Optimization of Job Allocation in Construction Organizations to Maximize Workers' Career Development Opportunities

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Abstract: Workforce planning in the construction industry too often ignores the symbiotic relationship between employee and employer objectives by overly concentrating on corporate objectives such as maximizing productivity at the expense of construction workers' career development needs. Overall, the consequence of this approach is suboptimal performance. To address this problem, this paper presents an innovative multiobjective model that enables managers to optimize the relationship between these interdependent corporate priorities. The proposed model was implemented and solved using mixed-integer nonlinear programming on a case study involving the allocation of tasks to employees with different skill levels in a multidisciplinary engineering consulting company. While leading to a small loss of productivity, the results show a significant improvement in the career development of workers compared to conventional productivity-oriented workforce planning models, with on average 8.6% improvement in employees' closeness to their ideal skill set. Furthermore, the model produced Pareto-optimal points and a Pareto curve that enabled client-model users to select optimum job allocation based on their preferences. This research represents a paradigm shift toward a new class of socially responsible workforce planning models in which the objectives of both employees and employers are optimized. **DOI: 10.1061/(ASCE)CO.1943-7862.0001652.** *© 2019 American Society of Civil Engineers.*

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Introduction

The construction industry is a key global employment sector which employs more people than any other industry and is anticipated to grow by more than 70% to $15 trillion worldwide by 2025 (Global Construction Perspectives and Oxford Economics 2013). According to Betts et al. (2011), the global construction industry will constitute 13.2% of global gross domestic product (GDP) by 2020. In 2016, the construction industry's dollar value added $784 billion to the US economy, which was equal to 4.2% of the GDP, with a gross output of $1.433 trillion (Migliaccio and Holm 2018). According to the US BLS (2017), about 6.7 million people were employed in the US construction industry in 2016 and 6.9 million in 2017. In 2015, about 14.2 million people were employed in the construction sector of the 28 member countries of the European Union (EU-28) (Baradan et al. 2018). In the United Kingdom, it contributes to approximately 10% of the country's GDP, and employs approximately 2 million people annually (Ruan et al. 2016). In Australia, the construction industry employed 1,033,100 people in 2014 and contributed around 8% of GDP (Hu and Liu 2016; ABC 2014). In many countries, the construction industry is facing a major skills shortage at a time of unprecedented infrastructure and construction investment. For example, in Australia, there is a planned AUD 150 billion infrastructure pipeline across federal and state governments and there is an aging construction workforce undermined by decades of underinvestment in apprenticeships, training, and workforce development (ABC 2017; MBA 2017; ABC 2016; CICA 2015). Estimates suggest that 50% of all construction occupations will be in shortage over the next 5 years and the Australian construction industry is estimated to need an extra 13,000 to 15,000 new apprentices per year and an additional 300,000 skilled workers nationally over the next decade, a 30% increase on the current workforce of 1,033,000 people (CICA 2015; ABC 2017; MBA 2017). In other countries like the United Kingdom, serious skills shortages are also predicted, with Farmer (2016) identifying skills shortages as the biggest constraint on the UK construction industry in meeting the urgent housing needs of 1 million homes in 2015. As Barbosa et al. (2017) noted, in the United Kingdom, two-thirds of 8,500 small- and midsize construction firms regularly turn down work because they do not have enough employees, and in the United States, 69% of nearly 1,500 construction firms are having trouble filling hourly craft positions. While some countries have turned to informal or migrant labor to fill the labor gap, this is not considered a sustainable long-term solution because such workers are transient, and employers have no

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incentive to invest in training beyond what is required for their project.

In response to these challenges and constraints, initiatives to address skills shortages and improve construction productivity have received increasing attention within the construction industry in recent years (Yi and Chan 2013; Mani et al. 2017; Vereen et al. 2016; Kazaz et al. 2008). A recent global review of construction productivity by Barbosa et al. (2017) concluded that globally, construction sector labor-productivity growth averaged 1%/year over the past two decades, compared with 2.8% for the total world economy and 3.6% for manufacturing. It also concluded that by acting in several areas, the industry could boost productivity by 50% to 60%. At the heart of these recommendations was the need to develop better models of workforce development, apprenticeships, and workforce planning to ensure that the construction workforce has the skills and knowledge it needs for the future. Workforce planning is defined as the strategic alignment of an organization's human capital with its business direction. It is a methodical process of analyzing the current workforce, determining future workforce needs based on strategic goals, identifying the gap between present and future workforce needs, and implementing solutions to address the gap so the organization can accomplish its mission, goals, and objectives (HRS 2013). As Ahmadian Fard Fini et al. (2017) pointed out, workforce planning plays a pivotal role in smooth execution of construction projects especially in the context of growing infrastructure demand and the growing demographic challenges around skills shortages and development, aging and workforce attraction, and retention, which plague the industry.

Growing interest in workforce planning has led to the development of numerous novel conceptual and mathematical workforce planning techniques in recent years with varying focuses including improving the productivity of workers through optimizing the hiring and firing decisions (Blatter et al. 2012; David et al. 2007), multiskilling strategies (Gomar et al. 2002), training of existing workers (Othman et al. 2012), effect of job insecurity on productivity and creativity (Probst et al. 2007), optimization of crew composition (Ahmadian Fard Fini et al. 2015), optimizing the job allocation (Ahmadian Fard Fini et al. 2016), and work assignment optimization (Ballard and Howell 1998). However, current optimization models are largely targeted at corporate demands for increased productivity, while overlooking the objectives and needs of the workers. This is despite contemporary theories of workforce planning recognizing that workforce planning is not just about maximizing organizational objectives but is also concerned with aligning the needs and priorities of the organization with those of its workforce, based on significant and long-standing evidence that there is a symbiotic relationship between the needs of workers and productivity (Batton 2017). Yet as Dainty and Loosemore's (2013) critique of strategic human resource management practices in the construction industry showed, despite a close correlation between organizations that balance the needs of workers and corporate performance, construction research is replete with strategies for achieving this objective.

Workforce planning is particularly challenging in construction due to the subcontracting model of organization and the shifting multiproject environment, which leads to constantly changing resource requirements and changing demands over a project's life cycle (Raiden et al. 2008). As Dainty and Loosemore (2013) showed, construction businesses have long underinvested in workforce planning, training, and development. Furthermore, human resource management practices in construction are largely disconnected from contemporary theory, which recognizes the two-way relationship that exists between employer and employee and that the employment relationship has a psychological dimension beyond the legal and formal one in which an employee simply obtains work from an employer in return for a reward. This psychological contract defines the informal beliefs of each of the parties as to their mutual obligations within the employment relationship and is important because it allows employment contracts to be seen as a two-way exchange process, rather than one imposed by employers for their own interests, often at the expense of the employees'.

Contemporary theory recognizes that effective workforce planning balances both employer and employee interests and involves plans for future needs of employees, their required skills, acquisition of employees, and personnel development (Werther and Davis 1985; Moore et al. 2002). The objectives and needs of employees that should be considered in workforce planning include, but are not limited to, career opportunities and financial rewards (Brown 2002a); work values and job rewards (Kalleberg 1977); work-life balance (WLB) (Lingard et al. 2007); job satisfaction (Morganson et al. 2010); successful workplace learning and mentoring (Smith 2003); integration of workers' differences, personalities, and motivation into workforce planning (Othman et al. 2012); and receiving assistance in meeting the new demands of the ever-changing work environment (Matthews 1999). This paper focuses on career development as one dimension of the workforce planning function because it has been widely recognized as key to meeting the psychological contract between construction employees and employers, which leads to positive corporate citizenship behaviors and in turn better construction project performance (Lim and Loosemore 2017; Loosemore and Lim 2017; Nguyen and Hadikusumo 2017). More specifically, it focuses on the opportunities allocation and structuring of work as an innovative mechanism for worker career development, while also maximizing the often competing goals of maximizing project productivity in a highly time- and resource-constrained environment. Providing workers with on-the-job learning opportunities through assigning them to the tasks outside their current area of expertise may not always be in favor of maximizing the overall productivity because the experienced workers are likely to have considerably higher initial productivity than less experienced workers in the same trade (Medoff and Abraham 1980). This potential misalignment between employers' productivity goals and employees' career development goals transforms the task allocation problem into a multiobjective optimization problem with competing objectives.

There is currently a lack of systematic methods to resolve these competing objectives. This could be partly due to difficulties in modeling career development as a measurable variable that can be optimized as well as difficulties in enhancing career development opportunities without compromising the construction crew's productivity. The existing literature on career development opportunities in workforce planning is mainly limited to (1) qualitative models of career interests, choice, and development (Holland 1985, 1997; Parsons 1909; Peterson et al. 1991; Lent et al. 1994; Brown 1995, 2002b), and (2) theoretical propositions such as psychological theory of work adjustment (Dawis and Lofquist 1984), developmental theory of occupational aspirations (Gottfredson 1981), social learning theory of career decision making (CDM) (Mitchell 1974; Krumboltz et al. 1979), and theories rooted in logical positivism and social constructionism (Collin and Young 1986; Hoshmand and Tsoi 1989; Wilber 1989). To address this gap in knowledge, this paper presents an innovative mathematical model for multiobjective optimization of task allocation to workers, with two objectives: (1) maximizing career development opportunities available to construction workers, and (2) maximizing the overall productivity of the construction crew. The proposed model is applied to and solved for an illustrative case project involving the allocation of tasks to workers with different skill levels in a multidisciplinary engineering consulting company.

Mathematical Model Formulation

The model proposed in this study aims to solve the problem of optimizing job allocation in construction organizations to maximize career development opportunities as well as overall productivity. It was assumed that employees begin their career from entry level and promotions to higher levels are based on achieving the competency requirements for different skills required for the relevant level. Furthermore, it was presumed that the information with regards to breakdown of the project activities to be performed, quantity of the work, available workers, and attributes of each worker including skills, level of expertise, and historical learning rates are available. The objective was to distribute the given workload among individual workers in such a way that not only the overall productivity of the crew is maximized but also the on-the-job career competency development opportunities available to workers are maximized. The latter involves selecting the tasks assigned to each worker by considering the experience of a worker in one of the areas required for promotion to a higher level, while taking into account the ideal long-term promotion objectives of the worker.

The model is capable of considering a wide range of practical applications by adjusting employment parameters and various constraints. For instance, (1) having single-skilled and multiple-skilled workers, (2) having several skill levels from novice and beginner to expert and advanced level for each skill trade such as engineering design, (3) including full-time, part-time and casual employment status, and (4) having lower and upper bounds for working times enables the model to represent many practical cases.

The proposed formulation could provide significant savings in productivity for the contractor and consultant companies and efficient career development for the working crew. In the context of a multiproject problem, the optimization process can be executed once per project.

Terminology and Notation

We denote $\mathbf{I}$ as the set of primary skills of workers. For instance, if the skill sets required in an engineering consulting firm include engineering design, documentation, and marketing skills, these three primary skills are elements of the set $\mathbf{I}$.

The skill level of the employee is denoted by set $\mathbf{E}$. Five stages of skill development were presumed based on the human expertise model suggested by Dreyfus (1982). The abilities and requirements of each skill level are explained in Table 1. A common factor determining the stage of skill development of each worker, as used in this paper, is the worker's years of experience (Majozi and Zhu 2005; De Bruecker et al. 2015). Following this assumption, the skill levels were as follows: $e = 1$ indicates a novice worker (0–3 years of experience), $e = 2$ represents an advanced beginner worker (3–7 years of experience), $e = 3$ denotes a competent one (7–15 years of experience), $e = 4$ indicates a worker with proficient skill level (15–22 years of experience), and $e = 5$ shows an expert worker (22–30 years of experience). Employees' average years of experience in skill level e is represented by $\mathbf{B_e}$. Multiskilling status of workers is shown by set $\mathbf{Z}$, which takes values of $z = 0, 1$ for a single-skilled and multiskilled worker, respectively. The employment status of each worker is shown by set $\mathbf{T}$, which takes values of $t = 1$, 2, 3 for full-time, part-time, and casual employment, respectively.

Table 1. Five-stage skill acquisition

Skill level	Title of skill level	Description
1	Novice	Limited, inflexible, rule-governed behavior necessary to operate a device at a novice level or to begin to learn the motor tasks required in a particular skill.
2	Advanced beginner	In addition to the set of rules, the learner begins to learn some of the important situational aspects of the task but may not be able to differentiate the importance of those aspects.
3	Competent	The learner sees actions in terms of goals and plans, based on the selection of important features of the situation, which are used to guide action.
4	Proficient	The performer is able to select the best action plan unconsciously and summarize situations swiftly.
5	Expert	The performer acts intuitively from a deep understanding of the situation, appears unaware of rules and features, and performs with fluidity, flexibility, and high proficiency.

Source: Data from Dreyfus (1982).

The type of the activity is denoted by set $\mathbf{J}$. In the classification adopted by this study, each activity is comprised of several tasks which are denoted by set $\mathbf{M}$. Furthermore, each task $m \epsilon M$ corresponds to one or more required skill(s) $i \epsilon I$.

Learning Rate

The rate at which a worker's skill level and productivity are improved is the worker's learning rate. The workers' learning process is influenced by several factors including structure of training programs (Azizi et al. 2010), workers' motivations in performing the tasks (Agrell et al. 2002), prior experience in the task (Nembhard and Osothsilp 2002), and task complexity (Pananiswami and Bishop 1991). The way these factors impact the workers' learning process can be analyzed by mathematical models called learning curves (LCs) (Anzanello and Fogliatto 2011). A learning curve is a mathematical description of workers' performance in repetitive tasks (Fioretti 2007). Over time, workers spend less time to do repetitive tasks because of familiarity with the operation and tools, along with possible shortcuts to task execution that are found (Dar-El 2013; Wright 1936).

Wright (1936) originally proposed learning curves to account for observed cost reduction due to repetitive procedures in production plants. Since then, LCs have been utilized to estimate the time required to complete production runs and the decrease in production costs as learning takes place, as well as to assign workers to tasks based on their performance profile (Anzanello and Fogliatto 2011). The LC has proven to be an efficient tool to monitor workers' performance in repetitive tasks (Dar-El 2013). LCs have been used to allocate tasks to workers according to their learning profiles (Heimerl and Kolisch 2010) and to measure production costs as workers acquire experience in a particular task (Wright 1936).

The expected learning rate while performing activity j is indicated by $\mathbf{l^j}$. The value of $\mathbf{l^j}$ should be estimated using the historical data on performance records for different types of activities. The learning rate of a worker with primary skill i, skill level e, and multiskilling status z while doing activity j is then defined as follows (Ahmadian Fard Fini et al. 2015):

$$\mathbf{l}^{\mathbf{j}}_{\mathbf{iez}} = f(i, e, \mathbf{l}^{\mathbf{j}}) \tag{1}$$

This function presumes that any increase in learning rate of an individual is associated with an increase in the number of new skills to be learned by the worker during performing activity j and a decrease in the worker's experience (Ahmadian Fard Fini et al. 2015).

Productivity

In the proposed model, the productivity of a worker with primary skill i, experience category e, and multiskilling status z in performing a particular task m, involved in a particular activity j, is denoted by $\mathbf{P}^{\mathbf{jm}}_{\mathbf{iez}}$ and estimated using the following equations:

$$\mathbf{P}^{\mathbf{jm}}_{\mathbf{iez}} = \frac{\mathbf{P}^{\mathbf{jm_o}}}{\mathbf{FA_z} \times \mathbf{FA_{mi}}}$$
$$\mathbf{FA_z} = \begin{cases} 1.15, & z = 1 \\ 1.00, & z = 0 \end{cases}$$
$$\mathbf{FA_{mi}} = \begin{cases} (1 + \mathbf{B_e})^{\mathbf{l^{m_o}}} & i = m \\ 1.0, & i \neq m \end{cases} \tag{2}$$

where $\mathbf{p}^{\mathbf{jm_0}}$ = initial productivity of a novice worker in doing task m in activity j as indicated by the historical or relevant data; $\mathbf{l^{m_0}}$ = average learning rate in task m, regardless of the activity type, and can be extracted from reference data (Gottlieb and Haugbølle 2010; Zahran et al. 2016); and $\mathbf{FA_z}$ accounts for the additional improvements in productivity of the multiskilled workers compared to single-skilled ones (Ahmadian Fard Fini et al. 2015). In this study, this productivity surplus was assumed to be 15% (Rodriguez 1998). In contrast, $\mathbf{FA_{mi}}$ accounts for the effect of years of a worker's past experience ($\mathbf{B_e}$) in a similar task according to the Stanford-B equation of learning theory (Anzanello and Fogliatto 2011). There is generally a relationship between complexity and the level of the details involved in the task and its learning rate. Based on this formulation, simple and easy-to-learn tasks generally have a higher learning rate, leading to smaller differences between productivity of workers with different levels of experience. In contrast, a decrease in the learning rate (which is usually associated with an increase in the complexity and level of details involved in the task) tends to increase the gap between the productivity of the workers from various experience categories.

Decision Variables and Objective Functions

As highlighted previously, the objectives targeted in this study were to maximize the workers' career development opportunities and productivity. The decision variables were the amounts of works allocated to each worker ($\mathbf{y_{ik}}$). It was assumed that a worker is qualified for promotion to the next career level when the worker meets the minimum experience level in all the skills required by the next-level position (Brown 2002a). Eq. (3) was defined to account for improvement in skill level of individual k in skill i after performing the allocated tasks

$$\mathbf{S_{ik}} = \underline{\mathbf{S}}_{\mathbf{ik}} + \boldsymbol{\alpha}_{\mathbf{ik}}\mathbf{y_{ik}} \tag{3}$$

where $\underline{\mathbf{S}}_{\mathbf{ik}}$ = initial level of experience of individual k in skill i; $\mathbf{y_{ik}}$ = amount of work related to skill i that is allocated to individual k; $\mathbf{S_{ik}}$ = improved skill level of individual k in skill i after performing the allocated task; and $\boldsymbol{\alpha}_{\mathbf{ik}}$ = skill development rate coefficient that determines the level of on-the-job training required for the worker to achieve the next competency level in skill i. The value of $\boldsymbol{\alpha}_{\mathbf{ik}}$ may vary from one skill to another and should be determined based on records of the organization. It was assumed that this value is determined by the company and their view on how much a repetitive task should be performed to be eligible for promotion to a higher skill level. This is dependent on task type, which indicates that the required repetitive task performance for promotion is different for each task such as administrative works, engineering design, and laborious jobs. We propose that a reliable resource to obtain this coefficient is the historical employment records highlighting the level of experience of current and previous personnel employed at different skill levels.

A major challenge in quantifying the career development of individual workers is the difference in the perceptions of different workers toward what they consider as the ideal position in the organization. In other words, the organizational hierarchy usually comprises several distinct promotion paths from entry level to senior management level. On the other hand, the ideal job of a worker may not necessarily be at the climax of the organizational chart. To account for this, in the present study, a parameter named ideal position was defined for each individual worker, where the ultimate goal of the worker is to progress from the current position to the ideal position by gaining a sufficient level of experience in its required skills. Parsons (1909) argued that allowing employees to actively interfere in selecting their career path can lead to improved job satisfaction and efficiency. We assumed that the minimum experience level in different skill sets required by each position can be obtained from human resource (HR) records in the organization, which include the skill levels of the employees currently or previously holding the position. In this study, parameter $\overline{\mathbf{S}}_{\mathbf{ik}}$ is defined to represent skill level associated with the ideal job for candidate k. The initial skill levels ($\underline{\mathbf{S}}_{\mathbf{ik}}$) and those associated with the ideal position of the workers are defined by vectors presented in Eqs. (4) and (5), respectively

$$\underline{\mathbf{S}}_{\mathbf{ik}} = (\underline{\mathbf{S}}_{\mathbf{1k}}, \underline{\mathbf{S}}_{\mathbf{2k}}, \ldots, \underline{\mathbf{S}}_{\mathbf{ik}}) \tag{4}$$

$$\overline{\mathbf{S}}_{\mathbf{ik}} = (\overline{\mathbf{S}}_{\mathbf{1k}}, \overline{\mathbf{S}}_{\mathbf{2k}}, \ldots, \overline{\mathbf{S}}_{\mathbf{ik}}) \tag{5}$$

A value of 0 for the level of a particular skill ($\underline{\mathbf{S}}_{\mathbf{ik}}$) is possible and means no experience in that particular skill. In order to monitor the closeness and progress of each worker toward the worker's ideal position, a distance function was defined that quantifies the distance between the worker's current level of skills and the level of skills required by the ideal position

$$\mathbf{D_k} = \sqrt{(\overline{\mathbf{S}}_{\mathbf{1k}} - \mathbf{S_{1k}})^2 + (\overline{\mathbf{S}}_{\mathbf{2k}} - \mathbf{S_{2k}})^2 + \cdots + (\overline{\mathbf{S}}_{\mathbf{ik}} - \mathbf{S_{ik}})^2} \tag{6}$$

The lower the distance, the closer the worker to the ideal skill level, i.e., the more skill levels are developed. Accordingly, to maximize the career development opportunities for each worker, the first objective function is defined as

$$\text{minimize} \max_{\{k \in K\}} \mathbf{D_k} \tag{7}$$

To ensure the career development is not achieved at the expense of considerable loss of productivity, the second objective function is defined to minimize total time of project in order to maximize overall productivity

$$\text{minimize} \sum_{i \in I} \sum_{k \in K} \mathbf{y_{ik}} \tag{8}$$

Constraints

The constraints of the proposed formulation are described in the following. Eq. (9) sets the total amount of work allocated to workers to be equal to the total amount of work to be done in the project for each construction trade ($\mathbf{H_i}$). The distributive justice targeted in this study included the fair distribution of hiring, promotion, and workload allocation over individuals (Colquitt 2001). In order to account for distributive justice, two constraints were defined. The first constraint ensured that the maximum working hours per week for each worker do not exceed the specified limit value ($\mathbf{U_k}$) [Eq. (10)], while the second constraint ensured a minimum weekly work allocation ($\mathbf{L_k}$) for each worker [Eq. (11)]. In these two constraints, w is the total number of weeks in life span of the project

$$\sum_{k\in K}\frac{\mathbf{y_{ik}}}{\mathbf{P^{m}_{iez}}}=\mathbf{H_i}\quad \forall\ i\in I,\quad \forall\ m\in M \tag{9}$$

$$\sum_{i\in I}\mathbf{y_{ik}}\leq \mathbf{U_k}w\quad \forall\ k\in K \tag{10}$$

$$\sum_{i\in I}\mathbf{y_{ik}}\geq \mathbf{L_k}w\quad \forall\ k\in K \tag{11}$$

In addition to the preceding constraints, there are several technical constraints that directly influence work method and cannot be neglected. The technical constraints highlighted widely in the available literature include crew size restrictions (Long and Ohsato 2009), safety and quality mandates (Safe Work Australia 2014), and skill requirements of the jobs (Srour et al. 2006). Eqs. (12)–(17) account for these three types of constraints, respectively.

The crew size limitation in this study was specified mainly by training capacity limitations. Eq. (12) ensures that the number of workers trained in skill i does not exceed the available capacity for training. The training capacity can be limited by several factors including insufficient number of experienced workers to mentor new trainees or inadequate training centers or facilities. In this constraint, $\sum_{k\in K}\mathbf{T_{ik}}$ is the number of workers who will be trained in skill i and $\mathbf{C_i}$ is the number of available mentors in skill i for training purposes (capacity). Eq. (13) ensures that the number of workers assigned to different tasks does not exceed the number of available workers with the required skills. In this constraint, $\mathbf{n_i}$ represents the number of available workers with skill i and $\mathbf{x_{ik}}$ is a binary variable that is 1 if the worker k with skill i is assigned to work, and is otherwise 0

$$\sum_{k\in K}\mathbf{T_{ik}}\leq \mathbf{C_i}\quad \forall\ i\in I \tag{12}$$

$$\sum_{k\in K}\mathbf{x_{ik}}\leq \mathbf{n_i}\quad \forall\ i\in I \tag{13}$$

Eqs. (14)–(16) were imposed to meet the health and safety requirements. Eq. (14) was imposed to ensure working time of employees is less than allowable working hours ($\mathbf{Q_i}$) for certain hazardous manual tasks ($\mathbf{I_h}$). Eq. (15) limits the number of workers with skill i to a threshold ($\overline{\mathbf{n}}_\mathbf{i}$) of those allowed to work in certain condition of confined space ($\mathbf{I_c}$). Eq. (16) indicates that skill level of individual k for performing high-risk works ($\mathbf{I_{hr}}$) should be equal to or greater than certain value of $\widetilde{\mathbf{S}}_\mathbf{i}$, which is determined based on level of difficulty and requirement of the task in particular

$$\mathbf{y_{ik}}\leq \mathbf{Q_i}w\quad \forall\ k\in K,\quad \forall\ i\in \mathbf{I_h}\quad \text{(hazardous tasks)} \tag{14}$$

$$\sum_{k\in K}\mathbf{x_{ik}}\leq \overline{\mathbf{n}}_\mathbf{i}\quad \forall\ i\in \mathbf{I_c}\quad \text{(confined space)} \tag{15}$$

$$\mathbf{S_{ik}}\geq \widetilde{\mathbf{S}}_\mathbf{i}\mathbf{x_{ik}}\quad \forall\ k\in K,\quad \forall\ i\in \mathbf{I_{hr}}\quad \text{(high-risk works)} \tag{16}$$

When looking retrospectively at human occupational history, we realized that a lot of individuals have had no real choice in their occupational choice and development, either due to cultural norms or economic limitations. But it has become available for many workers in the recent century (Kester 2014). Accordingly, Eq. (17) is considered to allocate jobs to workers in their area of expertise and the skills they intend to further develop and to avoid unnecessary development of skills that are not important in the employee's prospective career plan

$$\underline{\mathbf{S}}_\mathbf{ik}\leq \mathbf{S_{ik}}\leq \overline{\mathbf{S}}_\mathbf{ik}\quad \forall\ k\in K,\quad \forall\ i\in I \tag{17}$$

The entire optimization problem is summarized in Eq. (18)

$$\text{minimize}\ \max_{\{k\in K\}}\mathbf{D_k} \tag{18a}$$

$$\text{minimize}\ \sum_{i\in I}\sum_{k\in K}\mathbf{y_{ik}} \tag{18b}$$

subject to

$$\sum_{k\in K}\frac{\mathbf{y_{ik}}}{\mathbf{P^{m}_{iez}}}=\mathbf{H_i}\quad \forall\ i\in I,\quad \forall\ m\in M \tag{18c}$$

$$\sum_{i\in I}\mathbf{y_{ik}}\leq \mathbf{U_k}w\quad \forall\ k\in K \tag{18d}$$

$$\sum_{i\in I}\mathbf{y_{ik}}\geq \mathbf{L_k}w\quad \forall\ k\in K \tag{18e}$$

$$\mathbf{y_{ik}}\leq \mathbf{Q_i}w\quad \forall\ k\in K,\quad \forall\ i\in \mathbf{I_h}\quad \text{(hazardous task)} \tag{18f}$$

$$\sum_{k\in K}\mathbf{x_{ik}}\leq \mathbf{n_i}\quad \forall\ i\in I \tag{18g}$$

$$\sum_{k\in K}\mathbf{x_{ik}}\leq \overline{\mathbf{n}}_\mathbf{i}\quad \forall\ i\in \mathbf{I_c}\quad \text{(confined space)} \tag{18h}$$

$$\mathbf{S_{ik}}=\underline{\mathbf{S}}_\mathbf{ik}+\boldsymbol{\alpha}_\mathbf{ik}\mathbf{y_{ik}}\quad \forall\ k\in K,\quad \forall\ i\in I \tag{18i}$$

$$\mathbf{S_{ik}}\geq \widetilde{\mathbf{S}}_\mathbf{i}\mathbf{x_{ik}}\quad \forall\ k\in K,\quad \forall\ i\in \mathbf{I_{hr}}\quad \text{(high-risk works)} \tag{18j}$$

$$\underline{\mathbf{S}}_\mathbf{ik}\leq \mathbf{S_{ik}}\leq \overline{\mathbf{S}}_\mathbf{ik}\quad \forall\ k\in K,\quad \forall\ i\in I \tag{18k}$$

$$\mathbf{y_{ik}}\geq 0\quad \forall\ k\in K,\quad \forall\ i\in I \tag{18l}$$

$$\mathbf{x_{ik}}\in \{0,1\}\quad \forall\ k\in K,\quad \forall\ i\in I \tag{18m}$$

Case Study, Results, and Discussion

The case scenario was selected from an engineering consultancy company because the workforce is the main capital of such firms, and therefore resilience of their business is highly reliant on workforce productivity and workforce development (Russell 2002). The chosen firm has specifically placed emphasis on providing on-the-job growth opportunities for its staff as a means that can simultaneously contribute to productivity improvement and staff development strategies.

Table 2. Description of skill levels

Skill level	Description	Average years of experience	Duties and responsibilities
1	Entry-level undergraduate and graduate engineers	0–2	Limited engineering (basic) tasks under the supervision of more senior engineers
2	Engineers who have completed a graduate program or have a minimum of 2 years of engineering experience	2–4	Greater independence in doing basic tasks; require supervision in doing advanced engineering tasks
3	Senior engineers with sound technical knowledge and mentoring skills	4–8	Greater independence in doing advanced engineering tasks; review works for technical accuracy
4	Principal engineers and design project managers who have a high level of proficiency in management and technical knowledge	8–12	Independency in advanced engineering tasks; independent decisions on engineering procedures; provision of technical advice to lower level engineers and allocation of work to engineers
5	Team managers and executives mainly involved in the administrative and commercial side of engineering	12+	Managing several professionals, bidding for future projects, building client relationships and overseeing all operational risks

Table 3. Workforce availability

Level	Availability		
	Full time	Part time (load)	Total
1	9	0	9
2	16	13 (0.5)	29
3	26	9 (0.5)	35
4	12	6 (0.5)	18
5	3	0	3

In the case study, allocation of tasks to employees with five skill levels in a multidisciplinary engineering consulting company was assessed. Description of skill levels and workforce availability at each skill level are presented in Tables 2 and 3, respectively. The type of tasks, number of working hours, learning rates, and coefficient of $\boldsymbol{\alpha}_{\mathbf{ik}}$ are shown in Table 4. The case study has taken into account three main features including total work quantity for the project, having lower and upper bounds for each employee's working time, and having high-risk activities. Engineering advanced and engineering review are considered to be high-risk activities due to high financial and legal consequences associated with potential issues in such activities. Therefore, the minimum skill levels of the individuals to whom the activities engineering advanced and engineering review can be assigned are 2 and 3, respectively.

We implemented the proposed model using AMPL, an algebraic modeling language for mathematical computing (Fourer et al. 2003) and we used the mixed-integer nonlinear programming (MINLP) solver COUENNE. COUENNE is an open-source code for solving MINLP problems to global optimality (Belotti 2009).

The solutions obtained from applying the proposed model to the case study are discussed subsequently. The results including the amount of hours allocated to each worker ($\mathbf{y}_{\mathbf{ik}}$), developed skill levels, initial distance measure (distance between initial skill level from skill level required by ideal position) [Eq. (19)], final skill distance measure (distance between developed skill level from skill level required by ideal position) [Eq. (20)], and improved closeness [Eq. (21)] are presented in Table 5 for 10 randomly chosen employees with different initial skill levels and the corresponding Pareto-optimal point (maximum distance, total time) = (2.05, 37,395). Table 6 shows all Pareto-optimal points obtained from model outcomes. Fig. 1 shows the Pareto curve consisting of the objective functions of career development (maximum value of skill distance measure among all workers) and productivity (total time to perform the project) on the vertical and horizontal axes, respectively

Initial distance measure:

$$\underline{\mathbf{D}}_{\mathbf{k}} = \sqrt{(\overline{\mathbf{S}}_{\mathbf{1k}} - \underline{\mathbf{S}}_{\mathbf{1k}})^2 + (\overline{\mathbf{S}}_{\mathbf{2k}} - \underline{\mathbf{S}}_{\mathbf{2k}})^2 + \cdots + (\overline{\mathbf{S}}_{\mathbf{ik}} - \underline{\mathbf{S}}_{\mathbf{ik}})^2} \tag{19}$$

Final distance measure:

$$\overline{\mathbf{D}}_{\mathbf{k}} = \sqrt{(\overline{\mathbf{S}}_{\mathbf{1k}} - \mathbf{S}_{\mathbf{1k}})^2 + (\overline{\mathbf{S}}_{\mathbf{2k}} - \mathbf{S}_{\mathbf{2k}})^2 + \cdots + (\overline{\mathbf{S}}_{\mathbf{ik}} - \mathbf{S}_{\mathbf{ik}})^2} \tag{20}$$

$$\text{Improved closeness: } \mathbf{I}_{\mathbf{k}}(\%) = \frac{\underline{\mathbf{D}}_{\mathbf{k}} - \overline{\mathbf{D}}_{\mathbf{k}}}{\underline{\mathbf{D}}_{\mathbf{k}}} \times 100 \tag{21}$$

Table 5 demonstrates the optimal job allocation among the selected workers. In this table, as shown, all employees have been assigned to jobs by considering the workload limits due to their type of employment (i.e., full time or part time). This indicates the

Table 4. Type of tasks, number of hours, and learning rates

Type	Category	Definition	Number of working hours ($\mathbf{H}_\mathbf{i}$)	Learning rate (%)	α_{ik}	Assignable to skill level
Engineering	Basic	Technical works of ongoing projects that involve basic computations	3,850	90	0.003	1, 2
	Advanced	Complex design and analytical tasks of ongoing projects	4,300	85	0.001	2, 3, 4
	Review	Reviewing both basic and advanced engineering documents	3,300	90	0.002	All except 1, 2
Administrative	—	Ongoing paperwork and internal meetings	1,350	95	0.003	All
Marketing	—	Preparation of proposals, client management, and any tasks related to potential future projects	625	90	0.001	All

Table 5. Model outcomes

Worker	Skill	Initial skill level ($\underline{\mathbf{S}}_{\mathbf{ik}}$)	Ideal skill level ($\overline{\mathbf{S}}_{\mathbf{ik}}$)	Developed skill level ($\mathbf{S}_{\mathbf{ik}}$)	Allocated hours ($\mathbf{y}_{\mathbf{ik}}$)	Initial distance measure ($\underline{\mathbf{D}}_{\mathbf{k}}$)	Final distance measure ($\overline{\mathbf{D}}_{\mathbf{k}}$)	Improved closeness [$\mathbf{I}_{\mathbf{k}}$ (%)]
Worker_{12}	Engineering basic (S_1)	2	3	2.6	300	2.236	2.039	8.82
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2	0	—	—	—
Worker_{13}	Engineering basic (S_1)	2	3	2.43	428	2.236	2.051	8.28
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2.06	21	—	—	—
Worker_{14}	Engineering basic (S_1)	2	3	2.9	300	2.236	2.002	10.47
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2	0	—	—	—
Worker_{41}	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	3	4	3	0	—	—	—
	Engineering review (S_3)	3	4	3	0	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3.3	300	—	—	—
Worker_{42}	Engineering basic (S_1)	0	0	0	0	2.000	1.735	13.25
	Engineering advanced (S_2)	3	4	3.9	300	—	—	—
	Engineering review (S_3)	3	4	3	0	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker_{43}	Engineering basic (S_1)	0	0	0	0	2.000	1.777	11.15
	Engineering advanced (S_2)	3	4	3.6	300	—	—	—
	Engineering review (S_3)	3	4	3	0	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker_{71}	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	3	4	3.3	150	—	—	—
	Engineering review (S_3)	3	4	3	0	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker_{72}	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	3	4	3	0	—	—	—
	Engineering review (S_3)	3	4	3.3	150	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker_{90}	Engineering basic (S_1)	0	0	0	0	2.000	1.841	7.95
	Engineering advanced (S_2)	4	5	4.30	97	—	—	—
	Engineering review (S_3)	4	5	4.05	54	—	—	—
	Administrative (S_4)	4	5	4	0	—	—	—
	Marketing (S_5)	4	5	4	0	—	—	—
Worker_{91}	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	4	5	4.3	150	—	—	—
	Engineering review (S_3)	4	5	4	0	—	—	—
	Administrative (S_4)	4	5	4	0	—	—	—
	Marketing (S_5)	4	5	4	0	—	—	—

model has been successful in wide-range distribution of project tasks to all workers. Worker_{71}, Worker_{72}, Worker_{90}, and Worker_{91} are part-time employees who are expectedly allocated approximately half the job amount of full-time employees. As can be seen, the job assignment through the proposed model results in between 6.6% and 13.25% improvement in closeness of employees to the skill level required for their ideal position, indicating that all employees are one step closer to meeting the experience requirements of promotion to the ideal position. Results of the model indicate a noticeable contribution to career development of employees as indicated by the 13.25% and 8.6% increase in improved closeness to ideal skillset for Worker_{42} and on average, respectively. Furthermore, the results show that the preceding improvements are achievable with only a minor reduction in productivity.

Fig. 1 depicts the Pareto front for the two minimization objective functions; maximum distance ($\mathbf{D}_k$) and total time as a measure of productivity. Moreover, Table 6 presents the values associated with Pareto-optimal points on the Pareto front. As expected, the competing nature of the objectives considered in our model resulted in a parabolic Pareto curve. The results indicate that the reduction in distance measure, i.e., improved career development opportunities, was initially associated with no or little decrease in productivity (as shown by increase in total time). However, the rate of productivity loss was found to increase gradually with further

Table 6. Pareto-optimal points

Maximum distance	Total time (h)
2.426	37,195
2.367	37,196
2.338	37,197
2.310	37,198
2.282	37,199
2.253	37,200
2.226	37,202
2.174	37,203
2.162	37,209
2.148	37,216
2.130	37,225
2.119	37,233
2.115	37,240
2.111	37,246
2.108	37,253
2.100	37,266
2.091	37,284
2.083	37,302
2.074	37,319
2.072	37,325
2.066	37,343
2.060	37,361
2.053	37,382
2.050	37,393
2.047	37,406
2.042	37,429
2.038	37,451
2.035	37,472
2.032	37,493
2.030	37,513
2.028	37,526
2.025	37,546
2.023	37,566
2.020	37,586
2.018	37,606
2.016	37,626
2.014	37,645
2.012	37,665
2.01	37,684
2.008	37,703

decrease in the distance measure. As can be seen in Fig. 1, the job allocation generated by the proposed model at the current Pareto point (maximum distance, total time) = (2.05, 37,395) led to 0.51% decrease in project productivity. Project productivity, as the competing objective with career development, decreased by 0% and 1.05% at two extremes of Pareto curves, i.e., where skill distance measure was 2.200 and 2.019, respectively. As can be realized, the Pareto front resulted from the proposed model can provide decision makers with valuable decision support information to identify the optimal job allocation based on the relative importance of productivity and career development objectives within the organization. The user can pick any of these points, knowing that they are all efficient and optimized cases of work allocation. However, based on the policies of the company or user preferences, one user might be inclined to place a higher weight for one of these objectives, e.g., productivity. In this case, the user can pick a point from the left tail of the Pareto curve where more productivity is achieved at the cost of losing career development. Overall, model outcomes demonstrate a comprehensive and purposefully optimized job allocation to workers, which has led to the highest possible career development of employees without considerable loss of productivity.

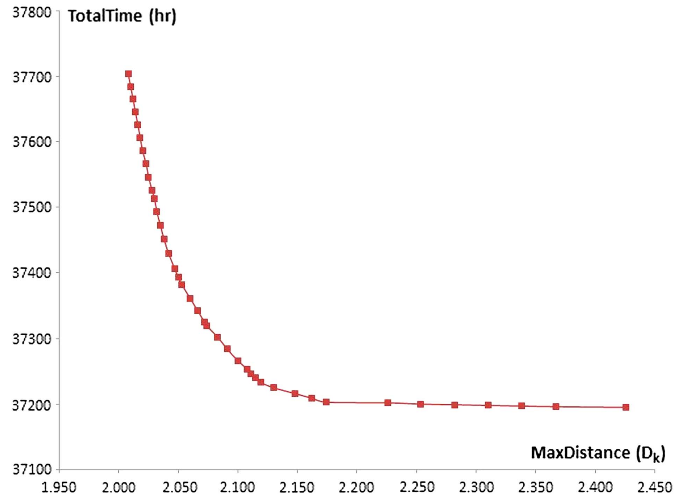

Fig. 1. Pareto front for the two objective functions.

Sensitivity Analysis

Similar to any other model, the outcome of our proposed optimization model is highly dependent on its input information and therefore might be affected by career goals of other workers, changes in crew composition, and work availability. Project activities that can increase the skill level of a worker, if assigned to the worker, are limited. Therefore over, under, or inefficient assignment of activities to a worker can adversely affect the career goals of others. Accordingly, the optimization process attempts to find a way to have all workers develop their career objectives. In this paper, the optimization process has provided a satisfactory distribution of project activities, and consequently development of career goals for all workers without over or under task assignment to any worker. Changes in crew composition do not impact the individual career developments since the ideal skill level and desired career path for each worker are considered individually in the model. To explain further, each individual worker will be assigned a certain amount of work based on the worker's predefined career goals, regardless of possible changes in the crew composition, by the end of the optimization procedure. To assess the effect of work availability, it is noted that the model uses project information from early project phases, i.e., project initiation and planning. Therefore, work and workforce availability are specified for the total time span of the project. With this assumption, the allocation of work hours and consequently skill level development for workers is performed regardless of temporary fluctuations in work availability.

A sensitivity analysis on career goals of workers was performed to evaluate its effect on the results. Five workers, Worker_{41} to Worker_{45}, were assumed to set their ideal skill levels to be 5, instead of the previous value of 4. The results of new job allocation including allocated working hours and improved closeness to ideal position are demonstrated in Table 7. As expected, the results indicate that the changes in career goals of selected workers affected the career goals of others. As can be seen, more working hours have been allocated to Worker_{41} to Worker_{43}, while working hours of some other workers such as Worker_{13} reduced from 449 to 300 h. Subsequently, Worker_{43} developed his skill levels significantly and became very close to his ideal position. This is indicated by an increase in improved closeness to 20% compared to the previous value of 11.15% for Worker_{43}, which is the maximum amount between all workers. Meanwhile, Worker_{13} became farther away from his ideal position by a decrease to 5.23% from 8.28%.

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Table 7. Sensitivity analysis

Worker	Skill	Initial skill level ($\underline{\mathbf{S}}_{\mathbf{ik}}$)	Ideal skill level ($\overline{\mathbf{S}}_{\mathbf{ik}}$)	Developed skill level ($\mathbf{S}_{\mathbf{ik}}$)	Allocated hours ($\mathbf{y}_{\mathbf{ik}}$)	Initial distance measure ($\underline{\mathbf{D}}_{\mathbf{k}}$)	Final distance measure ($\overline{\mathbf{D}}_{\mathbf{k}}$)	Improved closeness [$\mathbf{I}_{\mathbf{k}}$ (%)]
Worker$_{12}$	Engineering basic (S_1)	2	3	2.6	300	2.236	2.039	8.82
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2	0	—	—	—
Worker$_{13}$	Engineering basic (S_1)	2	3	2.3	300	2.236	2.119	5.23
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2.0	00	—	—	—
Worker$_{14}$	Engineering basic (S_1)	2	3	2.9	300	2.236	2.002	10.47
	Engineering advanced (S_2)	2	3	2	0	—	—	—
	Engineering review (S_3)	2	3	2	0	—	—	—
	Administrative (S_4)	2	3	2	0	—	—	—
	Marketing (S_5)	2	3	2	0	—	—	—
Worker$_{41}$	Engineering basic (S_1)	0	0	0	0	4.000	3.522	11.94
	Engineering advanced (S_2)	3	5	3	0	—	—	—
	Engineering review (S_3)	3	5	3.208	104	—	—	—
	Administrative (S_4)	3	5	3.906	302	—	—	—
	Marketing (S_5)	3	5	3.0	0	—	—	—
Worker$_{42}$	Engineering basic (S_1)	0	0	0	0	4.000	3.527	11.81
	Engineering advanced (S_2)	3	5	3.606	202	—	—	—
	Engineering review (S_3)	3	5	3	0	—	—	—
	Administrative (S_4)	3	5	3	0	—	—	—
	Marketing (S_5)	3	5	3.419	143	—	—	—
Worker$_{43}$	Engineering basic (S_1)	0	0	0	0	4.000	3.200	20.0
	Engineering advanced (S_2)	3	5	3.292	146	—	—	—
	Engineering review (S_3)	3	5	3.663	221	—	—	—
	Administrative (S_4)	3	5	3	0	—	—	—
	Marketing (S_5)	3	5	3.76	38	—	—	—
Worker$_{71}$	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	3	4	3.3	150	—	—	—
	Engineering review (S_3)	3	4	3	0	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker$_{72}$	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	3	4	3	0	—	—	—
	Engineering review (S_3)	3	4	3.3	150	—	—	—
	Administrative (S_4)	3	4	3	0	—	—	—
	Marketing (S_5)	3	4	3	0	—	—	—
Worker$_{90}$	Engineering basic (S_1)	0	0	0	0	2.000	1.817	9.14
	Engineering advanced (S_2)	4	5	4.45	150	—	—	—
	Engineering review (S_3)	4	5	4.0	0	—	—	—
	Administrative (S_4)	4	5	4	0	—	—	—
	Marketing (S_5)	4	5	4	0	—	—	—
Worker$_{91}$	Engineering basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Engineering advanced (S_2)	4	5	4.3	150	—	—	—
	Engineering review (S_3)	4	5	4	0	—	—	—
	Administrative (S_4)	4	5	4	0	—	—	—
	Marketing (S_5)	4	5	4	0	—	—	—

Therefore, as shown by outcomes of sensitivity analysis, boosted career goals of several workers can adversely affect career goals of other workers.

As indicated by the results of the case study, the task allocation model presented in this paper can be used to effectively improve workers' work experience requirement for progression toward their ideal position. This study, therefore, opens a new class of job allocation models in which objectives of both the employers and employees are taken into consideration. The concept presented in this study can be expanded to incorporate other social impact considerations such as equal opportunity, gender equity, and job satisfaction in the job allocation optimization problem. The model presented in this study also has a number of limitations that should be taken into account. The model assumes that progression toward the ideal job is a merit-based system in which meeting the skill requirements of a job results in being qualified for promotion. However, career progression in practice requires several other important characteristics such as social skills, which have not been considered in this model. The optimization also assumes that the workers' personal training desires and potential external affiliations are not in conflict with the on-the-job training path proposed by the model. The limitations on workers' training preferences and acceptable job assignments can be introduced through additional constraints. Furthermore, the proposed model requires the availability of information with regards to job preferences of workers as well as experience and skill requirements of different positions, which may not be available in all organizations. Also, noted that the presented case study does not reflect the full potential of the proposed model, particularly with respect to the constraints of on-site job allocations. The need for more case studies to refine the model under different scenarios is acknowledged. In addition, the work assignment in the proposed model was performed for a single project with specified work and workforce availability for the total time span of the project. We acknowledge the limitations of this study in terms of considering dynamic job assignment in dynamic projects. Finally, while the effectiveness of the proposed optimization model was mathematically illustrated, actual measurement of skill improvements and productivity levels after implementation of the proposed framework is required to verify that the mathematically demonstrated benefits of this model can be achieved in practice.

Conclusion

The aim of this paper was to address the limitations of current workforce planning models by developing a new multiobjective optimization model that enables managers to maximize productivity while maximizing career development opportunities available to construction workers. The effectiveness of the proposed model was tested in a case study involving allocating tasks to workers within a multidisciplinary team. AMPL modeling language along with the solver COUENNE were utilized to implement the model and obtain a global optimum. The results of the case study showed a significant improvement in the career development of workers compared to the conventional productivity-oriented models, with on average 8.6% advancement in employees' closeness to their ideal skill set. In addition, the model produced Pareto-optimal points and a Pareto curve that enables client or model users to select optimum job allocation based on their preferences. Maximizing the career development opportunities available to workers through implementing the proposed model in practice is expected to lead to an increase in job satisfaction of workers and attractiveness of construction industry to skilled workers. Through incorporating the career development opportunity maximization in the job allocation problem, the model presented represents a paradigm shift in job allocation models in which the objectives of both employees and employers are taken into consideration. However, the proposed model has a number of limitations that should be taken into account prior to implementation in practice. First, the model does not take into account social skills required for career progression in practice. Furthermore, implementation of the proposed model requires the availability of detailed information on skills and ideal job preference of individual workers, which may not be readily available in all organizations.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal*'s data-sharing policy can be found here: http://ascelibrary.org/doi/10.1061/(ASCE)CO.1943-7862.0001263.

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