SVR and GA Aided Lean Six Sigma Method for Planning in Modular Construction

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Abstract –

Modular construction presents a strong alternative to traditional construction, offering advantages such as improved productivity, and better quality. However, the prefabrication of module components follows a make-to-order process, resulting in customized module components. This design customization, along with various factors such as worker skill levels, and defects in shop drawings causes significant variability in the process times for prefabricating module components at workstations. This variability leads to imbalanced production line, and idle time at workstations, which increases the overall completion time of fabricating module components. To address these challenges, this paper develops a Lean Six Sigma based method that comprises three modules. In the first module, the production line that requires improvements is identified and project objectives are defined. In the second module, the process time data of module components at workstations are collected to identify and analyse inefficiencies in the production line utilizing six sigma performance metrics. The third module focuses on improving and controlling the production line process using support vector regression (SVR) and meta-heuristic optimization. A light gauge steel (LGS) wall panel production line in Edmonton, Canada was analysed to demonstrate the use of the developed method and test its performance. The results show that, after addressing the production line bottlenecks, the sigma level improves to 1.85 σ compared to 1.41 σ earlier. This method can help production managers identify wastes and bottlenecks in the production line, enabling them to plan their processes more efficiently.

Keywords –

Modular Construction; Lean; Six Sigma; Support Vector Regression; Optimization

1 Introduction

For many years, construction professionals have drawn to the idea of making construction practices after those in manufacturing, as this approach leads to substantial improvements in productivity and quality [1]. In this regards, modular construction has been applied to a wide range of projects, from large-scale industrial buildings to residential housing. The modular construction process is based on two strategies: (i) the product approach, which seeks to minimize on-site construction by turning buildings into unique products (i.e., module components) that can be prefabricated in a factory environment; and (ii) the process approach, which applies a production line principle to the prefabrication process [2]. As a result, companies that have adopted prefabrication have seen significant productivity gains within a few years. Despite the advantages highlighted above, the high degree of design customization in module components (i.e., variation in design specifications of module components), often result in each module being a unique product. For example, on the same production line not all produced wall panels are identical. Wall Panels are rather customized to accommodate dynamically changing owners' requirements and is identified as a key factor preventing modular construction from realizing its full potential benefits. This design customization results in differing process times for module components at each workstation, in turn leading to different production rates, imbalanced production lines, and an increased total completion time (i.e., makespan) [3-4]. To reduce completion time, it is crucial to identify sources of waste (e.g., overproduction and waiting) within a production line so that improvement efforts can be directed towards these areas. Lean manufacturing principles, originally developed in the manufacturing industry, have proven to be applicable to identify waste in modular construction

[2]. Although lean focuses on eliminating waste in production, it does not specifically address process variation such as the time taken to prefabricate wall panels in the production line and employ statistical analysis [5]. Meanwhile, Six Sigma can identify/reduce variations, eliminate waste and is a supplement to lean manufacturing principles. Moreover, Six Sigma DMAIC method provides a standardized and step-by-step approach unlike lean for: (i) comprehensive analysis to identify root causes to the production line waste, (ii) reducing process variations and (iii) providing solutions to achieve process improvements (i.e., minimizing completion time) [6-7].

In this respect, the primary goal of this study is to minimize the makespan by identifying and eliminating production line waste through integration of Six Sigma's DMAIC approach with machine learning and optimization techniques. The developed method encompasses: (i) defining the production line that requires improvements; (ii) identifying factors that causes variations in process time at workstations and developing a Six Sigma production line performance (PL_P) metric to assess performance; and (iii) developing a prediction model using support vector regression (SVR) and implementing GA for hyperparameter tuning. Additionally, the 5 Whys technique to reach to the root cause of the issues and simulated annealing optimization for determining optimal sequences of module components are employed to eliminate waste and minimizing makespan.

2 Literature Review

2.1 Application of Six Sigma

The Six Sigma principles are applied using a problem-solving approach like DMAIC (Define, Measure, Analyze, Improve, Control). The DMAIC method aligns with strategy for addressing problems by recognizing the root causes of variations in the production line and utilizing statistical methods to maintain continuous improvements [8]. In the construction industry, the application of Six Sigma principles for performance evaluation, especially for controlling variability, began in 2000. Buggie [9] introduced Six Sigma as a method to enhance productivity by focusing on reducing cycle time and eliminating defects in processes. Meanwhile, Han et al. [5] utilized a Six Sigma-based approach to enhance performance in construction operations by establishing quantitative metrics. Despite the numerous benefits of the Six Sigma approach, its application in modular construction has been limited. To the authors' knowledge, there have been almost no project-specific case studies in modular construction aimed at enhancing production performance while achieving appropriate sigma levels. Additionally, previous studies have not identified the list of possible factors that could impact the process time for prefabricating module components at workstations.

2.2 Data Analytics

The highly customized nature of module components, along with factors such as worker skills, on-site change orders, and defects during prefabrication, leads to uneven distribution of process times across workstations. This unevenness results in various forms of waste (e.g., overproduction and waiting) and increases the total completion time for prefabricating module components [10]. Therefore, it is crucial to accurately estimate process times for production line planning considering the design variations and other factors. In this context, Six Sigma's DMAIC method has been used to remove bottlenecks and enhance the production line process by employing statistical techniques such as t-test and linear regression. However, these techniques are not effective when dealing with large, complex and non-linear data [4]. As a result, researchers have recommended combining Six Sigma with machine learning techniques for accurate predictions of process times, enabling production line managers to make better decisions [10].

Support Vector Regression (SVR), a machine learning algorithm that adapts the principles of Support Vector Machines (SVM), has been studied by various researchers for regression tasks with non-linear datasets [11]. For instance, Tsarouhas et al. [12] combined the Six Sigma method with machine learning techniques to predict outcomes for future injection moulding processes. On the other hand, Wauters and Vanhoucke [12] used SVR in a project control setting to develop more accurate time and cost forecasts by utilizing periodic data from Earned Value Management. However, these methods have overlooked the hyperparameter tuning. Several researchers have employed genetic algorithms (GA) for hyperparameter tuning in the fields of construction and manufacturing engineering [13-14] to improve the accuracy of their prediction model. Given the advantages of GA and its effectiveness for fine tuning parameters, this paper applies GA to identify the optimal parameters for an SVR algorithm in order to efficiently predict process times of module components in the production line.

3 Developed Method

Fig. 1 shows the Six Sigma-based method for enhancing production line processes in modular construction. This method emphasizes the use of DMAIC (Define, Measure, Analyse, Improve, and Control), a core component of Six Sigma focusing on continuous improvement. This method integrates machine learning (Support Vector Regression) and optimization (Genetic Algorithm and Simulated Annealing) within DMAIC process to identify production line wastes and enhance the production line performance.

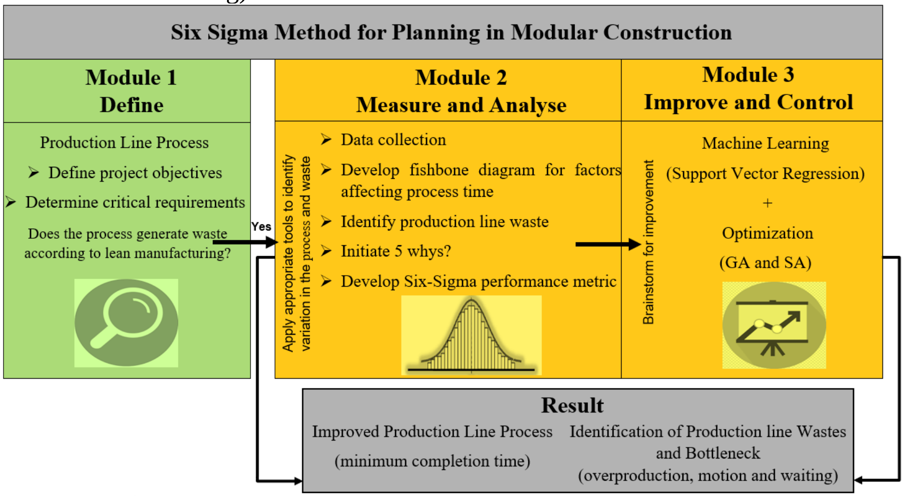


Fig 1: Main components of Six Sigma DMAIC method

The developed method includes: (i) define module, which focuses on identifying the problem that requires improvement and setting the project objectives. In this paper, the process selected is the wall panel production line, with the aim of reducing the total completion time for prefabricating module components; (ii) measure and analyse module to identify production line inefficiencies (waste) and determine their root causes. The process starts with collecting the process time data for module components at each workstation using the C-track app [19]. Statistical analysis is performed to assess the extent of variations and deviations in the process times for module components at workstations. Additionally, a fishbone diagram is created to list the factors affecting the process times and pinpoint potential causes of these variations. Analyzing these root causes and their impacts is crucial for reducing completion times. This module also identifies potential wastes (such as overproduction, waiting, and motion) and bottlenecks within the production line. Along with fishbone diagram, the '5 Whys' technique is used to uncover issues and solutions within the production line such as workstations, that takes more time to prefabricate module components compared to other workstations. By continuously asking ‘why’ for each identified issue, this approach helps to pinpoint the root cause of the problem, ensuring that solutions address the fundamental issues. To assess the sigma level and measure performance, this module includes a Six Sigma Production Line Performance (PL_P) metric (Eq. (1) and (2)). This PL_P metric is modified from the process capability index metrics commonly found in Six Sigma literature. Production line performance is expressed by following equation:

$$PL_P = \frac{(USL-CT)}{(3 \times STDEV)} \qquad (1)$$

$$\sigma = 3 \times PL_P \qquad (2)$$

where USL= upper specification limit; CT= completion time; and STDEV= standard deviation of the process time data.

For instance, if the completion time and standard deviation are 50 and 10 minutes, respectively, and the USL for the completion time is set at 55 minutes, the current PL_P is calculated to be 0.16, with a sigma level of 0.5 σ. This indicates a low performance level, suggesting that improvements are needed in the production line. (iii) the third module, which is improve and control, address the issue of variability in process time at workstations to enhance the production line process. To achieve this, it is crucial to predict process times based on design factors and the number of workers at each workstation, which significantly influence the process. This research utilizes SVR to develop prediction models for workstations in the production line. The data is pre-processed and split into training (80%) and testing (20%) subsets. Additionally, to avoid overfitting, K-fold cross-validation is employed, to assess model performance. Initially, default parameter values, including C (regularization), gamma, and the kernel, are used in the SVR model. Subsequently, the GA is applied for hyperparameter tuning (C and Gamma) with the goal of reducing the mean absolute error (MAE). Given the successful implementation of GA in the literature for tuning the parameters of machine-learning models and avoiding local optima [4], the present study implements GA to determine the optimal parameters for an SVR-based process time prediction model. It is worth mentioning that in the SVR model, C and gamma play crucial roles with regards to controlling the error rate and model complexity; therefore, tuning the C and gamma is crucial to achieve optimal predictive performance in SVR. Fig. 2 illustrates the GA-based hyperparameter tuning process, which begins by creating an initial population of chromosomes, each representing different configurations of C and gamma. This population is generated randomly, with the size of the population determining the number of chromosomes. The structure of the generated chromosome (Fig. 2), represents a potential solution. For example, in the chromosome “0,1,0,0,0,1,1,0,1,0” the first five digits encode the value for C, while the remaining digits represent gamma.

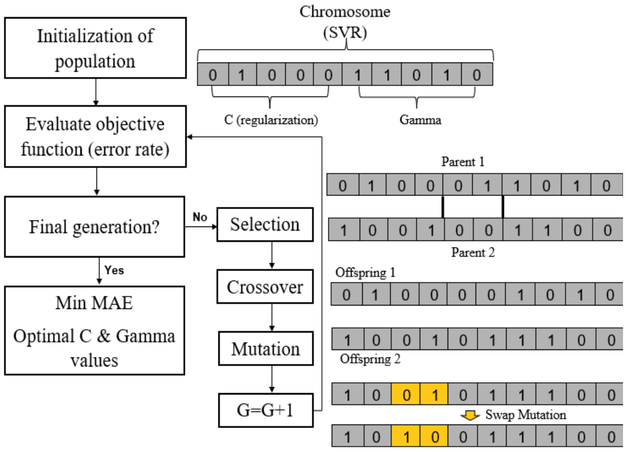


Fig 2. GA based hyperparameter tuning

These binary strings are then decoded using Eq. (3) to convert the encoded parameters back into their real-world values.

$$D = (\Sigma bit \times 2^{i}) \times P + \alpha \quad (3)$$

$$P = \frac{b-a}{2^{l}-1} \quad (4)$$

Where D denotes the decoding process, and P represents the parameter (as indicated in Eq. (4)). The variables a and b specify the lower and upper bounds of the parameter (e.g., gamma), while l refers to the length of the chromosome. For instance, to decode the variable Gamma, which has lower (a) and upper (b) bounds of 0.05 and 0.99, respectively, and a chromosome length of 5 (Fig. 3), the decoded value (D) is 0.81, which falls within the acceptable range (i.e., 0.05 to 0.99).

1	1	0	1	0
2^4	2^3	2^2	2^1	2^0

Fig 3. Decoding of chromosome (Gamma parameter)

Later, the process of evaluation, where fitness values of each chromosome are evaluated based on the optimization criteria (i.e., minimum error rate); Third, the selection process involves choosing the best chromosomes (i.e., potential parents) from the population as the best solution (i.e., the best combination of Gamma and C) based on their fitness value. This paper uses tournament selection due to its efficiency, ease of implementation, and relatively low computational time compared to other methods (e.g., roulette wheel selection) [15]. In the tournament selection technique, a number of chromosomes (represented as k, i.e., the tournament size) are randomly selected from the population, and the chromosome with the best fitness score among the k chromosomes is selected as parent 1. This process is repeated until the desired number of parents for crossover is selected. For example, in a population of 10 with a tournament size (k) of 3, chromosomes 1, 2, and 3, with fitness values of 0.75 min, 0.82 min, and 0.68 min, respectively, are randomly picked. The chromosome with the best fitness (i.e., minimum error rate)—in this case, chromosome 3 (fitness 0.68)—is selected as the first parent, and the process continues with the identification of a second parent. In the next step, finally, after selecting two parents, crossover is performed using two-point crossover to create new chromosomes for the next generation. Mutation is subsequently performed, and this process (i.e., the sequence of selection, crossover, and mutation) continues, until the termination criteria (i.e., maximum number of generations) are met.

The predictive process times generated by the SVR-based model are used as input for SA optimization. This optimization process focuses on solving the bottleneck, in the production line by optimizing the sequence of module components in with the goal of minimizing the completion time (as indicated in Eq. (5)) and achieve the desired sigma level. Although, the effectiveness of optimization algorithms varies depending on the scheduling problem and objective, the positive reviews of SA algorithms, known for providing effective solutions and good computing capabilities in solving production line scheduling problems, justifies their selection to optimize the sequences in this study [4].

$$Min\ (Max\ C_{m,w};\ \forall\ m \in M,\ w \in W) \quad (5)$$

Where $C_{m,w}$ is the completion time of module component at workstation. M = {1, 2…… m} and W = {1, 2…… w} are set of 'm' number of module components to be scheduled at a set of 'w' workstations.

4 Case Study and Results

The developed method was applied to a wall panel production line consists of three primary workstations: (i) assembly, (ii) framing, and (iii) sheathing (Fig. 4). The fabricator produces a range of LGS wall panels for multi-storey residential buildings. Process times for each workstation, comprising 200 data series, were recorded using the C-track app.

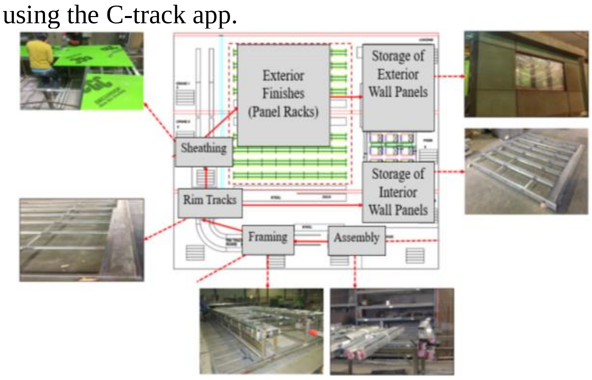


Fig. 4. Production line layout

The statistical details, including the mean and standard deviation, for each workstation on the production line were calculated. For instance, the average process time at the assembly workstation is 37.86 minutes, with a standard deviation of 23.47 minutes. A high standard deviation relative to the mean suggests high variation in the process times, with data points dispersed over a broader range. Additionally, at the assembly station, wall panel processing times range from 7 to 102 minutes. This considerable variation is attributed to factors such as design specifications (e.g., number of windows and studs), and the number of workers at each workstation, which impact the daily productivity and overall completion time of the workstations. Therefore, to assess performance, the Six-Sigma production line performance (PL_P) metric was utilized to calculate the sigma level. The current production line has a sigma level of 1.41 σ, which indicates that the high variation in the process time of prefabricating module components at workstations is causing waste in the production line and leading to low sigma level. In this respect, a fishbone diagram (Fig. 5) was created to illustrate the various factors contributing to process time variation at workstations. The high variation in process times was attributed to factors such as customized panel designs, worker-related issues, on-site conditions, and inventory management. The diagram further details specific causes within these factors, such as suboptimal worker allocation, inadequate skills or experience, learning curves, and space congestion around workstations, which affects worker coordination. This space congestion was also reported by Zhang et al. [16], which disrupts workflow and reduces productivity at the workstation level.

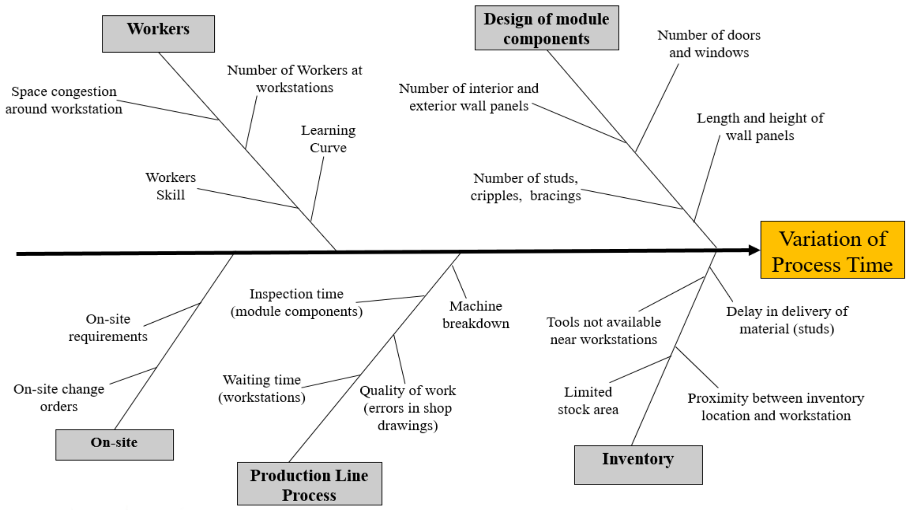


Fig. 5: Fishbone diagram for factors affecting process time

Based on the identified factors affecting process time and observations over several months, various lean manufacturing waste were detected, including overproduction, waiting, motion, and overprocessing. For example: (i) workers at the assembly workstation had to frequently move to retrieve materials (e.g., studs and bracings), which increased motion waste and prolonged process times; (ii) the workload was uneven, with the framing station having longer process times compared to the other workstations, leading to an imbalanced production line, waiting time of workers at the sheathing station, and overproduction at the assembly station; (iii) the cutting machine was located far from the framing workstation, causing workers to frequently move to cut bracings for wall panels, resulting in motion waste; and (iv) quality issues, such as errors in shop drawings (e.g., incorrect stud spacing or missing components), causing defects that required corrections at downstream stations, contributing to increased process times. In this respect, this study utilized the 5 Whys iterative questioning technique to identify solutions to some of the problems. By repeatedly asking 'why' a problem occurred, the root causes were determined, and potential solutions were documented. Table 1 provides an example related to the waste of motion observed at the assembly workstation. The first question posed was, why are some wall panels taking so long in the assembly process? The documented reason was, because workers take time to find specific materials (e.g., header and sill track, studs). The follow-up question was, why do workers take time to find specific materials? The reason noted was, because materials were not arranged properly in their designated locations. This questioning process continued through five iterations, ultimately leading to the proposed solution of 5S implementation, efficient layout design, and standardization. To further reduce production line waste (e.g., waiting and overproduction) and enhance performance by reducing completion time, it was crucial to accurately predict process times. To achieve this, design factors (e.g., the number of studs, cripples) and the number of workers at each workstation were used as inputs in SVR algorithm to forecast process times. Before developing the prediction model, data preprocessing steps were conducted, including removing outliers, normalizing the data, and identifying significant design factors that impact process time. In this study, correlation analysis was employed to identify significant design factors. Factors were selected if their correlation coefficient, indicating the strength of the relationship between the dependent variable (duration) and independent variables, was greater than 0.65 (Fig. 6). For instance, at the assembly workstation, four factors (the number of studs, studs with foam, cripples, and plates) had correlation coefficients exceeding 0.65.

Table 1: 5 whys example

Why 1?	Why 1 Reason	Why 2?	Why 2 Reason	Why 3?	Why 3 Reason	Why 4?	Why 4 Reason	Why 5?	Why 5 Reason
Why the assembly process taking so long for some of the wall panels?	Because workers spend time searching for specific materials (e.g., sill track, studs).	Why workers take time to search a specific material?	Because the materials are not properly organized in their designated locations.	Why material is not arranged properly and placed at specific location?	Because there are no designated storage areas for some of the material	Why there are no designated storage areas for some of the material	Because of poor plant layout	Why the storage and plant layout are poor?	Because there is no 5S implementation and standardized workflow

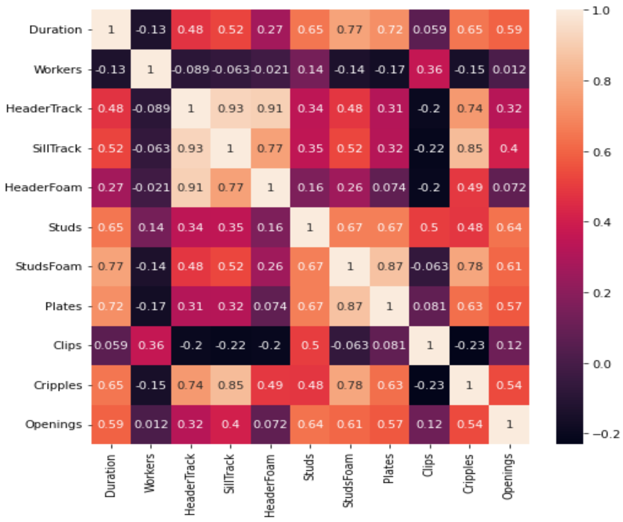


Fig.6: Correlation heatmap for assembly station

SVR models were developed on training dataset (80%) utilizing the significant design factors. As a result, shown in Table 2, MAE for the assembly station was 5.25 minutes. It is important to note that the initial SVR model was created using default parameters (i.e., C=1, Gamma (γ)=scale).

Table 2: Mean absolute error measurement for SVR

Workstation	C	γ	SD (min)	MAE (min)	MAPE (%)
Assembly	1	Scale	23.4	5.25	27.8
Framing	1	Scale	22.1	5.29	23.3
Sheathing	1	Scale	24.3	12.22	30.2

To further reduce the MAE in the prediction model, hyperparameter tuning of C (regularization) and Gamma was performed using a GA. The parameter C was selected because it controls the penalty for errors, while Gamma is crucial as it ensures the model captures the data's underlying structure accurately without being overly sensitive to noise. For SVR, there are various types of kernel functions such as linear, polynomial, RBF and sigmoid. However, it should be noted that in this research only linear and RBF were tested and compared due to their (i) good generalization capabilities; (ii) better computation and (iii) capability to avoid overfitting in nonlinear data set [17]. Table 3 shows the results, indicating a reduced MAE and MAPE after hyperparameter tuning. For instance, at the assembly workstation, the MAE was reduced to 1.78 minutes. The GA parameters include: (i) a population size of 40; (ii) a maximum of 20 generations; (iii) a mutation probability of 0.3; (iv) a crossover probability of 1; (v) a tournament size of 3; (vi) C ranging from 10 to 1000; and (vii) Gamma ranging from 0.05 to 0.99. The GA parameter values are determined by experimenting with various values and selecting the one yielding the best results. Additionally, it is worth noting that, C range (10–1000) allows control over model complexity, avoiding extreme underfitting or overfitting; and Gamma range (0.05–0.99) ensures non-linearity is captured effectively. These ranges cover a broad spectrum of hyperparameter values for SVR in order to achieve near-optimal solution in a reasonable run time (i.e., explore broad search space, while achieving computational efficiency).

Table 3: MAE values for SVR after parameter tuning

Workstation	C	γ	Kernel	MAE (min)	MAPE (%)
Assembly	977.5	0.9	Linear	1.7	13.3
Framing	110.5	0.5	RBF	5.1	21.2
Sheathing	13.8	0.2	RBF	11.1	26.4

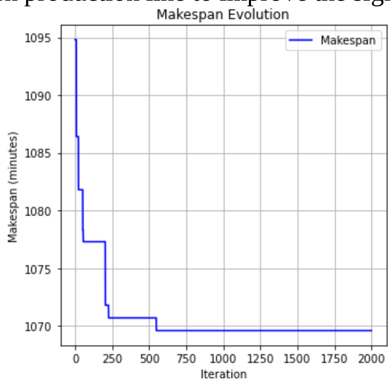
As previously mentioned, the framing workstation acts as the bottleneck in the production line. To address this, SA optimization was used to reflect the practical scenario when determining the optimal sequence of panels by considering an additional framing station to the production line to reduce completion time (i.e., improving sigma level), allowing two wall panels to be prefabricated concurrently. To reflect this practical case of capturing parallel workstations in the optimization algorithms, Eq. (6, 7 and 8) outlines the constraint concerning workstation capacity (X) and start time of wall panel. For example, Eq. (7) outlines the constraint, which stipulates that the start time of a wall panel (i.e., panel 'm') at parallel workstations must be equal to the completion time of the same wall panel at previous workstation. This can reduce the waiting times of wall panels between workstations, and allows the parallel workstation to work on two wall panels simultaneously. The detailed discussion regarding SA implementation for optimization is detailed in Bhatia [4].

$$\text{Max } X_2 \leq 2;\ \forall\ S_{m,2} \quad (6)$$

$$S_{m,\,2} = C_{m,\,1} \quad (7)$$

$$S_{m,\,2} \geq \min\,(C_{m\text{-}1,\,2};\ C_{m\text{-}2,\,2}) \quad (8)$$

Figure 6 shows the completion time results for 30 wall panels: with one framing station (7 a), the completion time was 1069.59 minutes, which was reduced to 1057.2 minutes with a parallel framing workstation (7 b). In other words, optimizing the sequencing of wall panels and addressing bottlenecks at the framing workstation improved the sigma level (i.e., 1.85 σ with two framing stations compared to 1.41 σ with one framing station). It is worth noting that the factors affecting the process time in this study are a function of the given module component (wall panel) design specifications and tasks performed at the workstations of the case study production line. For other modular construction cases, practitioners would need to modify the data analysis phase based on the given design specifications in order to identify the factors and developing process times prediction models based on those inputs. Additionally, the practitioners need to identify the bottlenecks and sources of waste according to their given production line to improve the sigma level.



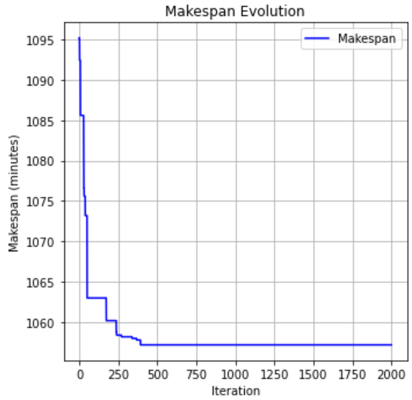


Fig 7: completion time: (a) one framing workstation and (b) two framing workstations

Conclusion

In a modular construction production line, process time is influenced by several factors, including the customized design of wall panels and worker-related variables. These factors cause a high level of variation in process time, resulting in production line waste, such as unbalanced production line, overproduction, and idle time at some workstations. This increases total completion time for prefabricating modules as demonstrated through the case study. Therefore, to ultimately minimizing makespan, it is significant to identify the list of factors impacting the process time for prefabricating module components at workstations, and utilize them to identify and eliminate production line waste. Moreover, application of six-sigma to the project-specific case studies in modular construction is required in order to enhance production performance while achieving appropriate sigma levels. In this regards this paper introduces a novel method that incorporates historical process time data from a wall panel production factory into the Six Sigma DMAIC framework. First, process time prediction models were developed where design factors and the number of workers were used as inputs into SVR model. Subsequently, the GA optimization technique was applied for hyperparameter tuning, specifically to determine the optimal values for C and Gamma. The hyperparameter tuning in the wall panel production line showed a reduction in the MAE to 1.78, 5.10, and 11.15 minutes compared to 5.25, 5.29, and 12.22 for the assembly, framing, and sheathing workstations, respectively. Additionally, this paper provides a solution to eliminate a bottleneck by considering an optimization scenario where an additional framing station allows two wall panels to be prefabricated concurrently. The optimal sequences of wall panels were generated using the SA algorithm, which reduced the total completion time and improved the sigma level to 1.85 σ. The contributions of this study are: (i) implementing GA to find the optimal hyperparameters for SVR; (ii) identifying the various factors (e.g., workers, inventory and design of module components) influencing process time at workstations, which leads to production line waste and low sigma level; and (iii) aiding production managers in gaining insights into the production line, thereby reducing the prefabrication time of module components at workstations.

However, this study is subject to some limitations. First, it does not explore means for eliminating other types of production line waste (e.g., motion, inventory and defects). Therefore, it is recommended for future work to collect data regarding these production line waste and applying lean principles along with simulation, where the former will be used for gaining a deeper understanding of the production line to reduce these production line waste, while the latter will be used for evaluating various production scenarios before implementing them in real production line. Second, future research could investigate other metaheuristic algorithms, such as particle swarm optimization (PSO) for hyperparameter tuning and compare their outcomes with those of GA. Third, the current optimization does not consider fine tuning different kernel functions. The future research would consider hyperparameter tuning of kernel functions in order to test their performance with regards to minimizing MAE.

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