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 sub-optimal performance. To address this problem, this paper presents an innovative multi-objective model which enables managers to optimize the relationship between these interdependent corporate priorities. The proposed model is implemented and solved using a mixed-integer nonlinear programming on a case study involving the allocation of tasks to employees with different skill levels in a multi-disciplinary engineering consulting company. While having 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

which enabled client/model users to select optimum job allocation based on their preferences. This research represents a paradigm shift towards a new class of socially responsible workforce planning models in which the objectives of both employees and employers are optimized.

Keywords: Construction Industry, Career Development Opportunity, Mathematical Optimization Modelling, Human Resource Management, Job Allocation

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 (Perspectives and 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 U.S. economy, which was equal to 4.2% of the GDP, with a gross output of $1,433 billion (Migliaccio and Holm 2018). According to the US Bureau of Labour Statistics (BLS 2017) (BLS), 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 (EU-28) (Baradan, Dikmen, and Akboga Kale 2018). In UK, it contributes to approximately ten percent of the UK's GDP, and employs approximately two million people annually (Ochieng et al. 2018). 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 AU$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; Australia 2017; MBA 2017). In other countries like the UK, serious skills shortages are also predicted with Farmer (2016) identifying skills shortages as the biggest constraint on the UK construction industry in meeting urgent housing needs of one million homes in 2015. As Barbosa et al. (2017) noted, in the UK, two-thirds of 8,500 small and midsize construction firms regularly turn down work because they don't have enough employees and in the US, 69 percent of nearly 1,500 construction firms are having trouble filling hourly craft positions. While some countries have turned to informal or migrant labour to fill the labour gap, this is not considered a sustainable long-term solution because such workers are transient, and employers have no incentive to invest in training beyond what is required for their project. In response to the above 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, Rasdorf, and Hummer 2016; Kazaz, Manisali, and Ulubeyli 2008). A recent global review of construction productivity by Barbosa et al. (2017) concluded that globally, construction sector labor-productivity growth averaged 1 percent a year over the past two decades, compared with 2.8 percent for the total world economy and 3.6 percent for manufacturing. It also concluded that by acting in several areas, the industry could boost productivity by 50 to 60 percent. 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) point 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, ageing and workforce attraction, retention, which plague the industry.

Growing interest in workforce planning has led to development of numerous novel conceptual and mathematical workforce planning techniques in recent years with varying focus including: improving the productivity of workers through optimizing the hiring and firing decisions (Blatter, Muehlemann, and Schenker 2012; David, Kerr, and Kugler 2007); multiskilling strategies (Gomar, Haas, and Morton 2002); training of existing workers (Othman, Bhuiyan, and Gouw 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 the 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 (2013) critique of strategic human resource management practices in the construction industry showed, despite a close correlation between organizations which 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 multi-project environment which leads to constantly changing resource requirements and changing demands over a project's life cycle (Raiden, Dainty, and Neale 2008). As Dainty and Loosemore (2013) show, construction businesses have long under-invested 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 where 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 they allow 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 Jr and Davis 1985; Moore, Cheng, and Dainty 2002). The objectives and needs of employees which 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, Bhuiyan, and Gouw 2012); and receiving assistance in meet the new demands of the ever changing work environment (Matthews 1999). This paper focusses 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 focusses 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 be always in favor of the 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 multi-objective 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 modelling the career development as a measurable variable that can be optimized as well as, difficulties in enhancing the 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; Holland 1997; Parsons 1909; Peterson, Sampson Jr, and Reardon 1991; Lent, Brown, and Hackett 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, Mitchell, and Jones 1979), and theories rooted in logical positivism and social constructionism (Collin and Young 1986; Hoshmand 1989; Wilber 1989). To address this gap in knowledge, this paper presents an innovative mathematical model for multi-objective 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 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 multi-disciplinary 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 is 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 is 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 is to distribute the given workload among individual workers in such a way that not only the overall productivity of the crew is maximised but also the on-the-job career competency development opportunities available to workers are maximised. The latter involves selecting the tasks assigned to each worker by considering the experience of 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, a) having single-skilled and multiple-skilled workers, b) having several skill levels from novice and beginner to expert and advanced level for each skill trade such as engineering design, c) including full-time, part-time and casual employment status, and d) having lower and upper bounds for working times enables the model to represent many practical cases. Some real-world applications include bridge construction, tunnel construction, residential and commercial building projects. 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 multi-project problem, the optimization process can be executed once per project.

Terminology and Notation

We denote 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 I.

The skill level of the employee is denoted by set E. Five stages of skill development are 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 are as follows: $\mathrm{e} = 1$ indicates a novice worker (0–3 years of experience), $\mathrm{e} = 2$ represents an advanced beginner worker (3-7 years of experience), $\mathrm{e} = 3$ denotes a competent one (7-15 years of experience), $\mathrm{e} = 4$ indicates a worker with proficient skill level (15-22 years of experience), and $\mathrm{e} = 5$ shows an expert worker (22-30 years of experience). Employee's average years of experience in skill level e is represented by B_e. Multi-skilling status of workers is shown by set Z which takes values of $\mathrm{z} = 0, 1$ for a single skilled and multi-skilled worker, respectively. The employment status of each worker is shown by set T which takes values of $t = 1, 2, 3$ for full-time, part-time, and casual employment, respectively.

The type of the activity is denoted by set J. In the classification adopted by this study, each activity is comprised of several tasks which are denoted by set 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. Workers' learning process is influenced by several factors including structure of training programs (Azizi, Zolfaghari, and Liang 2010), workers' motivations in performing the tasks (Agrell, Bogetoft, and Tind 2002), prior experience in the task (Nembhard and Osothsilp 2002), and task complexity (Pananiswami and Bishop 1991). The way these factors impact 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). Overtime, workers spend less time to do repetitive tasks because of familiarity with the operation and tools, along with possible shortcuts to task execution which 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 l^j. The value of 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):

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

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 learnt by the worker during performing activity *j* and a decrease in his 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 P_{iez}^{jm} and estimated using the following equations:

$$P_{iez}^{jm} = \frac{P^{jm_0}}{FA_z \times FA_{mi}}$$

$$FA_z = \begin{cases} 1.15, & z = 1 \\ 1.00, & z = 0 \end{cases} \qquad FA_{mi} = \begin{cases} (1 + B_e)^{l^{m_0}}, & i = m \\ 1.0 \quad , & i \neq m \end{cases} \tag{2}$$

Where p^{jm_0} is the initial productivity of a novice worker in doing task m in activity j as indicated by the historical or relevant data. 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 is assumed to be 15% (Rodriguez (1998)). FA_{mi}, in contrast, accounts for the effect of years of worker's past experience (Be) in a similar task according to the Stanford-B equation of learning theory (Anzanello and Fogliatto 2011) where l^{m_0} is average learning rate in task m, regardless of the activity type and can be extracted from reference data

(Gottlieb and Haugbølle 2010; Zahran, Nour, and Hosny 2016). 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 earlier, the objectives targeted in this study are to maximize the workers' career development opportunities and productivity. The decision variables are the amounts of works allocated to each worker (y_{ik}). It is assumed that a worker is qualified for promotion to the next career level when he/she meets the minimum experience level in all the skills required by the next level position (Brown 2002a). Eq. (3) is defined to account for improvement in skill level of individual k in skill i after performing the allocated tasks.

$$S_{ik} = \underline{S}_{ik} + \alpha_{ik}\, y_{ik} \tag{3}$$

Where $\underline{S}_{ik}$ is the initial level of experience of individual k in skill i, y_{ik} is amount of work related to skill i which is allocated to individual k, S_{ik} is the improved skill level of individual k in skill i after performing the allocated task, and α_{ik} is the skill development rate coefficient which determines the level of on-the-job training required for the worker to achieve the next competency level in skill i. The value of α_{ik} may vary from a skill to another and should be determined based on records of the organisation. We have assumed this value is determined by the company and their view on how much repetitive task should be performed to be eligible for promotion to higher skill level. This is dependent on task type which indicates necessary repetitive task performing for promotion is different for each task such as administrative works, engineering design, and laborious jobs.

A major challenge in quantifying the career development of individual workers is the differences in the perceptions of different workers towards 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 is 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 sufficient level of experience in its required skills. Parsons (1909) argues that allowing employees to actively interfere in selecting their career path can lead to improved job satisfaction and efficiency. We assume that the minimum experience level in different skill sets required by each position can be obtained from Human Resource (HR) records in the organisation which include the skill levels of the employees currently or previously holding the position. In this study, parameter $\overline{S}_{ik}$ is defined to represent skill level associated with the ideal job for candidate k. The initial skill levels ($\underline{S}_{ik}$) and those associated with the ideal position of the workers are defined by vectors presented in equations (4) and (5), respectively.

$$\underline{S}_{ik} = \left(\underline{S}_{1k}, \underline{S}_{2k}, \dots, \underline{S}_{ik}\right) \tag{4}$$

$$\overline{S}_{ik} = \left(\overline{S}_{1k}, \overline{S}_{2k}, \dots, \overline{S}_{ik}\right) \tag{5}$$

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

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

The lower the distance, the closer the worker to his 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:

$$\text{minimize } max_{\{k \in K\}} D_k \quad (7)$$

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:

$$\text{minimize} \sum_{i \in I} \sum_{k \in K} y_{ik} \quad (8)$$

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 (H_i). The distributive justice targeted in this study includes the fair distribution of hiring, promotion, and workload allocation over individuals (Colquitt 2001). In order to account for distributive justice, two constraints are defined. The first constraint ensures that the maximum working hours per week for each worker does not exceed the specified limit value (U_k) (Eq. (10)), while the second constraint ensures a minimum weekly work allocation (L_k)

for each worker (Eq. (11)). In these two constraints, w is the total number of weeks in lifespan of the project.

$$\sum_{k \in K} \frac{y_{ik}}{P_{iez}^{m}} = H_i \qquad \forall i \in I, \forall m \in M \tag{9}$$

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

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

In addition to the above 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 (SafeWorkAustralia 2014), and skill requirements of the jobs (Srour, Haas, and Morton 2006). Equations (12 and 13), equations (14-16), and equation (17) account for these three types of constraint, respectively.

The crew size limitation in this study is 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, $\sum_{k \in K} T_{ik}$ is the number of workers who will be trained in skill i and 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, n_i represents the number of available workers with skill i and

x_{ik} is a binary variable which is 1 if the worker k with skill i is assigned to work (used by the model), otherwise 0.

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

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

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

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

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

$$S_{ik} \geq \widetilde{S}_i \qquad \forall k \in K, \forall i \in I_{hr} \text{ (high risk works)} \tag{16}$$

When looking retrospectively at human occupational history, we realize 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 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 have further development on and to avoid unnecessary development of skills which are not important in the employee's prospective career plan.

$$\underline{S}_{ik} \leq S_{ik} \leq \overline{S}_{ik} \qquad \forall k \in K, \forall i \in I \qquad (17)$$

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

	minimize $max_{\{k \in K\}}\, D_k$			(18a)
	minimize $\sum_{i \in I} \sum_{k \in K} y_{ik}$			(18b)
	Subject to			
	$\sum_{k \in K} \frac{y_{ik}}{P_{iez}^{m}} = H_i$	$\forall i \in I, \forall m \in M$		(18c)
	$\sum_{i \in I} y_{ik} \leq U_k\, w$	$\forall k \in K$		(18d)
	$\sum_{i \in I} y_{ik} \geq L_k\, w$	$\forall k \in K$		(18e)
	$L_k\, w\, x_{ik} \leq y_{ik} \leq U_k\, w\, x_{ik}$	$\forall k \in K, \forall i \in I$		(18f)
	$y_{ik} \leq Q_i\, w$	$\forall k \in K, \forall i \in I_h$ (hazardous task)		(18g)
	$\sum_{k \in K} x_{ik} \leq n_i$	$\forall i \in I$		(18h)
	$\sum_{k \in K} x_{ik} \leq \overline{n}_i$	$\forall i \in I_c$ (confined space)		(18i)
	$S_{ik} = \underline{S}_{ik} + \alpha_{ik}\, y_{ik}$	$\forall k \in K, \forall i \in I$		(18j)
	$S_{ik} \geq \tilde{S}_i x_{ik}$	$\forall k \in K, \forall i \in I_{hr}$ (high risk works)		(18k)
	$\underline{S}_{ik} \leq S_{ik} \leq \overline{S}_{ik}$	$\forall k \in K, \forall i \in I$		(18l)
	$y_{ik} \geq 0$	$\forall k \in K, \forall i \in I$		
	$x_{ik} \in \{0, 1\}$	$\forall k \in K, \forall i \in I$		

Case Study, Results, and Discussion

The case scenario was selected from an engineering consultancy company as the workforce is the main capital of such firms and hence, 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.

In the case study, allocation of tasks to employees with five skill levels in a multi-disciplinary engineering consulting company is assessed. Description of skill levels and workforce availability at each skill level is presented in Table 2 and Table 3, respectively. Type of tasks, number of working hours, learning rates, and coefficient of α_{ik} are shown in Table 4. The case study has taken into account four main features including total work quantity for the project, having lower, and upper bounds for each employee' working time, along with having high risk activities. 'Engineering advanced' and 'engineering review' are considered to be high risk activities due to high financial and legal consequences if are performed improperly. Therefore, minimum skill levels of the individuals to whom the activities 'engineering advanced' and 'engineering review' can be assigned are 2 and 3, respectively.

We implement the proposed model using A Mathematical Programming Language (AMPL), an algebraic modeling language for mathematical computing (Fourer, Gay, and Kernighan 2003) and we use the mixed-integer nonlinear programming (MINLP) solver Convex Over and Under ENvelopes for Nonlinear Estimation (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 below. The results including the amount of hours allocated to each worker (y_{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 ten randomly chosen employees with different initial skill levels and the corresponding Pareto optimal point (max distance, total time) = (2.05, 37395). 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) in vertical and horizontal axes, respectively.

Initial distance measure: $$\underline{D}_k = \sqrt{(\overline{S}_{1k} - \underline{S}_{1k})^2 + (\overline{S}_{2k} - \underline{S}_{2k})^2 + \cdots + (\overline{S}_{ik} - \underline{S}_{ik})^2} \quad (19)$$

Final distance measure: $$\overline{D}_k = \sqrt{(\overline{S}_{1k} - S_{1k})^2 + (\overline{S}_{2k} - S_{2k})^2 + \cdots + (\overline{S}_{ik} - S_{ik})^2} \quad (20)$$

Improved closeness: $$I_k(\%) = \frac{\underline{D}_k - \overline{D}_k}{\underline{D}_k} \times 100 \quad (21)$$

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 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 propose model results in between 6.6% to 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 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 above improvements are achievable with only minor reduction in productivity.

Fig. 1 depicts Pareto front for the two minimization objective functions; maximum distance (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 is 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 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 (max distance, total time) = (2.05, 37395) 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 is 2.200 and 2.019, respectively. As it can be realized, the Pareto front resulted from 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, user can pick a point from left tail of Pareto curve where more productivity is achieved in cost of losing career development. Overall, model outcomes demonstrate a comprehensive and purposefully optimized job allocation to workers which has led to highest possible career development of employees without considerable loss of productivity.

Sensitivity Analysis

It is explained that how career development of one worker might be affected by career goals of other workers, changes in crew composition, and work availability. Project activities which can increase the skill level of a worker, if assigned to him, are limited. Therefore over, under, or inefficient assignment of activities to a worker can adversely affect the career goals of others. It is worth mentioning the optimization process is trying 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 is considered individually in the model. To explain further, each individual worker will be assigned a certain amount of work based on his predefined career goals, regardless of possible changes in his crew composition, by the end of optimization procedure. To assess the effect of work availability, it is noted that the model inputs project information from early project phases, i.e. project initiation and planning. Therefore, work and workforce availability is 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 is performed to evaluate its effect on model results. In this analysis, five workers, $Worker_{41}$ to $Worker_{45}$, have set their ideal skill levels to be 5, instead of previous value of 4. Results of new job allocation including allocated working hours and improved closeness to ideal position are demonstrated in Table 7. According to our expectations, changes in career goals of some workers have affected the career goals of others. As it 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$_{13}$ has reduced from 449 to 300 hours. Subsequently, Worker$_{43}$ has developed his skill levels significantly and become very close to his ideal position. This is indicated by an increase in improved closeness to 20% compared to previous value of 11.15% for Worker$_{43}$ which is the maximum amount between all workers. Meanwhile, Worker$_{13}$ has become farther away from his ideal position by a decrease to 5.23% from 8.28%. Therefore, as shown by outcomes of sensitivity analysis, ~~increased~~ 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 towards 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 which should be taken into account. Firstly, the model assumes a progression towards job allocation is based on 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. Secondly, the proposed model requires 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. Thirdly, the case study does not reflect 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.

Conclusion

The aim of this paper was to address the limitations of current workforce planning models by developing a new multi-objective optimization model which 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 multi-disciplinary 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 Pareto curve which enables client/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 which 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.

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Table 1. Five-stage skill acquisition (source: (Dreyfus 1982))

Skill level	Title of skill level	Description
1	Novice	Limited, inflexible, rule-governed behaviour 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 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.
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.

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 two years 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

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

Type	Category	Definition	Number of working hours (H_i)	Learning rate (%)	α_{ik}	Assignable to skill level
Engineering	Basic	Technical works of ongoing projects which involve basic computations	3850	90	0.003	1, 2
	Advanced	Complex design and analytical tasks of ongoing projects	4300	85	0.001	2, 3, 4
	Review	Reviewing both Basic and Advanced engineering documents	3300	90	0.002	All except 1, 2
Administrative	-	Ongoing paperwork and internal meetings	1350	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

Workers	Skill	Initial skill level ($\underline{S}_{ik}$)	Ideal skill level ($\overline{S}_{ik}$)	Developed skill level (S_{ik})	Allocated hours (y_{ik})	Initial distance measure ($\underline{D}_k$)	Final distance measure ($\overline{D}_k$)	Improved closeness ($I_k(\%)$)
Worker$_{12}$	Eng- Basic (S_1)	2	3	2.6	300	2.236	2.039	8.82
	Eng- Advanced (S_2)	2	3	2	0			
	Eng- Review (S_3)	2	3	2	0			
	Administrative (S_4)	2	3	2	0			
	Marketing (S_5)	2	3	2	0			
Worker$_{13}$	Eng- Basic (S_1)	2	3	2.43	428	2.236	2.051	8.28
	Eng- Advanced (S_2)	2	3	2	0			
	Eng- Review (S_3)	2	3	2	0			
	Administrative (S_4)	2	3	2	0			
	Marketing (S_5)	2	3	2.06	21			
Worker$_{14}$	Eng- Basic (S_1)	2	3	2.9	300	2.236	2.002	10.47
	Eng- Advanced (S_2)	2	3	2	0			
	Eng- Review (S_3)	2	3	2	0			
	Administrative (S_4)	2	3	2	0			
	Marketing (S_5)	2	3	2	0			
Worker$_{41}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Eng- Advanced (S_2)	3	4	3	0			
	Eng- Review (S_3)	3	4	3	0			
	Administrative (S_4)	3	4	3	0			
	Marketing (S_5)	3	4	3.3	300			
Worker$_{42}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.735	13.25
	Eng- Advanced (S_2)	3	4	3.9	300			
	Eng- Review (S_3)	3	4	3	0			
	Administrative (S_4)	3	4	3	0			
	Marketing (S_5)	3	4	3	0			
Worker$_{43}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.777	11.15
	Eng- Advanced (S_2)	3	4	3.6	300			
	Eng- Review (S_3)	3	4	3	0			
	Administrative (S_4)	3	4	3	0			
	Marketing (S_5)	3	4	3	0			
Worker$_{71}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Eng- Advanced (S_2)	3	4	3.3	150			
	Eng- Review (S_3)	3	4	3	0			
	Administrative (S_4)	3	4	3	0			
	Marketing (S_5)	3	4	3	0			
Worker$_{72}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Eng- Advanced (S_2)	3	4	3	0			
	Eng- Review (S_3)	3	4	3.3	150			
	Administrative (S_4)	3	4	3	0			
	Marketing (S_5)	3	4	3	0			
Worker$_{90}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.841	7.95
	Eng- Advanced (S_2)	4	5	4.30	97			
	Eng- Review (S_3)	4	5	4.05	54			
	Administrative (S_4)	4	5	4	0			
	Marketing (S_5)	4	5	4	0			
Worker$_{91}$	Eng- Basic (S_1)	0	0	0	0	2.000	1.868	6.6
	Eng- Advanced (S_2)	4	5	4.3	150			
	Eng- Review (S_3)	4	5	4	0			
	Administrative (S_4)	4	5	4	0			
	Marketing (S_5)	4	5	4	0			

Table 6. Pareto optimal points

Maximum Distance	Total Time	Maximum Distance	Total Time
2.426	37195	2.066	37343
2.367	37196	2.060	37361
2.338	37197	2.053	37382
2.310	37198	2.050	37393
2.282	37199	2.047	37406
2.253	37200	2.042	37429
2.226	37202	2.038	37451
2.174	37203	2.035	37472
2.162	37209	2.032	37493
2.148	37216	2.030	37513
2.130	37225	2.028	37526
2.119	37233	2.025	37546
2.115	37240	2.023	37566
2.111	37246	2.020	37586
2.108	37253	2.018	37606
2.100	37266	2.016	37626
2.091	37284	2.014	37645
2.083	37302	2.012	37665
2.074	37319	2.01	37684
2.072	37325	2.008	37703

Table 7. Sensitivity analysis

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

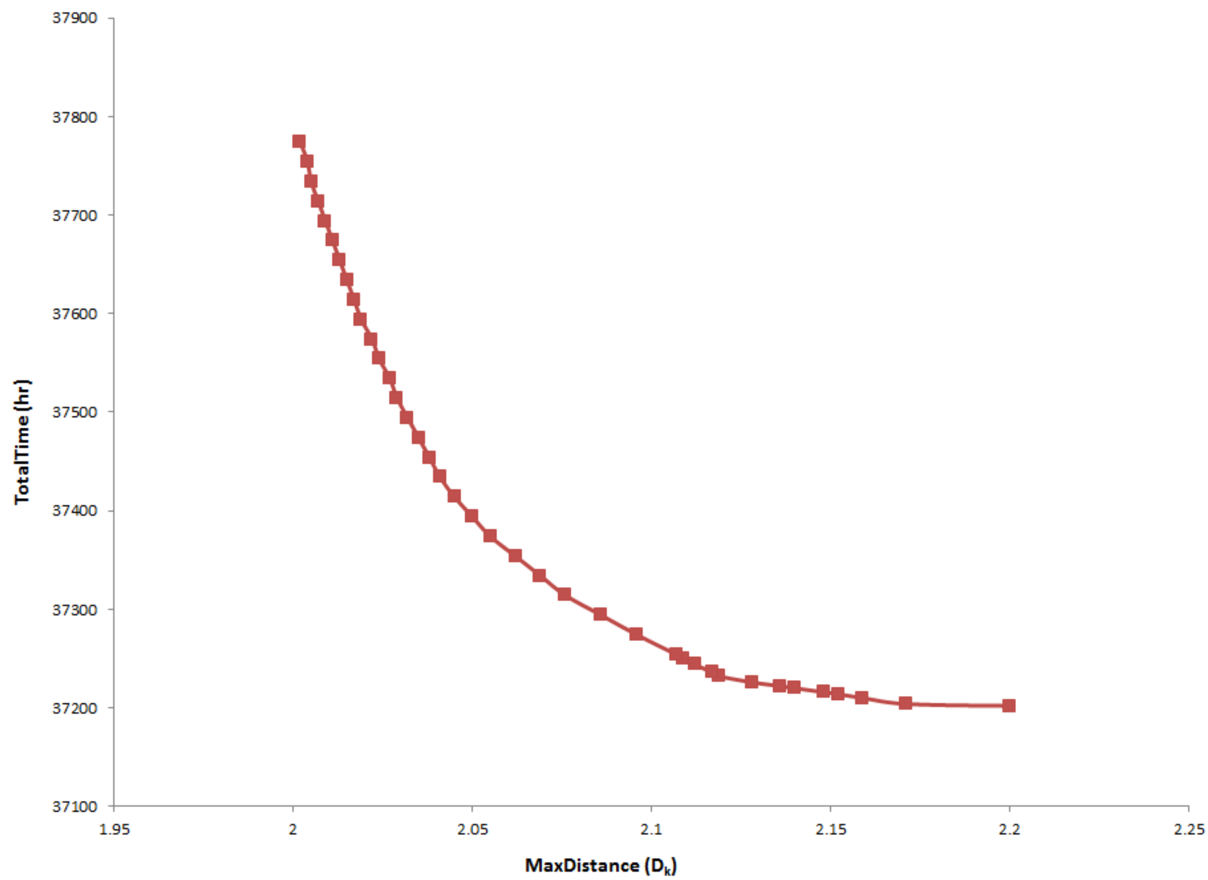

Figure 1. Pareto front for the two objective functions