Optimal Work Assignment to Multiskilled Resources in Prefabricated Construction

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Abstract: Multiskilling allows for dynamic reallocation of workers from one stage of production to another in response to bottleneck configurations and, therefore, has been advocated as a potential strategy to improve productivity in off-site construction. The aim of this research is to investigate the extent to which operational benefits associated with different resource management policies pertaining to bottleneck configurations can be achieved in off-site construction. To this end, the flow shop environment is recognized as an appropriate operational framework for modeling production dynamics. A quadratic resource allocation model was developed to expose different operational performances corresponding to different resource management strategies. Different resource management policies included no cross-training, hiring single-skilled crew, direct capacity balancing, chaining, and hiring multiskilled crew. Operational performance encompassed makespan and labor costs. Production data from a prefabrication factory based in Melbourne, Australia, were fed to the model, providing the basis for comparison of different resource management policies. Research findings contribute to resource planning and management in off-site construction. **DOI: 10.1061/(ASCE)CO.1943-7862.0001627.**

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Introduction

The construction industry is experiencing major challenges with regard to the increase in workforce wages (Leu and Hwang 2002), shortage of skilled workforce (Ho 2016), and inability to meet productivity and completion time demands (Hegazy et al. 2011). Off-site prefabrication is advocated as a potential solution to alleviate such issues by reducing the reliance of construction operations on scarce skilled workers and maximizing the productivity of construction crew through automation (Leu and Hwang 2001). Furthermore, precast construction has been reported to reduce the costs of site supervision (Frondistou-Yannas et al. 1977), reduce the delay in project completion (Chan and Hu 2002), and lead to an improved construction quality (Ko and Wang 2010). However, in the absence of systematic coordination between its operations, off-site production can turn into disintegrated processes with significant negative impact on productivity (Arashpour et al. 2015). A major challenge in eliminating the risk of such coordination problems is the lack of sufficient skilled resources to address the bottlenecks in the production line (Arashpour et al. 2016). A potential solution to address workforce-related productivity and heterogeneity issues in prefabricated construction is the cross-training of construction workers (Arashpour et al. 2018).

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Cross-training or multiskilling refers to training workers in multiple skills and competencies so that they can be assigned when and where they are needed (Hopp and Oyen 2004). The positive effects of cross-training of workers in different skills in productivity in construction projects have been widely highlighted in the available literature (Florez 2017; Lill 2009; McGuinness and Bennett 2006; Pollitt 2010). The productivity improvements due to the implementation of cross-training are achieved mainly through improved flexibility in optimizing resource utilization in projects (Hopp and Oyen 2004). Moreover, multiskilling has been reported to considerably benefit construction workers by improving their employment duration (Burleson et al. 1998), employability (Haas et al. 2001), job satisfaction (Carley et al. 2003), and safety (Teizer et al. 2013).

However, despite the extensive literature on multiskilling in construction projects, a majority of previous studies are focused on multiskilling in on-site construction projects (Burleson et al. 1998; Florez 2017; Gomar et al. 2002; Hegazy et al. 2000; Lill 2009; Sacks et al. 2015), and little effort has been made to investigate the potential benefits of multiskilling in off-site construction by recruiting a flexible workforce. In particular, the existing literature on multiskilling in prefabricated construction is limited to (1) qualitative studies on the need for multiskilling in off-site construction and its potential benefits (Goodier et al. 2007; McGuinness and Bennett 2006); and (2) simulation-based and multicriteria decision-making methods to identify the appropriate cross-training configuration in the prefabricated construction (Arashpour et al. 2015, 2018). There is currently a lack of a systematic method to implement multiskilling strategies in prefabricated construction through optimizing the jobs assignment to a combination of multiskilled and single-skilled workers (Nasirian et al. 2018). The ability to allocate appropriate workers to relevant tasks by considering the aim of multiskilling (Haas et al. 2001) is crucial to ensuring that the benefits of multiskilling are fully realized (Gomar et al. 2002). Identifying the optimal job assignment in prefabricated construction projects involving multiskilled workers is, however, challenging due to the numerous alternative ways in which workers can be allocated to tasks and numerous constraints pertaining to production sequence and layout

(Arashpour et al. 2018). In this study, a mathematical optimization model is proposed for assigning construction activities in a prefabricated project to multiskilled workers, with the objective of minimizing the makespan in off-site construction projects, while considering the constraints of typical prefabricated construction projects. The proposed method is applied to an illustrative case study to highlight its applications and benefits in practice.

Literature Review

The cross-trained resource allocation problem is a subset of the resource allocation problem in which all or some human resources are multiskilled, providing the flexibility to have them allocated to different tasks to improve resource utilization. The aim is to optimize the resource use and allocation to either maximize or minimize certain functions related to performance and productivity (Bouajaja and Dridi 2016). The on-site construction literature has broadly investigated optimizing the allocation of multiskilled workers to achieve several important objectives (Nasirian et al. 2018).

A number of research have looked into decreasing project completion time. To minimize project delay, Hegazy et al. (2000) incorporated a heuristic algorithm that analyzed information about resources that could be substituted, in case there was a need for a less utilized workforce to be substituted in overutilized locations, taking into account productivity loss. They presented cost considerations were presented as opportunities for future research. Wongwai and Malaikrisanachalee (2011) developed a heuristic algorithm supplementing the study of Hegazy et al. (2000) by covering pre-emptive operations for which the required number of resources was not totally fulfilled. However, minimization of project cost was not guaranteed because it was possible for an available expensive resource to be substituted for a cheaper resource to finish the projects sooner. Liu and Wang (2012) proposed a constraint programming that minimized the duration of a bridge execution project. In addition to a single-skilled workforce, a multiskilled workforce capable of assisting with different operations was subcontracted to help with a specialized staff. The developed scheduling technique was investigated in a repetitive construction project in two different scenarios, including minimum total interruptions and no interruption. Even though the cost corresponded to the optimized value of time presented, cost optimization was not incorporated in the objective function of the mathematical model. In the concrete work of a residential building, Ahmadian Fard Fini et al. (2016) incorporated multiskilling and learning effects to minimize the duration of construction projects. A hybrid methodology encompassing constraint programming, statistical analyses, and a genetic algorithm, was used to demonstrate optimal crew compositions for different tasks included in the project.

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

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

However, regarding multiskilling in off-site construction (Arashpour et al. 2015; Benjaoran et al. 2005), specifically, optimization of prefabrication performance measures by incorporating cross-trained resources (Nasirian et al. 2018), attracted little attention. To this end, the authors of this paper present an optimization-based scheduling framework for single-skilled and multiskilled workforce allocation in the context of off-site construction. A quadratic mathematical model was developed to incorporate features of prefabricated construction. The developed model was linearized to solve the problem in a reasonable timeframe. The objective function of the model was minimizing project duration by taking into account labor costs pertaining to different compositions of single-skilled and multiskilled crews.

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

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

1994) and partial cross-training of crews (Daniels et al. 2004) is intensively investigated in the manufacturing literature; accordingly, the mathematical procedure of this paper is partially based on them.

Problem Description

A classic flow shop problem is defined as a problem consisting of two main elements: a group of m machines and a set of n jobs or products that should be processed in these machines (Hejazi and Saghafian 2005). There are four basic assumptions for a classic flow shop problem: the jobs should be processed in all machines, job splitting is not allowed, operations are non-pre-emptive, and setup times are included in the processing time. Extra assumptions to a classic flow shop problem that has makespan minimization as an objective function include permutation (Hejazi and Saghafian 2005), zero buffering (Allahverdi et al. 1999), blocking (Abadi et al. 2000), no wait (Aldowaisan and Allahverdi 1998), no intermediate queue (Abadi et al. 2000), and sequence-dependent setup (Tseng and Stafford 2001). Flow shop problems with and without permutation are the best fit to optimize the off-site construction scheduling problem (Yang et al. 2016).

Consider a set of products $\mathcal{N} = \{1, 2, \ldots, N\}$ that is going to be processed sequentially and in the same order in a set of workstations $\mathcal{M} = \{1, 2, \ldots, M\}$ that generates a flow shop problem, where N is the last product and M is the final workstation. The notation (n, m) is an indication of processing product n in workstation m, which is referred to as procedure (n, m) in this study. A limited number of workers from a set of workers $\mathbf{\Omega} = \{1, 2, \ldots, W\}$ can be allocated to a workstation on the basis of cross-training strategies, where W is the last worker. Moreover, $\mathbf{\Lambda} = \{1, 2, \ldots, K\}$ is a set of status that denotes the number of workers who can be engaged in procedure (n, m), where K is the maximum number of workers who can work in procedure (n, m). Also, $\mathcal{T} = \{1, 2, \ldots, T\}$ is the set of time periods that encompasses all possible values for the starting and completion times of a procedure, where T is the upper bound on a makespan. The objective function of this study is to minimize the makespan, as presented by Eq. (1)

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

where C_{Max} = makespan; and C_{nm} = completion time of procedure (n, m). Let us consider θ_{nmkt} as a binary variable that is equal to 1 if procedure (n, m) is processed with k resources and finished at time t. The non-pre-emptive condition of the flow shop requires each procedure to have a unique status, which results in a specific corresponding completion time. This requirement is satisfied in Eq. (2)

$$\sum_{k=1}^{K}\sum_{t=1}^{T} \theta_{nmkt} = 1 \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{2}$$

Let D_{nm} denote the duration of procedure (n, m). The duration of procedure (n, m) is a function of a different procedure status. Obviously, the allocation of a higher k will decrease the value of D_{nm}. Given that d_{nmk} is the duration of procedure (n, m) when k workers are assigned to it, the value of D_{nm} can be computed according to Eq. (3)

$$D_{nm} = \sum_{k=1}^{K}\sum_{t=1}^{T} d_{nmk}\theta_{nmkt} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{3}$$

Then C_{nm} is obtained as

$$C_{nm} = \sum_{k=1}^{K}\sum_{t=1}^{T} \theta_{nmkt} t \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{4}$$

Eqs. (5) and (6) satisfy the requirement for a flow shop problem with permutation. Eq. (5) limits the start time of processing a product in a workstation to always being more than the completion time in the previous workstation. Eq. (6) insures permutation exists in the flow shop

$$C_{nm} \geq C_{n(m-1)} + D_{nm} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{5}$$

$$C_{nm} \geq C_{(n-1)m} + D_{nm} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{6}$$

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

$$s_{wm} \geq a_{wmt} \qquad m \in \mathcal{M}, w \in \mathbf{\Omega}, t \in \mathcal{T} \tag{7}$$

Let q_w be the daily cost of worker a_{wmt}. Then, the total worker cost can be computed by Eq. (8)

$$\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{w=1}^{W} q_w a_{wmt} = Q \tag{8}$$

The constraint in Eq. (9) insures that in each interval of time each worker can be allocated to just one workstation

$$\sum_{m=1}^{M} a_{wmt} = 1 \qquad w \in \mathbf{\Omega}, t \in \mathcal{T} \tag{9}$$

The constraint in Eq. (10) designates the needed sum of workers to a specific procedure according to procedure status by converting the values of a_{wmt} to 1 until their summation satisfies the value of k

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W} \theta_{nmkt} a_{wmt} = \sum_{k=1}^{K}\sum_{t=1}^{T} k\theta_{nmkt} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{10}$$

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

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{t} \theta_{nmkt} a_{wml} = \sum_{k=1}^{K}\sum_{t=1}^{T} a_{wmt} d_{nmk}\theta_{nmkt} \qquad n \in \mathcal{N}, m \in \mathcal{M}, w \in \mathbf{\Omega} \tag{11}$$

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

Case Study

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

The duration of product completion and of operations in each workstation, bottleneck locations, set of products, and set of workers, were obtained by evaluating the production data and consulting the site manager. Additionally, the maximum number of workers who can work in a workstation was determined by the advice of the site manager. The binary skill parameter was constructed by reviewing the literature (Arashpour et al. 2015, 2018; Burleson et al. 1998; Wang et al. 2009) and interviewing the site manager. The effect of using a multiskilled workforce on the duration of operations was based on previous literature (Hopp and Oyen 2004; Qin et al. 2015; Qin and Nembhard 2015) and interviews with the site manager. Related data to different resource management policies (RMPs), including the number of workers, combination of skills, location, and cost of single-skilled and multiskilled workforces, are presented in Table 2. The cost of labor includes salary, tax, and the superannuation pension fund in the Australian context.

Fig. 1 visualizes the different RMPs investigated in this study. Workstations ($m \in \mathcal{M}$) and labors ($w \in \Omega$) are presented with the same notations as described in the "Problem Description" section. Vertical and horizontal arrows indicate initial and secondary skills, respectively. A worker is single-skilled if he or she has only a single vertical arrow. Horizontal and vertical arrows together indicate a multiskilled worker who has been also trained for a secondary skill. A worker with only horizontal arrows is a hired multiskilled worker.

As shown in Fig. 1(a), the prefabrication plant considered in this study comprises 12 workstations. The number of workers and the sequence of processes in the production line are based on the

Table 1. Workstations' operation

Workstation	Operation
1	Laboring
2	Caulking
3	Mechanical controlling
4	Tiling
5	Plumbing
6	Plastering
7	Carpentry
8	Electric work
9	Waterproofing
10	Glazing
11	Joining
12	Painting

Table 2. Worker number, skill set, and costs in different RMPs

	NF		HSC		DCB		CH		HMC	
Number	Labor skill	Labor cost[a]	Labor skill	Labor cost	Labor skill	Labor cost[a]	Labor skill	Labor cost[a]	Labor skill	Labor cost[a]
1	Laborer	180.16	Laborer	180.16	Laborer	180.16	Laborer and caulker	228.16	Laborer	180.16
2	Caulker	180.16	Caulker	180.16	Caulker and laborer	196.16	Caulker and mechanical controller	228.16	Caulker	180.16
3	Mechanical controller	219.28	Mechanical controller	219.28	Mechanical controller	219.28	Mechanical controller and tiler	243.28	Mechanical controller	219.28
4	Tiler	195.2	Tiler	195.2	Tiler and laborer	209.6	Tiler and plumber	243.28	Tiler	195.2
5	Plumber	224.96	Plumber	224.96	Plumber	224.96	Plumber and plasterer	256.96	Plumber	224.96
6	Plasterer	219.28	Plasterer	219.28	Plasterer	219.28	Plasterer and carpenter	259.28	Plasterer	219.28
7	Carpenter	234.64	Carpenter	234.64	Carpenter	234.64	Carpenter and electrician	266.64	Carpenter	234.64
8	Electrician	243.52	Electrician	243.52	Electrician	243.52	Electrician and waterproofer	275.52	Electrician	243.52
9	Waterproofer	220.16	Waterproofer	220.16	Waterproofer and carpenter	236.16	Waterproofer and glazer	252.16	Waterproofer	220.16
10	Glazer	189.92	Glazer	189.92	Glazer and carpenter	205.92	Glazer and joiner	229.92	Glazer	189.92
11	Joiner	234.64	Joiner	234.64	Joiner	234.64	Joiner and painter	266.64	Joiner	234.64
12	Painter	205.76	Painter	205.76	Painter and electrician	231.2	Painter and laborer	229.76	Painter	205.76
13	—	—	Laborer	180.16	—	—	—	—	Laborer, carpenter and electrician	248
14	—	—	Carpenter	234.64	—	—	—	—	Laborer, carpenter and electrician	248
15	—	—	Electrician	243.52	—	—	—	—	—	—

[a]In Australian dollars.

Fig. 1. RMPs: (a) NC; (b) HSC; (c) DCB; (d) CH; and (e) HMC.

actual conditions in the real fabrication layout of the case study factory. No cross-trained workers are employed in this production line, representing the no cross-training (NC) policy, in which one single-skilled worker is allocated to each workstation. This NC strategy is therefore adopted in this study as the benchmark for comparing other multiskilling policies (Qin et al. 2015; Qin and Nembhard 2015).

The site manager identified laboring, carpentry, and electric work workstations as the main bottlenecks. Accordingly, the site manager decided to add one more single-skilled worker to each bottleneck workstation to balance the production output in every workstation. At the time of inspecting the production line, the aforementioned workers were still apprenticed and not ready to be engaged in the production process. However, the site manager was unsure about the financial and operational justification of training single-skilled crew in additional skills and allocating them to potential bottleneck workstations. This decision is modeled in this study as hiring single-skilled crew (HSC) and is schematically presented in Fig. 1(b).

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

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

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

This investigation implemented the above strategies in three production cases. In the first case, all bathroom pods had identical specifications with the same operation durations. In the second case, there were small customizations in production, resulting in different procedures. However, the bottleneck spots were the same as in the first case. In the third case, the extent of customization was high, and some nonbottleneck workstations were converted to bottlenecks. In this case, 7 out of 10 modules were highly customized, and three modules had identical production data equal to the first case. Accordingly, Cases 1, 2, and 3 were denoted as no-variability (NV), medium-variability (MV), and high-variability (HV) cases, respectively.

By incorporating the collected data, the prefabrication assembly line was modeled using the optimization model presented in the "Problem Description" section. The production data were fed to the model, and different productivity measures including makespan and the cost associated with the implementation of different cross-training strategies were calculated. The output of the computation process is presented in Tables 2–4.

Results

Performance of All RMPs in Each Case

Table 3 shows the performance of different RMPs after implementing the NV strategy (Case 1). In NC, it took 44 days to complete 10 bathroom pods with a corresponding labor cost of AUD 73,886.

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

Table 4 reflects performance measures in the second case. In the base case with the NC strategy, the makespan was 46 days for producing 10 bathroom pods, leading to a labor cost of AUD 132,268. Similar to the first case, in the MV environment, HMC and DCB led

Table 3. RMPs' performance in NV

RMP	Extra skills	Extra single-skilled worker	Extra multiskilled worker	C_{Max}	Improvement in C_{Max} (%)	Cost of labor[a]	Fluctuation in cost of labor (%)
NC	0	—	—	44	0	73,886	0
HSC	—	3	—	32	27	131,789	+78
DCB	5	—	—	30	32	54,850	−25
CH	12	—	—	32	27	93,249	+26
HMC	—	—	3	26	41	91,062	+17

[a]In Australian dollars.

Table 4. RMPs' performance in MV

RMP	Extra skills	Extra single-skilled worker	Extra multiskilled worker	C_{Max}	Improvement in C_{Max} (%)	Cost of labor[a]	Fluctuation in cost of labor (%)
NC	0	—	—	46	0	132,268	0
HSC	—	3	—	34	26	81,969	−38
DCB	5	—	—	33	28	75,719	−42
CH	12	—	—	34	26	55,061	−58
HMC	—	—	2	29	37	104,966	+21

[a]In Australian dollars.

Table 5. RMPs' performance in HV

RMP	Extra skills	Extra single-skilled worker	Extra multiskilled worker	C_{Max}	Improvement in C_{Max} (%)	Cost of labor[a]	Fluctuation in cost of labor (%)
NC	0	—	—	49	0	150,734	0
HSC	—	3	—	38	22	101,747	−32
DCB	5	—	—	35	28	92,682	−38
CH	12	—	—	34	31	77,405	−49
HMC	—	—	2	34	31	111,261	+26

[a]In Australian dollars.

to the most enhancement in the makespan, with 37% and 28% improvements, respectively. HSC's and CH's performances were the same. However, the situation regarding cost fluctuations was different. HMC is the only strategy that caused extra costs. All other strategies induced a significant cost saving, equivalent to 58%, 42%, and 38%, corresponding to CH, DCB, and HSC, respectively.

The performance measures of different RMPs in Case 3 are illustrated in Table 5. It took 49 days to produce 10 bathroom pods, leading to a labor cost of AUD 150,734. In the HV environment, CH and HMC generated the best improvement in the makespan. Despite being similar to previous cases, HMC brought extra costs, whereas CH led to about a 50% cost saving, which makes the CH strategy the best one in an HV environment. Like previous cases, DCB outperformed HSC in terms of improvement in the makespan and cost saving.

Performance of Each RMP in All Cases

Fig. 2 illustrates the fluctuations in different productivity measures with the implementation of different RMPs in different cases. Different RMPs are outlined in the horizontal axis. The vertical axis shows the change in performance measures compared to NC in terms of percentage.

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

Cost–Time Performance of RMPs

Fig. 3 considers the influence of different strategies on performance in terms of both time and cost, which are the most important productivity criteria in the flow shop environment (Campbell 2011). Equal weights allocated to time and cost in Figs. 3(a and b) consider the weighting of cost to be twice that of time, and Fig. 3(c) assumes the weighting of time to be twice that of cost. Although the distribution of weights between cost and time varies in the literature and in practice, arguing about weight allocation is beyond the scope of this study.

Interestingly, in all of the mentioned situations, the figures share significant similarity, which is an indication that they are governed by the same rule in the mentioned priorities for cost and time. In all situations CH and HSC are not appropriate for an NV environment. However, in MV and HV environments, both strategies result in appropriate performance measures.

The performance of DCB in all cases is clustered in a close proximity, which makes it a reliable strategy in production environments that include all three cases of variability and different priorities for cost and time. When more weight is allocated to time, HMC gains more credibility. The high costs associated with HMC make this strategy inappropriate when crucial enhancement in the

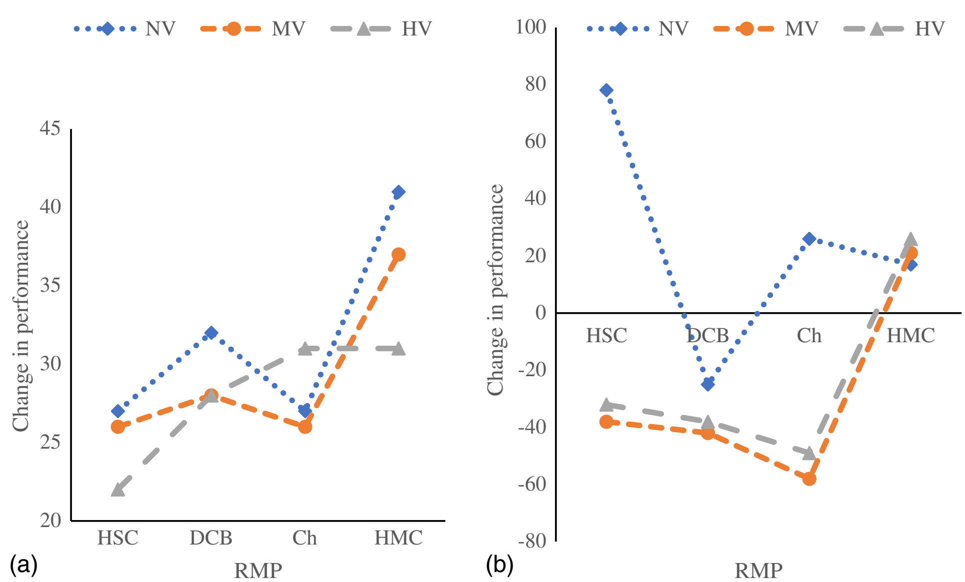

Fig. 2. Performance measures of RMPs: (a) makespan; and (b) cost.

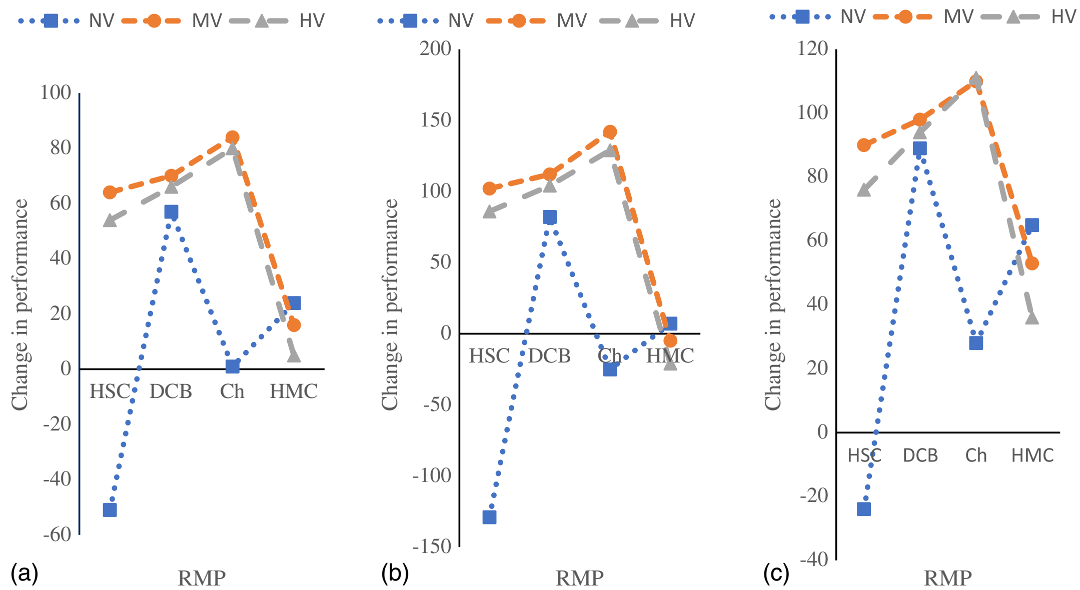

Fig. 3. Cost–time performance of RMPs: (a) with equal weights; (b) weighting cost as twice the weight of time; and (c) weighting time as twice the weight of cost.

makespan is not needed; however, in the case where minimizing the makespan is important, no strategy can perform as well as HMC.

Sensitivity Analysis

Figs. 4(a–c) present the results of the sensitivity analysis that was conducted to evaluate and compare the effects of variations in the input variables on the production performance of Cases 1, 2, and 3, respectively. In these charts, vertical and horizontal axes represent the makespan and the number of bottlenecks, respectively. A scenario considering three bottlenecks was considered to represent the actual situation observed in the case study factory, while five other scenarios with zero, one, two, four, and five bottlenecks were investigated to evaluate the sensitivity of the model to bottlenecks' configurations.

As shown in Fig. 4(a), in the NV case and no-bottleneck scenario, the performance of all multiskilling strategies was found to be the same. In the MV and HV cases and no-bottleneck scenario [Figs. 4(b and c), respectively], due to pre-existing variability in procedures, the makespan in NC was not necessarily the same as for the other strategies.

By adding one extra bottleneck, DCB, HMC, HSC, and CH significantly outperformed NC. This trend continues until more than three bottlenecks, after which CH exceeded other strategies.

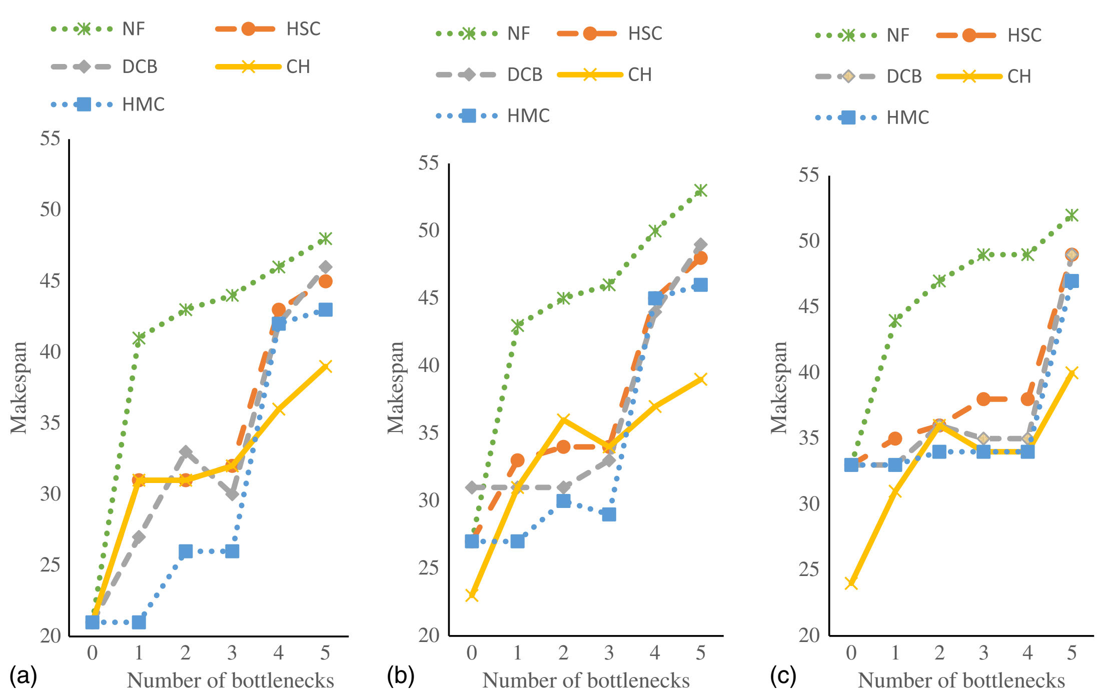

Fig. 4. Sensitivity analyses: (a) NV; (b) MV; and (c) HV.

J. Constr. Eng. Manage., 2019, 145(4): 04019011

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

This implies that HSC, HMC, and DCB should be designed according to the maximum possible number of bottlenecks in the production line because they became increasingly inefficient in response to even one extra bottleneck, but they are efficient in dealing with fewer bottlenecks. CH showed to be efficient in dealing with a wide range of bottlenecks and variability situations.

Conclusions and Contributions

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

The results of this study suggest that, as Hopp and Oyen (2004) argued, a resource management policy configuration is a highly context-specific issue, as dynamics of bottlenecks and variability should always be considered when it comes to advising a specific configuration. The findings of this research evaluate the resource management policy's performance under four different circumstances: (1) the performance of every resource management policy in each variability case; (2) the performance of each resource management policy on all variability cases collectively; (3) the cost–time performance of the resource management policy with different weightings for time and cost; and (4) the effects of different bottleneck locations in the resource management policy's performance.

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

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

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

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

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

A potential area for future studies is to optimize cross-training configuration by considering the trade-off between different productivity elements and collateral effects. Furthermore, future studies should focus on the precise calculation of operation duration corresponding to different combinations of single-skilled and multiskilled crews. Different levels of cross-trained skill competency should also be considered in modeling crews, including helpers, crew with middle level of skill, and supervisors. Adding a productivity ratio to formulations to reflect productivity of different skill levels would be useful to capture an optimal multiskilling strategy.

Appendix. Linearization Procedure

The following procedure explains how two quadratic constraints in Eqs. (10) and (11) are linearized.

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

$$x_i y_i = z_i \tag{12}$$

$$x_i \geq z_i \tag{13}$$

$$y_i \geq z_i \tag{14}$$

$$x_i + y_i - 1 \leq z_i \tag{15}$$

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

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W}\theta_{nmkt} + a_{wmt} = \lambda^{1}_{nmwkt} \qquad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{16}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W}\theta_{nmkt} \geq \lambda^{1}_{nmwkt} \qquad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{17}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W} a_{wmt} \geq \lambda^{1}_{nmwkt} \qquad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{18}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W}\theta_{nmkt} + a_{wmt} - \lambda^{1}_{nmwkt} \leq 1 \quad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{19}$$

Nonlinearity, which is exposed as a result of the product of two binary variables of θ_{nmkt} and a_{wml} in the constraint in Eq. (11) can be linearized as follows:

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{W}\theta_{nmkt}a_{wml} = \lambda^{2}_{nmwktl} \qquad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{20}$$

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{W}\theta_{nmkt} \geq \lambda^{2}_{nmwktl} \qquad n \in \boldsymbol{N}, m \in \boldsymbol{M} \tag{21}$$

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{W} a_{wml} \geq \lambda^2_{nmwktl} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{22}$$

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{W} \theta_{nmkt} + a_{wml} - \lambda^2_{nmwkl} \leq 1 \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{23}$$

Consequently, the constraint in Eqs. (10) and (11) in a linearized form can be written as the expressions in Eqs. (24) and (25), respectively.

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{w=1}^{W} \lambda^1_{nmwkt} = \sum_{k=1}^{K}\sum_{t=1}^{T} k\theta_{nmkt} \qquad n \in \mathcal{N}, m \in \mathcal{M} \tag{24}$$

$$\sum_{k=1}^{K}\sum_{t=d_{nmk}}^{T}\sum_{l=t-d_{nmk}+1}^{t} \lambda^2_{nmwktl} = \sum_{k=1}^{K}\sum_{t=1}^{T} \lambda^1_{nmwkt} d_{nmk} \qquad n \in \mathcal{N}, m \in \mathcal{M}, w \in \mathbf{\Omega} \tag{25}$$

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.

Notation

The following symbols are used in this paper:

a_{wmt} = explained in problem description;
C_{nm} = completion time of procedure (n, m);
D_{nm} = duration of procedure (n, m);
d_{nmk} = duration of procedure (n, m) when k workers are assigned to it;
K = maximum number of workers who can work in workstation m;
M = last workstation;
$\mathcal{M}$ = set of workstations;
N = last product;
$\mathcal{N}$ = set of products;
Q = total salary of workers;
q_w = salary of worker w;
s_{wm} = skill matrix;
T = upper bound on makespan;
$\mathcal{T}$ = set of time periods;
t = time periods;
z_i = binary variable explained in Appendix;
θ_{nmkt} = binary variable explained in "Problem Description" section;
$\mathbf{\Lambda}$ = set of status;
λ^1_{nmwkt} = binary variable explained in Appendix;
λ^2_{nmwktl} = binary variable explained in Appendix; and
$\mathbf{\Omega}$ = set of workers.

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