise more periods.

Figure 5.6 illustrates how the time horizons affect the time performance across varying standard

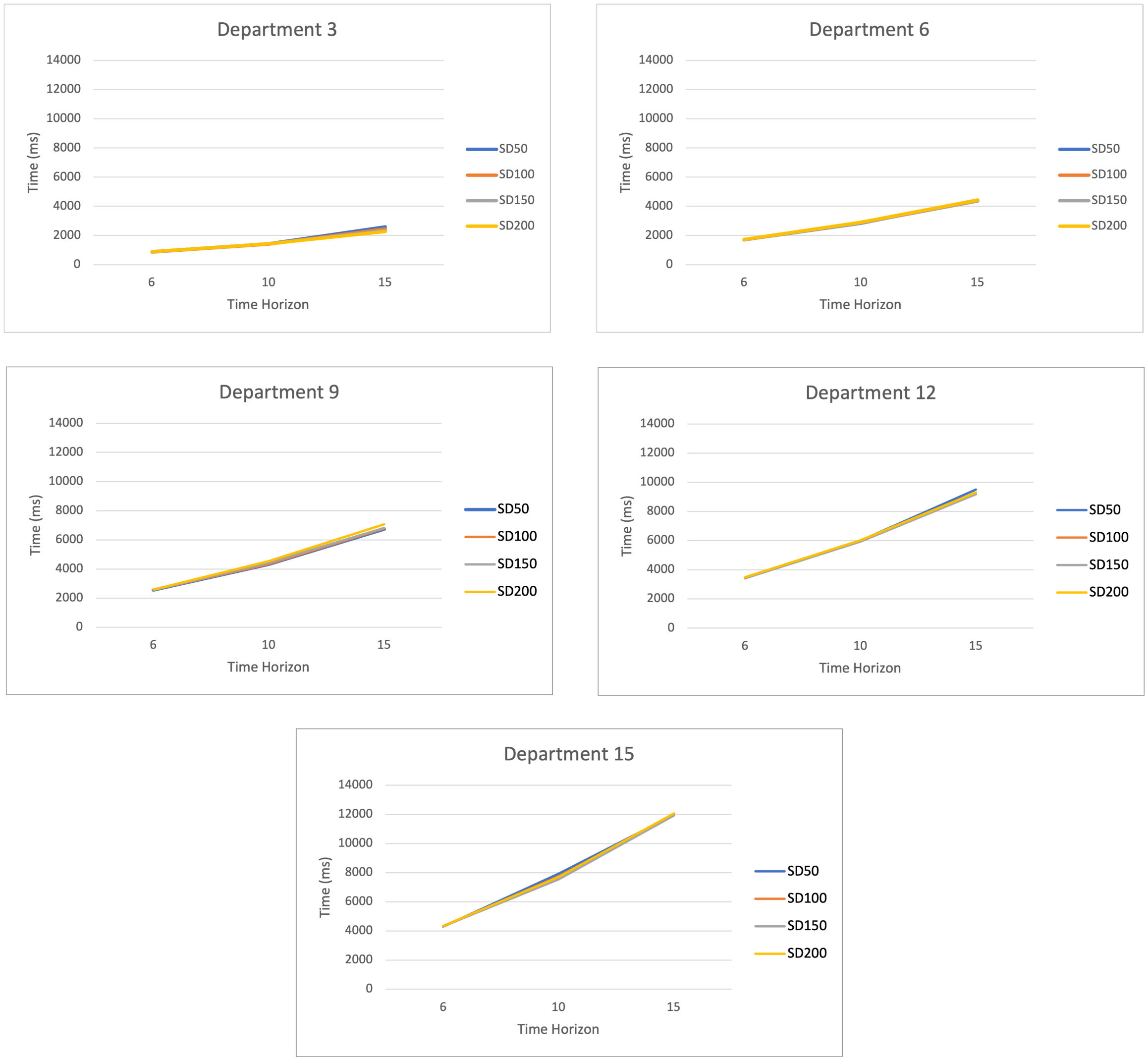

Figure 5.6: Time performance of time horizons and SD under fixed no. of departments

deviation values under a fixed number of departments. Similar to the previous analysis, the plots demonstrate a positive correlation in an exponential fashion, indicating that as the number of time horizons increases, the time required to generate planning solutions also rises exponentially. The plots reveal similar patterns as presented in Figure 5.5; although the time required to compute the model increase as the length of time horizon increase and the numbers of department increase, the plots with different value of standard deviation overlapped in each graph, which aligns with our observation from Figure 5.4 and Figure 5.5 that the value of standard deviation have insignificant impact on the model's time performance.

To summarize the findings observed from the sensitivity analysis regarding the model's time performance, similar to the observations made regarding cost performance, a significant positive correlation exists between time performance and both the total time horizon and the number of departments. However, the correlation between time performance and standard deviation appears to be insignificant, indicating that the model is not sensitive to larger fluctuations and remains to be time efficient even with larger value of standard deviation.

By integrating sensitivity analysis of both cost and time performance, our experiment revealed that all control variables, including the time horizon, total number of departments, and the standard deviation value, exhibited a positive correlation with cost performance. However, only the time horizon and the total number of departments showed a significant positive impact on the model's time performance. Furthermore, when the time horizon is held constant, the relationship between the number of departments and both cost and time performance tends to increase in an almost linear manner. In other scenarios, the results demonstrate a positive correlation in an exponential fashion, regardless of which performance aspect is being assessed. The analysis reveals that the time performance of the model is not sensitive to fluctuations, suggesting its robustness to handle real-world fluctuations with stable time performance. Although the cost performance sensitivity analysis suggests that the cost outcome of the model is more sensitive to fluctuations compared to the time performance, the results are within acceptable ranges that can be considered as effective.

The primary aim of this paper is to provide network planning solutions to the workforce uncertainty encountered by small and medium-sized enterprises in their daily operations. For the purposes of our experiment, we established an upper limit of 15 departments, as this was deemed appropriate for reflecting the scale of such businesses. Additionally, based on recommendations from prior research suggesting frequent planning to adapt to rapidly changing environments, we selected a time horizon of up to 15 periods as a suitable upper boundary for the study. The experimental results indicated that the solutions obtained were practically acceptable, demonstrating the effectiveness of the approach. Therefore, we opted to proceed directly to the conclusion without further refining heuristic approaches as additional development was not necessary.

Chapter 6

Conclusion

This research extends the framework of Song and Huang's multistage workforce capacity planning problem by developing a more flexible and robust model tailored specifically for small and medium-sized enterprises (SMEs). Our approach incorporates several key enhancements aimed at improving the model's adaptability and effectiveness. Firstly we introduced the concept of employee proficiency ranking. This allows us to evaluate the workforce capacity based on production rates rather than merely headcounts. By incorporating employee proficiency into the model, we provide a more accurate representation of the operational challenges that SMEs face, particularly in managing the uncertainties associated with workforce turnover. This refinement enables the model to better address the complexities of maintaining productivity amidst a highly dynamic and unpredictable workforce environment.

Drawing on the three main streams of approaches in prior research to solve the problem of workforce assignment using existing labour, labour training, and recruitment planning, we have integrated these strategies into a unified framework. Our model expands upon prior studies, such as Song and Huang's multistage workforce capacity planning problem(2008) and the shift scheduling patterns explored by Steenweg, Schacht, and Werner (2021), both of which highlighted the value of workforce flexibility through interdepartmental transfers. What sets our model apart is the incorporation of cross-training as a central component of workforce mobility. By emphasizing cross-training, the model not only facilitates flexible staffing but also enhances the ability of SMEs to adapt quickly to changes in labour demand, thereby minimizing the risk of operational disruptions.

A major challenge in workforce planning is managing the uncertainty caused by fluctuating employee turnover rates. While previous studies have often addressed this uncertainty through time-based cost structures, our approach diverges by incorporating production rates to account for variations that arise when employees with different proficiency levels are reassigned across departments. Inspired by Cavagnini, Hewitt, and Maggioni's (2020) study on the uncertain learning rates of labour during cross-training, we introduced a proficiency ranking system that captures the temporary decline in production rates that often accompanies workforce transfers. This approach allows for a more nuanced understanding of the impact of labour transfers on production efficiency. Unlike Edward and Anderson's study, which focused on penalizing mismatches between workforce capacity and demand, our model emphasizes optimizing workforce planning to meet demand without relying on penalties. By focusing on production rates rather than penalty costs, our approach seeks to provide an optimal solution that aligns workforce capacity with operational requirements in a more practical and cost-effective manner. Since SMEs typically operate with smaller, more specialized teams, integrating proficiency rankings provides a realistic means of evaluating the impact of workforce transfers on overall production efficiency. This approach captures the nuances of employee performance and its influence on productivity, thereby offering a more comprehensive strategy for workforce management in uncertain conditions.

Recognizing that production plants typically consist of departments with varying levels of technical expertise, our model incorporates the distinction between high-tech and low-tech departments. This differentiation addresses the variations in training requirements across departments, which in turn affects the proficiency rankings of employees when they are reassigned to departments with different skill demands. By assigning distinct production rates to employees based on their proficiency levels, the model takes into account differences in learning rates during cross-training. This approach ensures that the workforce planning solution is both comprehensive and resilient, capable of meeting production demands even when employee skill sets differ significantly across departments. The results of our numerical experiments validate the model's effectiveness, demonstrating that it offers a practical and robust solution for SMEs to tackle daily workforce planning challenges, particularly under conditions of uncertain labour capacity.

Our model was specifically designed to help SMEs adapt to rapidly changing environments. To achieve this goal, we structured our mathematical experiments to include a system with up to 15 departments and a time horizon of up to 15 periods to reflect typical SMEs characteristics. The results indicate that the model performs effectively in terms of both time and cost, demonstrating its feasibility for SMEs in generating workforce planning solutions. These findings underscore the model's practicality for regular, short-term workforce capacity planning, offering SMEs a valuable tool for managing labour resources amidst uncertainty. By addressing the unique challenges faced by smaller enterprises, the model enables more efficient allocation of workforce resources, thereby enhancing operational resilience.

While our study offers a practical approach for SMEs to manage workforce planning under conditions with stochastic turnover, we acknowledge there are certain limitations and areas for future research. The scope of our current study was limited by its focus on SMEs, and as a result, the problem size we analysed in the numerical experiments was relatively small. This allowed us to use a successive convex approximation method to compute solutions effectively. However, future studies could expand the problem size by increasing the value of controlled variables such as total number of departments and extending the time horizon to test the model's scalability for the application of larger production system.

As the problem size increases, the linear approximation method we employed may no longer be the most efficient or viable approach. Therefore, future studies could focus on developing alternative heuristic methods that are better suited for solving larger and more complex workforce planning problems. This would enhance the model's applicability, making it suitable not only for SMEs but also for larger enterprises or settings with more intricate workforce dynamics. Additionally, exploring advanced optimization techniques could provide further insights into how workforce planning solutions can be adapted to various industries and organizational structures, thus broadening the model's practical relevance. As the importance of a robust workforce planning is realized in terms of counteracting the impact of uncertainty, we expect that the topic of stochastic labour turnover management will receive increasing attention in the future.

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