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OPTIMIZING LABOR ALLOCATION IN MODULAR CONSTRUCTION FACTORY USING DISCRETE EVENT SIMULATION AND GENETIC ALGORITHM

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ABSTRACT

Modular construction is gaining popularity in the USA due to several advantages over stick-built methods in terms of reduced waste and faster production. Since modular construction factories operate as an assembly line, the number of workers at various workstations dictates the efficiency of the overall production. This paper presents a resource allocation framework combining discrete event simulation (DES) model and genetic algorithm (GA) to facilitate data-driven decision making. The DES model simulates the process of building modular units in the factory, and the GA optimizes the number of the worker at different workstations yielding to minimum makespan. A case study with a real-world modular construction factory showed that optimizing the assignment of available workers can reduce the makespan by up to 15%. This study demonstrates the potential of the proposed method as a practical tool to optimize resource allocation in the uncertain work environments in modular construction factories.

1 INTRODUCTION AND BACKGROUND

Off-site and modular construction methods are gradually becoming a desired alternative to traditional onsite stick-built construction methods with the highest degree of offsite modularization being the production of volumetric units which are installed on-site as load-bearing blocks, thereby ensuring minimum on-site work (Gibb and Isack 2003). The primary advantages of modular construction over the traditional stick-built site construction methods have been noted to be improved quality of the constructed product, increase speed and parallelization of construction activities, and potential for leveraging economies of scale and mass production (Lawson, Ogden, and Bergin 2011). There is a wide range of available sizes and shapes for modular units that are most frequently applied to cellular-type buildings for uses such as student housing, hotels, military accommodations, and multi-family housing. However, there has been an increase in modular construction for residential housings as well, including single-family homes, condo apartments, townhome and duplex type homes, and bungalows (Altaf et al. 2018). The construction process of these modular units in a factory closely resembles a manufacturing production line, where different workstations are dedicated to a specific type of activity (e.g., building floors and walls, installing walls, installing insulation, etc.), and through which the modular unit would travel travels through. Thus each component of the modular unit (e.g., wall, floor, ceiling, etc.), as well as the modular unit spends a different amount of time (i.e., cycle time) at each station based on their particular design specifications. Another important factor that has a direct impact on the cycle time is the number of workers working at the station, which is referred to as "labor allocation" in this paper. Thus, effective and data-driven labor allocation at various stations is a significant factor in improving productivity and maximizing the benefits of modular construction. To that end, this paper proposes an optimization framework for labor allocation in modular construction factory by utilizing discrete event simulation (DES) and genetic algorithm (GA). The DES methodology is used to model and simulate the process workflow while the GA searches for the labor allocation to workstations that results in the optimal solution (i.e. maximum production rate or minimum makespan) in the process workflow. The following section discusses previous studies related to simulation modeling and GA based optimization in construction.

In the context of this research, simulation modeling is the process of creating and analyzing a virtual model of a real-world process to predict and forecast its performance. Simulation modeling has been widely explored for on-site and off-site construction process in several previous studies (Afifi et al. 2017; Akhavian and Behzadan 2013; AlDurgham and Barghash 2008; Altaf et al. 2015, 2018; Hammad et al. 2002; Jeong et al. 2011; J. Louis, Dunston, and Martinez 2014; Joseph Louis and Dunston 2016; Zhang 2004). Altaf et al. (2018) proposed an integrated production planning and control system for panelized home building using DES and radio frequency identification (RFID)-based tracking. A discrete and continuous simulation approach was also explored to optimize the production of modular construction element (Afifi et al. 2017). AlDurgham and Barghash (2008) proposed a simulation-based approach to facilitate decision making for planning layout, material handling, scheduling, and manufacturing processes and resources for off-site house building. Lu and Olofsson (2014) proposed a framework consisting of building information modeling (BIM) and DES to enable the integration of DES in the planning and follow-up of construction activities.

Genetic algorithms (GAs) are optimization techniques that are based on the principles of Darwinian evolution which simulate biological evolution through stochastic search techniques (Holland 1975). GAs has been used for optimizing simulation models in construction, as well as in other fields. Yang et al. (2016) developed a flowshop scheduling optimization model for multiple production lines for precast production. In another effort, an adaptive GA was presented for resource-leveling as a flexible decision support system to enable practitioners to choose a feasible solution (Ponz-Tienda et al. 2013). GA, analytic hierarchy process, and computer simulation were integrated for optimization of operator allocation in the cellular manufacturing process (Azadeh et al. 2014). A combination of GA with simulated annealing (SA) was also adopted for generic multi-project scheduling optimization with multiple resources constrain in complex construction projects (Chen and Shahandashti 2009). Leu et al. (2000) presented a prototype of a decision support system for construction resource-leveling using GA to achieve an optimal or near-optimal combination of multiple construction resources.

This paper utilizes the capability of DES to model the interdependencies between workstations and dependence of productivity on available labor, along with the ability of GA to optimize simulation input parameters to determine the optimal number of workers at various workstations in a modular construction factory. The following section discusses the methodology developed in this study.

2 METHODOLOGY

The objective of this paper is to obtain the optimal number of workers at each workstation of the modular factory to minimize the makespan, which is defined as the amount of time each unit spends in the production line from start to end. Thus the two primary components of the proposed methodology are a DES model to simulate the process of the factory, and a GA to optimize the number of workers that yield the minimum makespan of the modular units. The proposed methodology is illustrated in Figure 1.

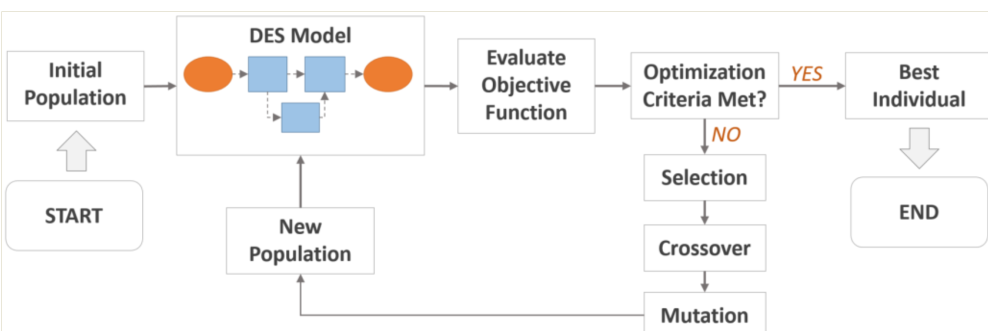

Figure 1: Overview of the proposed methodology.

As discussed previously, the methodology consists of two primary components; DES and GA. The DES model is created by modeling the interdependencies between the workstations. The duration of the activities at the workstations is modeled as a factor of the number of workers working at the corresponding stations using a linear relationship. The output of the simulation is the average makespan of the modular unit in 100,000 minutes of simulation time. The number of workers at the workstations is the input variables, and minimizing the makespan is the objective function of the GA. As shown in Figure 1, first an initial population (i.e., a vector containing number of workers in each workstation) is selected randomly and passed to the DES model. The DES model simulates the process of constructing modular units in the factory and average makespans for units are calculated. Then the objective function (i.e., to minimize makespan) is evaluated for each individual of the population to check whether it meets the optimization criteria (i.e., a threshold value for minimum makespan). If yes, this best individual from the population is selected as the best solution. If no, two pairs of individuals (i.e., vectors containing the number of workers) are selected as parents based on their fitness score (i.e., minimum makespan). For each pair of the parents to be mated, a crossover point is chosen at random from within their genes (i.e., index of the worker vector), and the offspring exchanges the genes of parents among themselves until the crossover point. After new offspring (i.e., a new vector of the number of workers) is created, some of their genes can be subjected to a mutation where some of the genes in the offspring can be flipped. An illustration of crossover and mutation is shown in Figure 2.

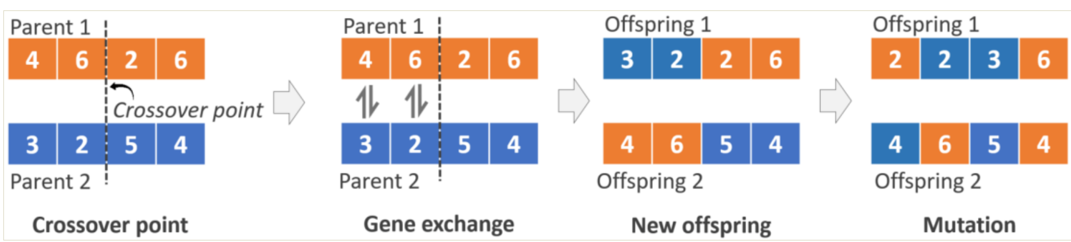

Figure 2: Crossover and mutation of GA.

After a new population is generated, they are again passed to the DES model to calculate makespan for construction modular units. This process of selection, crossover, and mutation continues until the optimization criteria are met. Pseudocode for the GA can be expressed as:

```
START
Generate the initial population
Compute fitness
REPEAT
    Selection
    Crossover
    Mutation
    Compute fitness
UNTIL population has converged
STOP
```

This methodology was validated using the data from a real-world modular construction factory, and the case study is presented in the following section.

3 CASE STUDY

To validate the proposed methodology, a real-world modular construction factory was selected. This factory makes volumetric modular units for projects like multi-family housing that are then shipped and set up on-site. There are several workstations in the factory dedicated to specific activities. The workstations in that particular factory can be divided into two categories: off-line stations and online stations. The panelized components of the unit, such as walls, floors, and ceilings are built from raw material in the off-line stations. The on-line stations are part of the assembly line for the volumetric unit, where various pre-made components (some from the off-line stations) are added and assembled to the modular unit. A schematic floor plan with the major workstations of the factory is shown in Figure 3. Three main off-line workstations clusters are *Partial Wall*, *Long Wall*, and *Ceiling* stations. Some of those off-line stations are further divided into several smaller stations dedicated to separate activities. For example, in the ceiling workstation, first, the ceiling frame and drywall are put and moved for rough plumbing and electrical station. Eventually, the final ceiling is built and moved to the online station to assemble to the modular unit. Each of the workstations (both online and off-line) are denoted with the number of worker and cycle time in Figure 3. For example, typically 5 workers are placed to the first online station, *Floor Build*, and it takes about 260 minutes to build a 50 feet floor. Cycle time and the typical number of workers were acquired from actual time study, expert opinion, as well as from the experience of floor manager of the factory.

After gathering the cycle time and worker data, a DES model of the factory floor was developed using *SimEvent* tool of *MathWorks*. Figure 4 shows the diagram of the DES model, where the three major off-line workstations (i.e., *Partial Wall*, *Long Wall*, and *Ceiling*) are denoted by rectangular borders. It should be noted that there are two different *Long Wall* (denoted as *Long Wall 1* and *Long Wall 2*) stations in the factory to build long walls of two sides of the modular units. The number "1" denoted at each activity represents the queue capacity of each station. In the factory, each station can only handle one component at a time. There are some surge spaces on the factory floor which work as queues with a FIFO (i.e., first-in-first-out) queue policy. Several assumptions were made while developing the DES model, such as the transfer of material from one station to another is instantaneous, there are no constraints for the workers to move from one station to another, every worker is eligible to work in any station, etc. The assumptions were made because the focus of this study is on the aspect of labor allocation.

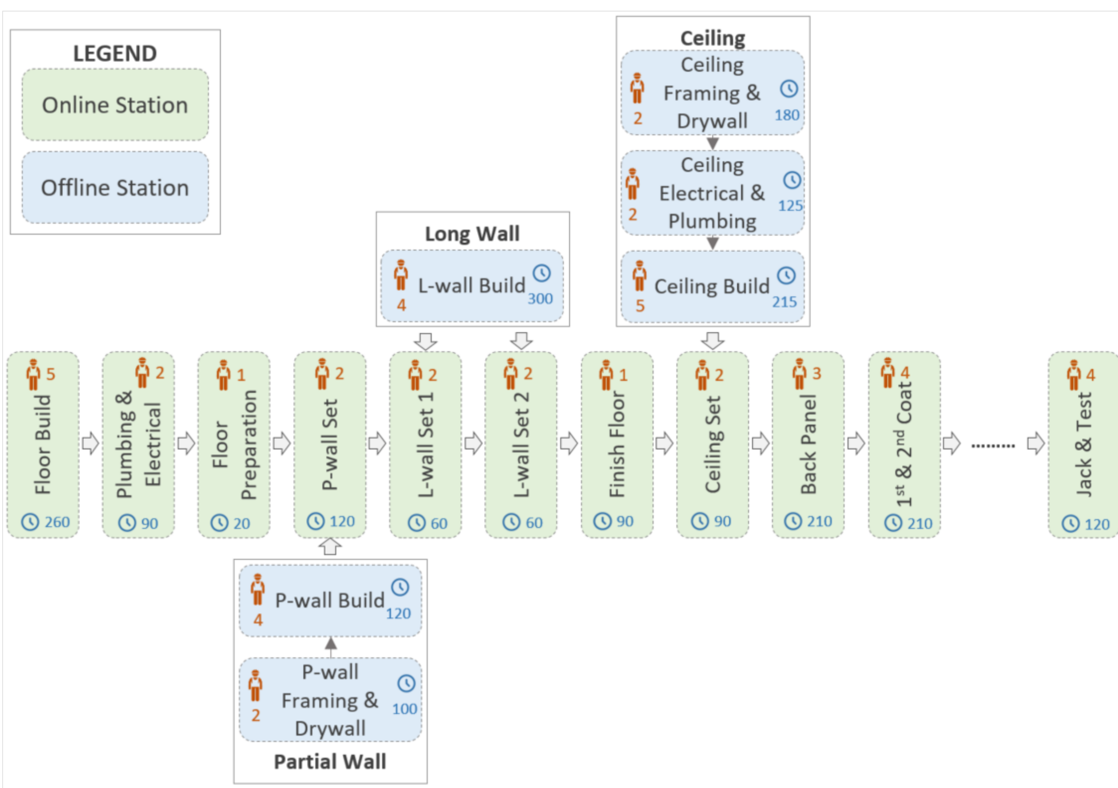

Figure 3: A schematic of the floor plan of the modular factory.

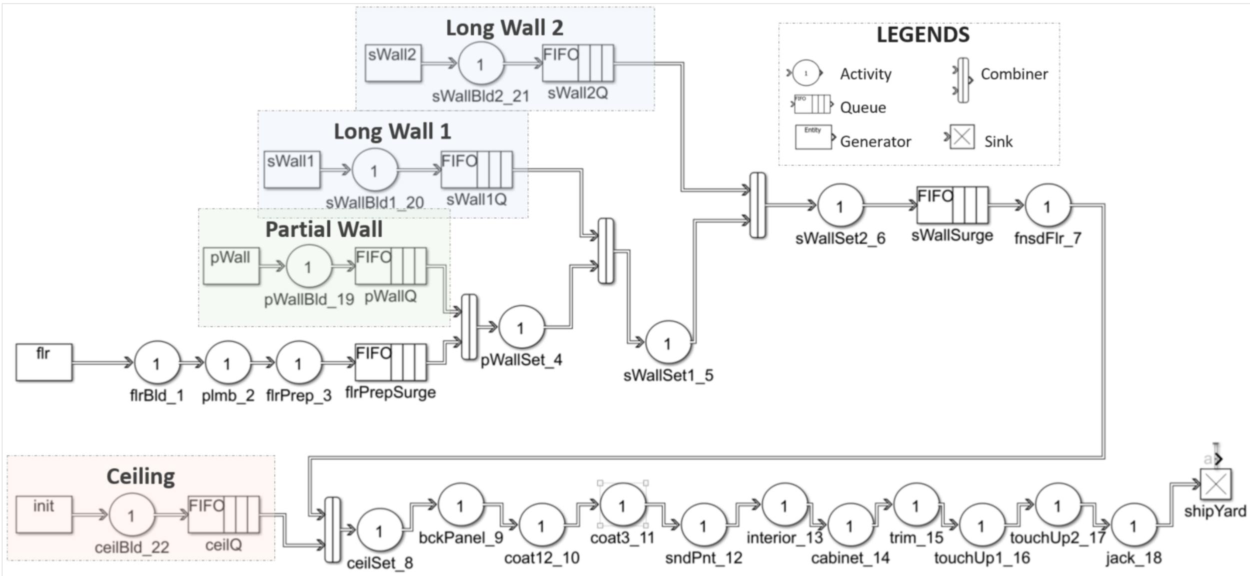

Figure 4: The DES model of the modular factory.

The cycle times of the activities were converted to worker-minutes and were set up as a function of the number of workers. A linear relationship was assumed between the number of workers at a station and its cycle time based on input from the factory manager. A genetic algorithm was developed where the variables were the number of workers at each workstation, and the objective was to minimize the makespan. The maximum number of workers in the factory was 74, which was the same as currently placed in the factory. The lower and upper bound of the worker number was set as one and eight, respectively. At each iteration of the simulation, the GA module sent an array to the DES model representing the number of workers at each workstation, the simulation model calculated the makespan and sent it to the GA module. Progressively the GA minimized the makespan and the simulation progress is shown in Figure 5. The GA was run for 1000 generations, each generation containing 30 populations. Figure 5 shows that the penalty value (i.e., average makespan) plateaued after 460 generations.

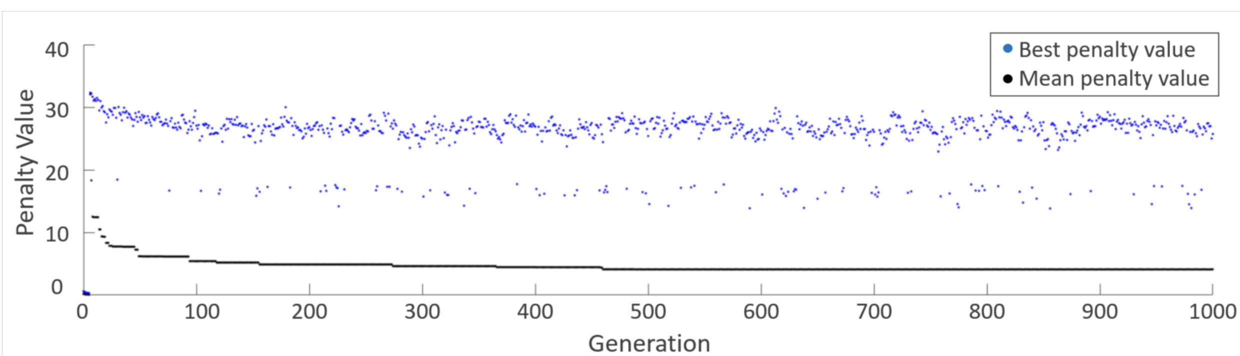

Figure 5: Optimization of the makespan using genetic algorithm.

The duration of each station was assumed to be a triangular distribution with 15% upper and lower bound. The average makespan was calculated for three different combinations of the number of workers. Figure 6 shows the boxplot containing makespan distribution of each of the three combinations The first boxplot shows the makespan with current “as is” labor allocation in the factory. The second boxplot is the makespan with an optimized number of workers by GA with a maximum 74 number of workers in the factory. The last boxplot illustrates the makespan with a maximum of 100 workers in the factory.

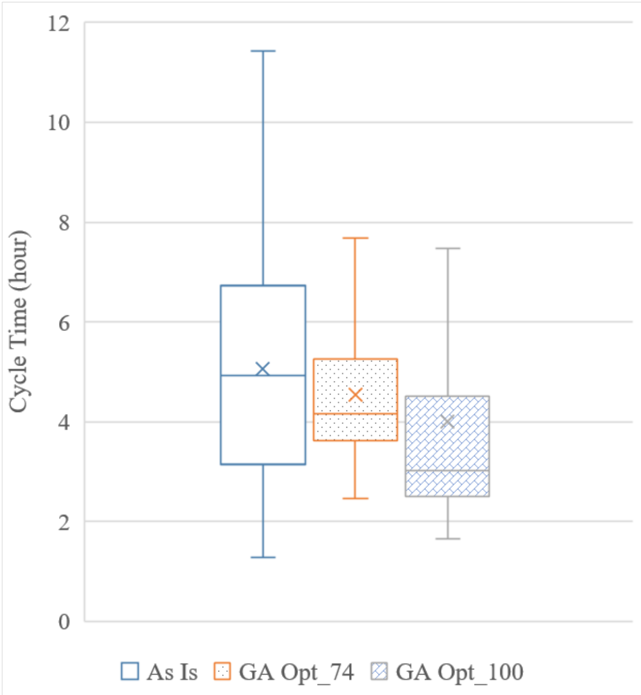

Figure 6: The DES model of the modular factory.

Median makespan for “as is” is 4.92 hours, “GA optimized with 74 workers” is 4.16 hours, and “GA optimized with 100 workers” is 3.02 hours. Thus, this analysis shows that the makespan can be reduced by about 15% with the same total number of workers currently situated in the factory, just by shuffling their numbers in a couple of stations. Moreover, if a decision is made to increase the total number of workers from 74 to 100, the makespan can be reduced by about 38%. Table 1 shows the result of the optimized number of workers at different workstations.

Table 1. Optimized number of workers at each workstation.

Station Name	**As-Is**	**GA Opt_74**
Floor Build	7	8
Plumbing	3	3
Floor Prep	2	2
P-Wall Set	2	2
S-Wall Set 1	2	2
S-Wall Set 2	2	2
Finished Floor	2	2
Ceiling Set	2	2
Back Panel	2	4
1st and 2nd Coat	5	6
3rd Coat	3	4
Sand and Paint	6	6
Interior	2	2
Cabinet	6	8

Trimming	2	2
Touch Up 1	4	3
Touch Up 2	6	3
Jack	4	2
P-Wall Build	4	3
S-Wall Build 1	2	2
S-Wall Build 2	2	2
Ceiling Build	4	4

Stations requiring a change in the number of workers are highlighted in the table. The analysis is suggesting to add workers to *Floor Build* (1 worker), *Back Panel* (2 workers), *1st and 2nd Coat* (1 worker), *3rd Coat* (1 worker), and *Cabinet* (2 workers) stations, and reduce worker from *Touch Up1* (1 worker), *Touch Up 2* (3 workers), and *Jack* (2 workers) station. However, in both cases, the total number of workers in the factory remains the same (74 workers).

4 SUMMARY AND CONCLUSIONS

This study presents a methodology for optimizing the number of workers at different workstations in a modular construction factory. This consists of a DES model and a GA to optimize the DES model. A vector consisting of the number of workers is sent to the DES model to calculate the average makespan, and the GA simultaneously tried to minimize the average makespan by performing selection, crossover, and mutation until the performance of the algorithm plateaued. A real-world modular construction factory was selected to validate the proposed methodology. In particular, there were 22 different workstations in the factory dedicated to various activities. The entire assembly line process of the modular construction factory was modeled using DES, and the GA optimization showed a makespan reduction of 15%. Specifically, if the total number of workers in the factory remains the same (i.e., 74), reallocating the number of workers based on the results of the analysis can yield 15% makespan savings. If the number of workers in the entire factory is increased to 100, the optimization showed a 38% reduction in makespan.

The real-world case study illustrated that the proposed approach can help management to optimize worker allocation in the complex modular construction factory. The dynamic approach of labor allocation presented in this paper can eliminate the limitations of traditional CPM-based resource allocation by updating the DES model at the desired interval. The integration of worker tracking technologies using an indoor positioning system (IPS) or computer vision with the DES model in the proposed system can unleash the true potential of a dynamic data-driven decision support system. The primary limitations of the DES model stem from the assumptions made in terms of instantaneous transfer of components, linear relationship between duration of an activity and the number of workers, and the same expertise level for all the workers. In the future, the abovementioned dependencies will be added to the DES model for a more realistic simulation of the process. Moreover, future research will be directed to develop multi-objective optimization, where other criteria (e.g., wait time, worker expertise, etc.) can be included in the objective function. An adaptive GA can be explored for real-time dynamic optimization of worker allocation in the future.

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