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OPTIMIZING PRODUCTION SCHEDULING FOR DECARBONIZATION IN OFF-SITE CONSTRUCTION

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ABSTRACT: The construction industry is under increasing pressure to mitigate its environmental impact. In Canada, the building sector ranks as the third-largest contributor to carbon emissions, accounting for 13% of the nation's total emissions. This underscores the urgent need for innovative construction paradigms to address environmental challenges (e.g., carbon emissions). While off-site construction (OSC) presents a promising solution due to its potential to reduce carbon emissions, OSC production factories face critical challenges in identifying an effective production sequence to minimize CO₂ emissions. Thus, developing an effective production scheduling method to minimize CO₂ emissions during the production stage is crucial. To address these challenges, this paper proposes an optimal production scheduling framework aimed at minimizing CO₂ emissions during the production stage in OSC. The methodology consists of two key procedures: (i) data collection and analysis to quantify CO₂ emissions for each panel at each workstation; and (ii) the development of a genetic algorithm (GA)-based optimization model to reduce CO₂ emissions through production sequencing. The proposed method is applied to a wood-based panelized wall production factory in Edmonton, Canada. The results demonstrate that the proposed optimization model effectively reduces CO₂ emissions by 4,000 kg annually from a single production line (i.e., the wall production line), thereby enhancing the environmental performance of OSC. This research offers a novel framework for quantifying and mitigating CO₂ emissions in OSC production through sequencing optimization, making a significant contribution to sustainable construction practices.

1. INTRODUCTION

Off-site construction (OSC) is widely recognized as a pivotal strategy for advancing sustainability and fostering low-carbon development in the construction sector. OSC is a process where building elements are manufactured in a factory and then transported to the construction site for installation (Jin et al. 2018). It has the potential to reduce environmental impacts (i.e., reduction of CO₂ emission) compared to stick-built construction methods (Al-Hussein et al. 2009; Han et al. 2015; Rahman and Sobuz 2018). Moreover, this approach achieves an 8.40% reduction in greenhouse gas emissions and an 11.35% decrease in material wastage (Sandanayake et al. 2019). Despite the advantages of OSC, production managers face significant challenges in minimizing CO₂ emissions during the production process due to the lack of effective production planning and scheduling methods. Excessive energy consumption (e.g., electricity, natural gas, fuel) due to longer project completion times (PCT) increases CO₂ emissions since critical resources (e.g., labor, forklifts,

CNC machines, lighting) consume more energy over the extended operational period (Schulz et al. 2022). Optimizing production scheduling may offer a viable solution to address this issue, as it can reduce PCT and ultimately CO₂ emissions. As such, developing an optimal production scheduling method to minimize CO₂ emissions during the production stage is imperative.

Toward this direction, limited research has focused on minimizing CO₂ emissions in OSC, which can be categorized into two distinct approaches: (i) CO₂ emissions in OSC (Barrett and Wiedmann 2007; Mao et al. 2013) and (ii) optimized production scheduling in OSC (Rahman and Han 2024a; Zheng et al. 2023). While prior studies have successfully achieved their objectives, a notable gap remains: no research has specifically focused on developing an optimal production scheduling method to minimize CO₂ emissions in wood-based OSC production lines. Previous studies have primarily concentrated on reducing energy consumption by minimizing transportation distances in precast fabrication systems and manufacturing industries (e.g., paper mills). As a result, the absence of an OSC-oriented scheduling method not only increases PCT, production costs, and reduces productivity but also contributes to higher CO₂ emissions.

To address these gaps, this paper proposes a production scheduling optimization method for minimizing CO₂ emissions in wood-based OSC. The proposed method consists of two key steps: (i) estimation of CO₂ emissions associated with each panel at each workstation (WS) and (ii) development of a CO₂ emissions optimization model using genetic algorithm (GA). The proposed framework provides a unique and comprehensive approach to developing an optimal production scheduling method that reduces CO₂ emissions, thus supporting the broader goal of sustainable construction practices in OSC.

2. LITERATURE REVIEW

The aim of this paper is to develop a production scheduling optimization method in OSC to reduce CO₂ emissions. To achieve this, relevant literature is thoroughly reviewed from two perspectives: (i) sources of CO₂ emissions in OSC; and (ii) optimized production scheduling in OSC.

2.1 CO₂ emissions in OSC

The OSC approach has gained popularity due to one of its significant benefits: a lower environmental impact compared to traditional on-site construction methods. To substantiate this advantage, several studies have compared the carbon footprint reduction performance of OSC to traditional stick-built construction methods. For instance, Gorkum (2010) systematically compared CO₂ emissions from on-site concrete construction with those associated with prefabricated construction methods using the Quick Scan Tool (QST). The results indicate that adopting prefabricated construction techniques can lead to a substantial reduction in CO₂ emissions, with a total decrease of 23%. Similarly, Li et al. (2014) meticulously investigated and compared CO₂ emissions associated with constructing a residential building, evaluating both stick-built and panelized methods while considering on-site winter heating. Their findings revealed that the panelized construction approach resulted in a significant 42.76% reduction in overall CO₂ emissions compared to the stick-built method. Although OSC offers a reduction in CO₂ emissions compared to traditional stick-built construction, the OSC production line itself remains a source of CO₂ emissions. During operation, emissions arise from various sources, including the embodied energy of materials, fuels (e.g., gas, diesel, propane), energy consumption (e.g., electricity), labor/crews, and material waste (Al-Hussein et al. 2009; Anowar et al. 2019). Nevertheless, these emissions can be further minimized through optimal production scheduling.

2.2 Optimized production scheduling in OSC

Effective schedule optimization in OSC can significantly reduce carbon footprints by minimizing project completion time (PCT) and reducing WS idle times. However, Gupta and Stafford (2006) highlighted that determining the optimal production schedule for industrial manufacturing is exceptionally challenging. Similarly, OSC-oriented optimal production scheduling methods aimed at minimizing CO₂ emissions can be classified as non-deterministic polynomial-time hard (NP-hard), as they are computationally expensive and may take a longer time to solve efficiently. To address this challenge, the application of meta-heuristic algorithms (e.g., GA), may offers a viable solution (Li et al. 2017). In this context, several studies have been

conducted which can be categorized into two main types. The first types mainly focus on minimization PCT and cost (Ko and Wang 2011; Rahman and Han 2024b). For instance, Ko and Wang (2010) developed a GA-based multi-objective optimization model to address the flow shop-sequencing issue in the manufacture of precast components (PC) while considering the buffer sizes between production stations. Yazdani et al. (2021) combined three metaheuristic algorithms, namely differential evolution (DE), imperialist competitive algorithm (ICA), and GA, to simultaneously minimize the duration and cost of precast production processes. Zhang et al. (2023) developed an NSGA-II model to solve the multi-objective optimization problem in off-site construction (i.e., precast production) schedules by considering the impact of disturbance events such as machine malfunctions, order modifications, and unexpected order insertions. More recently, Rahman and Han (2024a) developed a linear scheduling method-based multi-objective optimization model using NSGA-II to minimize PCT, workstation idle time (WIT), and work-in-progress (WIP) in OSC.

The second type of scheduling approach is designed to minimize CO₂ emissions in manufacturing environments. For instance, Li et al. (2017) developed a GA model to optimize labor allocation in labor-intensive production activities, aiming to minimize CO₂ emissions. The model addresses intricate CO₂ trade-offs between crew transportation and on-site winter heating. Schulz et al. (2022) proposed a Non-dominated Sorting Genetic Algorithm (NSGA-II) to simultaneously minimize makespan (i.e., PCT) and energy consumption associated with production and transportation in a distributed (i.e., decentralized) production facility. Liu et al. (2014) developed an NSGA-II-based optimization model to minimize both total electricity consumption and total weighted tardiness in manufacturing industries (e.g., automobile manufacturing). Zeng et al. (2018) conducted a performance comparison between NSGA-II and tabu search for energy-efficient scheduling in paper mills. Their findings indicated that tabu search outperformed NSGA-II. Saber and Ranjbar (2022) introduced a multi-objective decomposition-based heuristic (MODBH) algorithm and a multi-objective variable neighborhood search (VNS) algorithm to minimize both total tardiness and overall carbon emissions. Recently, Zheng et al. (2023) have developed a multi-objective optimization method using NSGA-II to minimize carbon emissions and earliness/tardiness penalties in a precast production factory.

In summary, although previous research has made significant contributions to reducing the carbon footprint, a notable gap remains. Specifically, there is a lack of studies focused on minimizing CO₂ emissions in wood-based OSC through production scheduling, leading to the generation of excessive CO₂ emissions beyond what is necessary. To address this gap, this paper proposes a GA-based optimization scheduling model to further enhance the environmental benefits of OSC by reducing CO₂ emissions.

3. PROPOSED METHODOLOGY

The research framework of this paper is outlined in Figure 1. It incorporates several key inputs, including the number of Ws, the number of panels, historical process times, energy consumption data, and carbon emission factors. The evaluation criteria are based on the Environmental Product Declaration (EPD) and Energy and Material Sustainability Declaration (EMSD) guidelines, as well as the sequencing of Ws. The primarily process of this framework is structured into two broad phases. Phase 1 involves calculating the CO₂ emissions associated for each panel at each WS. Phase 2 focuses on the development of a CO₂ emissions optimization model utilizing a GA. The outputs of this process include the optimized production sequence and the extent of CO₂ emissions reduction in an OSC production line.

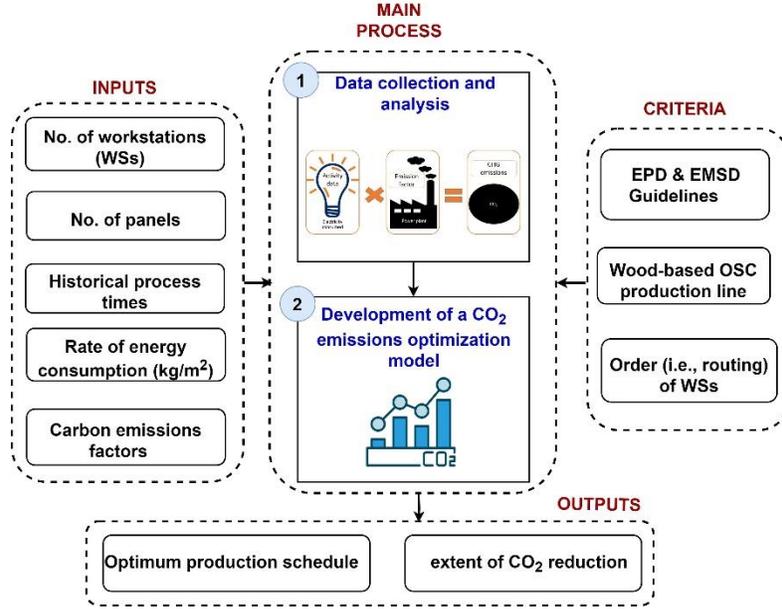


Figure 1: Proposed framework

3.1 Data Collection and Analysis

The objective of data collection and analysis is to determine the amount of CO₂ emissions during production for each panel at each WS, which can be used as input for the optimization model. To achieve this, the data analysis involves eight steps. Step 1 is to identify the sources of CO₂ emissions in the factory, including electricity, natural gas, and fuel (e.g., propane). Step 2 is to estimate the daily consumption of each type of energy in the production line. Step 3 is to identify the area of the panel (m²) manufactured every day. Step 4 is to calculate the amount of each type of energy consumed each day in the factory for manufacturing per unit area of the panel using Eq.[1]. Step 5 is to calculate the equivalent CO₂ emissions for each type of energy used in manufacturing per unit area of the panel in the production line, using Eq.[2] to Eq. [4]. Step 6 is to determine total CO₂ emissions in the production line for manufacturing per unit area of the panel using Eq. [5]. Step 7 is to calculate the amount of CO₂ emissions for each panel in the production line using Eq.[6]. Step 8, finally, is to calculate CO₂ emissions for manufacturing each panel at each WS using Eq.[7]. At this juncture, it should be acknowledged that the rate of CO₂ emissions is assumed to be directly proportional to the process time of each panel at each WS.

$$[1] \quad S_t = \frac{W_t}{A_j}, \quad t \in \{\text{electricity (e)}, \text{natural gas(g)}, \text{fuel(f)}\}$$

where S_t = amount of t -type energy consumption for manufacturing per unit area of a panel; W_t = amount of t -type energy consumption per day; and A_j = area of panel manufactures per day.

$$[2] \quad CO_2(e) = S_e(kWh) \times F_e^e$$

where, $CO_2(e)$ = CO₂ emissions from electricity in kg for per unit area of wall panel; $S_e(kWh)$ = electricity consumption in kWh; F_e^e = emission factor for electricity (kg CO₂/kWh), 0.66 kg CO₂/kWh (Environment Canada 2021).

$$[3] \quad CO_2(g) = S_g \times F_g^g$$

where, $CO_2(g)$ = CO_2 emissions from natural gas in kg for per unit area of wall panel; S_g = natural gas consumption in m^3 ; F_e^g = emission factor of natural gas ($kg\ CO_2/m^3$), $1.918kg\ CO_2/m^3$ (Environment Canada 2013).

$$[4] \quad CO_2(f) = S_f * F_e^f$$

where, $CO_2(f)$ = CO_2 emissions from fuel in kg for per unit area of wall panel; S_f = amount of fuel consumption (L); F_e^f = emission factor of fuel ($kg\ CO_2/L$), Gasoline: $2.725\ kg\ CO_2/L$, Diesel: $2.663\ kg\ CO_2/L$, Propane: $1.51\ kg\ CO_2/L$ (Environment Canada 2013).

$$[5] \quad CO_2(p) = CO_2(e) + CO_2(g) + CO_2(f)$$

where, $CO_2(p)$ = total CO_2 emissions in the production line for manufacturing per unit area of the panel.

$$[6] \quad CO_{2(j)} = CO_{2(p)} * A_j$$

where $CO_{2(j)}$ = amount of CO_2 emissions for j^{th} panel in the production line ($j=1, 2, 3, \dots, m$); m = total number of panels; and A_j = area of j^{th} panel.

$$[7] \quad CO_{2(i,j)} = \frac{P_{i,j}}{\sum_{i=1}^n P_{i,j}} * CO_{2(j)}$$

where $CO_{2(i,j)}$ = amount of CO_2 emissions for manufacturing j^{th} panel ($j=1, 2, \dots, m$) at i^{th} WS ($i=1, 2, \dots, n$); and $P_{i,j}$ = process time of j^{th} panel at i^{th} WS.

3.2 Optimization Model

To achieve the objective of this paper, a GA-based optimization model is proposed to minimize CO_2 emissions, with the objective function given in Eq. [8]. Notably, GA is chosen since it is based on the principles of natural selection and genetics, providing an effective tool for exploring decision spaces and finding optimal solutions (Li et al. 2017). The wall panel production sequence is the decision variable, while the constraints are as follows: (i) the wall panel must follow the sequence of WSs; (ii) each WS should process a single wall panel (i.e., one panel flow). As shown in Figure 2, the procedure for minimizing CO_2 emissions using GA involves seven steps. Step 1 is to import input data including panel-wise CO_2 emissions for each WS and number of WSs. Step 2 is to define GA parameters such as number of initial schedule (i.e., population), number of iterations, crossover, and mutation rate. Step 3 is to randomly create initial number of schedules. Step 4 is to calculate fitness value for each schedule using Eq.[8]. Step 5 is to implement selection process to randomly select schedule from initial schedule. During the selection phase, schedules with superior fitness are chosen to constitute a mating pool.

$$[8] \quad \min CO_{2(i,j)} = \begin{cases} e_{1,1} & \text{if } i=1 \text{ and } j=1 \\ CO_{2(i,j-1)} + e_{i,j} & \text{if } i=1 \text{ and } j>1 \\ CO_{2(i-1,j)} + e_{i,j} & \text{if } i>1 \text{ and } j=1 \\ \max(CO_{2(i-1,j)}, CO_{2(i,j-1)}) + e_{i,j} & \text{if } i>1 \text{ and } j>1 \end{cases}$$

where $CO_{2(i,j)}$ = total CO_2 emission from j^{th} panel ($j=1, 2, \dots, m$) at i^{th} WS ($i=1, 2, \dots, n$); $e_{1,1}$ = CO_2 emissions for 1st panel at 1st WS; $e_{i,j}$ = CO_2 emissions for j^{th} panel at i^{th} WS; $CO_{2(i,j-1)}$ = total CO_2 emissions from $(j-1)^{th}$ panel at i^{th} WS; and $CO_{2(i-1,j)}$ = total CO_2 emissions of j^{th} panel at $(i-1)^{th}$ WS.

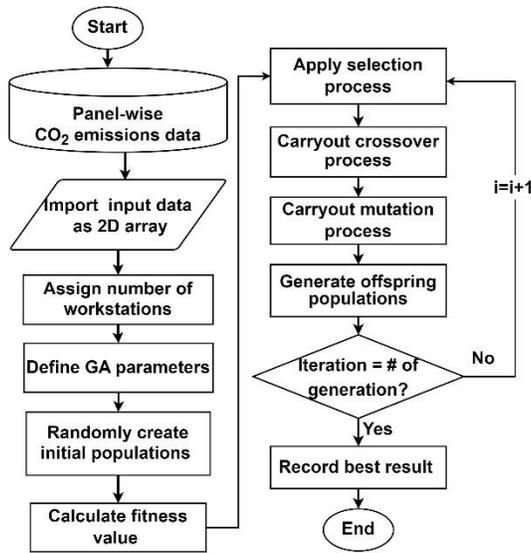
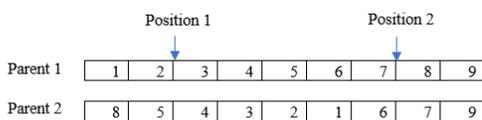


Figure 2: Process Flow of GA

Step 6 is to implement crossover, and mutation process to generate off-spring schedule for diversify the solution space. Notably, in this paper, position-based crossover (PBX) is introduced. This involves generating offspring solutions by randomly selecting position of gene (i.e., panel) from one parent and fill in the remaining positions from the other parent: The advantage PBX lies in its ability to preserve the order of panel within selected crossover segments, facilitating effective exploration and exploitation in permutation-based repetitive scheduling problem. As shown in Figure 3, the randomly selected crossover position is 3 and 7. Panel 3-7 in chromosome 1 (i.e., parent 1) is taken to create child 1 and the remaining positions of panel is taken from parent 2 and finally the child 1 is formed. Similarly, panel 4,3,2,1, and 6 is taken from parent 2 to generate child 2, and the remaining positions of child 2 is fill by taking the panel from parent 1. Furthermore, to preserve population diversity and avoid premature convergence, the mutation operation is employed as an effective strategy. In this paper, a two-point swap mutation technique is utilized, where a random pair of genes (i.e., panels) within the chromosome is chosen, and their positions are swapped to generate offspring, forming the foundation for the subsequent generation. As shown in Figure 4, child 1 swap the positions of panels 2 and 3, while child 2 swaps the positions of panels 3 and 8, leading to the creation of new child 1 and 2 respectively. Step 7, finally, is to check the termination criteria (i.e., whether the iteration has reached the maximum number of generations). If the condition is not satisfied, the process moves on to the next generation. On the other hand, if the condition is satisfied, the process ends with the recording of the optimum schedule.

Step 1: Randomly select crossover positions.



Step 2: Generate offspring by exchanging genetic information between parents.

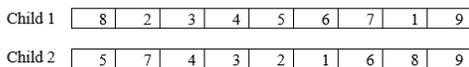


Figure 3: Crossover Process

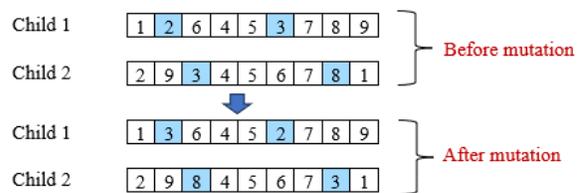


Figure 4: Mutation Process

4. CASE STUDY AND RESULTS

The proposed method is implemented in a wood frame panelized wall production line in Edmonton, Canada. As shown in Figure 5, the factory consists of two types of production flows: multi-panel and single-panel. For example, the first three WSs, such as framing, sheathing, and nailing, produce multi-panels (i.e., two wall

panels produced as a single component). In contrast, the spray foam, windows/door, window bypass, and siding WSs process single wall panels. This means that after the nailing WS, the multi-panel is cut into single wall panels (i.e., the multi-panel becomes multiple single panels). However, this paper considers only multi-panel WSs. At the framing WS, components of the wall frame, such as studs, header, cripples, and plate, are assembled. The frame then moves to the sheathing WS, where sheathing materials (e.g., wood or gypsum board) are placed and temporarily stapled onto the wall frame. Subsequently, the wall panel is transferred to the nailing WS, where the sheathing materials and wall frame are fixed by nailing. It is important to note that the framing WS is semi-automated (i.e., one worker and one machine), the sheathing WS is fully manual, and the nailing WS is fully automated. The historical process times for each panel at each WS, collected via RFID, are presented in Table 2. The implementation of the proposed method in the case project involves two phases: (i) estimation of CO₂ emissions for each panel at each WS, and (ii) implementation of the GA to optimize CO₂ emissions through production sequencing.

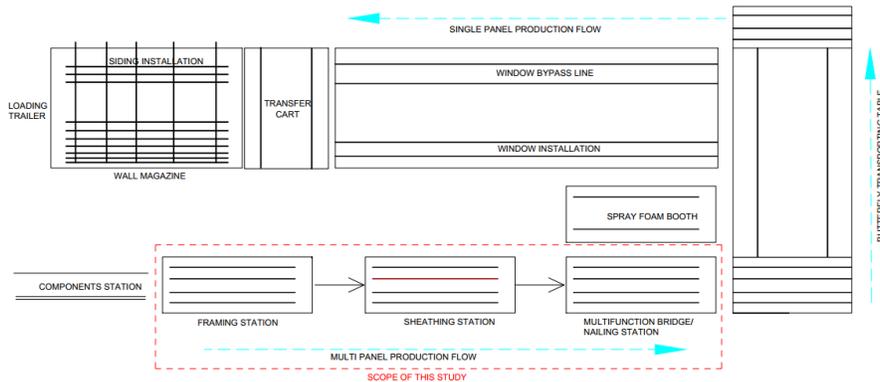


Figure 5: Factory Layout of the Case Project (Rahman and Han 2024a)

4.1 Estimation of CO₂ Emissions

Quantifying CO₂ emissions for each panel at each WS is crucial for minimizing them through production scheduling. In this case project, the quantification process involves four steps. Firstly, the sources of CO₂ emissions in the production line are identified, with electricity, natural gas, and fuel (i.e., propane) recognized as the primary contributors. Secondly, the rate of CO₂ emissions for producing per unit area of wall panel (kg/m²) is estimated using Eq.[1] to Eq.[5]. At this junction, it should be acknowledged that the CO₂ emission rates used in this paper are derived from a previous study conducted on the same production line by Li et al. (2014), which quantified carbon emissions during the production stage of off-site panelized wood frame standard residential houses in Edmonton, Canada. As shown in Table 1, the CO₂ emissions per square meter of wall panel are broken down by emission source. Accordingly, the estimated CO₂ emission rates from electricity, natural gas, and propane consumption are 5.549 kg/m², 2.68 kg/m², and 0.32 kg/m², respectively. Subsequently, using Eq. [5], the total CO₂ emissions for manufacturing per square meter of wall panel are calculated to be 8.55 kg/m² (5.549 + 2.68 + 0.32).

Table 1: Sources of CO₂ emissions in OSC factory (Li et al. 2014)

S/N	Sources of CO ₂ emissions	Rate of CO ₂ (kg/m ²)
1	Electricity	5.549
2	Natural gas	2.68
3	Propane	0.32
	Total CO ₂ emissions (kg/m ²)	8.55

The third step involves quantifying CO₂ emissions for the manufacturing of each wall panel in the production line. In this context, it is assumed that CO₂ emissions are uniform across all WSs. Since this paper considers only the first three WSs out of six, the total CO₂ emissions from these WSs are calculated to be 8.55/2 =

4.275 kg/m². As presented in Table 2, the CO₂ emissions for each panel in the production line (i.e., CO_{2,j}) are determined using Eq.[6]. For instance, the CO₂ emissions (CO_{2,j}) for panel no. 1 are calculated to be 8.55 × 3.23 = 13.79 kg. In the fourth and final step, CO₂ emissions for each panel at each WS are quantified using Eq.[7]. The CO₂ emissions for panel no. 1 at the framing WS are calculated to be (1.34*13.79)/(1.34+3.98+1.99) = 2.53 kg. Similarly, at the sheathing and nailing WSs, the CO₂ emissions are calculated to be 7.51 kg and 3.75 kg, respectively.

Table 2: CO₂ emissions from each panel at each WS

Panel no.	Area (m ²)	Historical process times (min)			CO _{2,j} (kg)	CO _{2(i,j)} (kg)		
		Framing	Sheathing	Nailing		Framing	Sheathing	Nailing
1	3.23	1.34	3.98	1.99	13.79	2.53	7.51	3.75
2	14.98	6.24	18.49	9.25	64.03	11.76	34.84	17.42
3	4.55	1.90	5.62	2.81	19.46	3.57	10.59	5.29
4	2.99	1.24	3.69	1.84	12.76	2.34	6.94	3.47
5	22.57	9.41	27.87	13.93	96.50	17.72	52.52	26.26
6	5.28	2.20	6.52	3.26	22.57	4.15	12.28	6.14
7	22.79	9.50	28.14	14.07	97.45	17.90	53.03	26.52
8	4.51	1.88	5.57	2.79	19.29	3.54	10.50	5.25
9	14.98	6.24	18.50	9.25	64.06	11.77	34.86	17.43
10	23.33	9.72	28.80	14.40	99.72	18.32	54.27	27.13

Note: "CO_{2(j)}" denotes total CO₂ emissions (kg) for each panel in the production line; and "CO_{2(i,j)}" denotes CO₂ emissions (kg) for each panel at each WS.

4.2 Implementation of GA

To achieve the objective of reducing CO₂ emissions during the production stage, this paper introduces a GA-based single-objective optimization algorithm (i.e., minimizing CO₂ emissions). Notably, this study utilizes a historical dataset of 63 wall panels, aligning with the industry partner's daily production target of 63 panels. The algorithm is executed with the following GA parameters: (i) number of initial populations = 20; (ii) mutation rate = 0.1; (iii) crossover rate = 0.8; and (iv) number of iterations = 2000. As illustrated in Figure 6, the CO₂ emissions decrease from 1780 kg to 1772 kg per day for the production of 63 wall panels. This reduction equates to approximately 2,000 kg annually, assuming a production schedule of 250 working days per year (8 kg per day × 250 days). Furthermore, since this study considers only three WSs out of six, the total CO₂ reduction from the wall production line can be estimated as 2,000 kg × 2 = 4,000 kg annually. The corresponding production sequence is presented in Figure 7, where production starts with panel index 2 and ends with panel index 7.

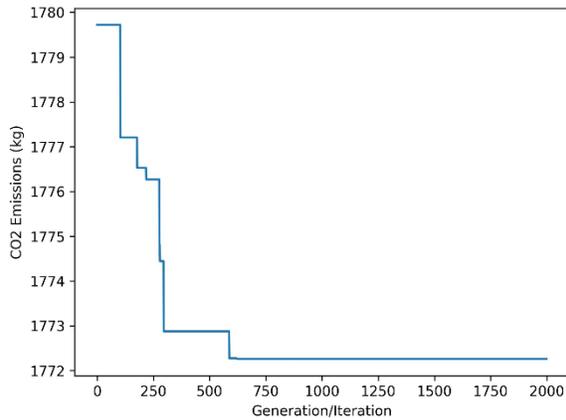


Figure 6: CO₂ reducing during each generation

[2, 13, 43, 23, 60, 61, 41, 33, 6, 54, 14, 34, 20, 3, 47, 51, 25, 49, 32, 45, 17, 55, 29, 46, 19, 26, 37, 11, 39, 57, 56, 9, 31, 40, 42, 10, 53, 38, 0, 5, 52, 21, 24, 30, 27, 18, 12, 8, 48, 44, 4, 62, 22, 58, 35, 15, 28, 50, 36, 1, 16, 59, 7]

Figure 7: Optimum production sequence (job index) of 63 wall panels

5. CONCLUSIONS

The OSC process involves the consumption of electricity, natural gas, and fuel, contributing to CO₂ emissions with implications for climate change. To address this environmental concern, this paper proposes an innovative methodology for minimizing CO₂ emissions during the production process by optimizing production sequencing, an approach that is pioneering within this domain. The approach involves two broad phases: (i) calculation of the CO₂ emissions associated with each panel at each WS; and (ii) development of a CO₂ emissions optimization model utilizing a GA. The findings of this paper indicate that the proposed scheduling method effectively reduces CO₂ emissions by 4,000 kg annually from a single production line.

This research makes a significant contribution to the body of knowledge by offering a practical and innovative solution in which production managers can not only increase productivity but also reduce PCT, production costs, and CO₂ emissions during production. Nonetheless, it is important to acknowledge certain limitations within this paper, including: (i) the proposed method is validated by analyzing three primary sources of CO₂ emissions: electricity, natural gas, and fuel (i.e., propane). However, in practice, additional emission sources may exist within OSC production that warrant further investigation. Accordingly, future research could incorporate additional energy sources, such as labor and diesel, to enhance the accuracy and comprehensiveness of the findings; (ii) while this paper does not consider dynamic events such as material unavailability, machine breakdowns, or logistics failures, these factors may occur in real-world scenarios and can be explored in future research; and (iii) scope of this study is confined to CO₂ emissions from the production line, suggesting that future research could broaden its scope to include the entire supply chain, thereby providing a more holistic understanding of the ecological impact.

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REFERENCES

- Al-Hussein, M., Manrique, J. D. and Mah, D. 2009. North Ridge CO₂ analysis report: comparison between modular and on-site construction. *University of Alberta, Canada*,
- Anowar, S., Rakib, F., Hasan, R. and Rahman, M. 2019. Assessment of greenhouse gas emissions in building construction: A case study of SWC building at Kuet in Bangladesh. *Journal of Construction Engineering*, 2: 215-229.

- Barrett, J. and Wiedmann, T. 2007. A comparative carbon footprint analysis of on-site construction and an off-site manufactured house. *Stockholm, Sweden: Stockholm Environment Institute, Environment Canada. (2013). Fuel Combustion.* <http://www.ec.gc.ca/gesghg/default.asp?lang=En&n=AC2B7641-1>
- Environment Canada. (2021). *National Inventory Report 1990-2021: Greenhouse Gas Source and Sink in Canada, Part 3.* <https://publications.gc.ca/site/eng/9.506002/publication.html>
- Gorkum, C. v. 2010. CO₂ emissions and energy consumption during the construction of concrete structures. *Delft University of Technology, Holland, pg, 4-3.*
- Gupta, J. N. and Stafford, E. F. 2006. Flowshop scheduling research after five decades. *European Journal of Operational Research*, 169: 699-711.
- Han, S. H., Hasan, S., Bouferguène, A., Al-Hussein, M. and Kosa, J. 2015. Utilization of 3D visualization of mobile crane operations for modular construction on-site assembly. *Journal of Management in Engineering*, 31: 04014080.
- Jin, R., Gao, S., Cheshmehzangi, A. and Aboagye-Nimo, E. 2018. A holistic review of off-site construction literature published between 2008 and 2018. *Journal of cleaner production*, 202: 1202-1219.
- Ko, C.-H. and Wang, S.-F. 2010. GA-based decision support systems for precast production planning. *Automation in Construction*, 19: 907-916.
- Ko, C.-H. and Wang, S.-F. 2011. Precast production scheduling using multi-objective genetic algorithms. *Expert Systems with Applications*, 38: 8293-8302.
- Li, H. X., Naseri Esfahani, M., Gul, M., Yu, H., Mah, D. and Al-Hussein, M. 2014. Carbon footprint of panelized construction: an empirical and comparative study. *Construction Research Congress 2014: Construction in a Global Network*, 494-503.
- Li, H. X., Zhang, L., Mah, D. and Yu, H. 2017. An integrated simulation and optimization approach for reducing CO₂ emissions from on-site construction process in cold regions. *Energy and Buildings*, 138: 666-675.
- Liu, Y., Dong, H., Lohse, N., Petrovic, S. and Gindy, N. 2014. An investigation into minimising total energy consumption and total weighted tardiness in job shops. *Journal of Cleaner Production*, 65: 87-96.
- Mao, C., Shen, Q., Shen, L. and Tang, L. 2013. Comparative study of greenhouse gas emissions between off-site prefabrication and conventional construction methods: Two case studies of residential projects. *Energy and Buildings*, 66: 165-176.
- Rahman, M. and Han, S. H. 2024a. Linear Scheduling Method-Based Multi-Objective Optimization for Off-Site Construction Manufacturing. *Automation in Construction*, 167: 105712.
- Rahman, M. and Han, S. H. 2024b. Performance Evaluation of Genetic Algorithm and Particle Swarm Optimization in Off-Site Construction Scheduling. *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction*, 41: 275-282.
- Rahman, M. and Sobuz, H. R. 2018. Comparative study of IPS & PPVC precast system—A case study of public housing buildings project in Singapore. *Proceedings of the 4th International Conference on Civil Engineering for Sustainable Development (ICCESD 2018), KUET, Khulna, Bangladesh*, 9-11.
- Saber, R. G. and Ranjbar, M. 2022. Minimizing the total tardiness and the total carbon emissions in the permutation flow shop scheduling problem. *Computers & Operations Research*, 138: 105604.
- Sandanayake, M., Zhang, G. and Setunge, S. 2019. Estimation of environmental emissions and impacts of building construction—A decision making tool for contractors. *Journal of building engineering*, 21: 173-185.
- Schulz, S., Schönheit, M. and Neufeld, J. S. 2022. Multi-objective carbon-efficient scheduling in distributed permutation flow shops under consideration of transportation efforts. *Journal of Cleaner Production*, 365: 132551.
- Yazdani, M., Kabirifar, K., Fathollahi-Fard, A. M. and Mojtahedi, M. 2021. Production scheduling of off-site prefabricated construction components considering sequence dependent due dates. *Environmental Science and Pollution Research*, 1-17.
- Zeng, Z., Hong, M., Li, J., Man, Y., Liu, H., Li, Z. and Zhang, H. 2018. Integrating process optimization with energy-efficiency scheduling to save energy for paper mills. *Applied Energy*, 225: 542-558.
- Zhang, R., Feng, X., Mou, Z. and Zhang, Y. 2023. Green optimization for precast production rescheduling based on disruption management. *Journal of Cleaner Production*, 420: 138406.
- Zheng, R., Li, Z., Li, L., Ma, S. and Li, X. 2023. Optimizing carbon emissions of precast production in off-site construction: a multi-objective scheduling approach with group technology.