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DETERMINING NEAR-OPTIMAL MODULARIZATION SOLUTIONS CONSIDERING MANUFACTURING OPERATIONS IN MODULAR CONSTRUCTION

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Abstract

Modular construction has great potential to address persistent problems in the construction industry, such as lack of labor and resources. In the implementation of modular construction, modularization is a crucial task that overwhelms designers. Different modular solutions influence manufacturing operations significantly, yet this has rarely been studied in the past. This paper proposed an optimization model considering the operations of manufacturing and set-up changes. A modified genetic algorithm was devised to solve the model. Its effectiveness and efficiency were demonstrated in a case study. This study contributes to the knowledge body by untangling the effects of modularity on manufacturing operations.

Introduction

The construction industry has been instrumental in worldwide development, which contributes to GDP growth, creates jobs, and provides substantial built infrastructure for economic development (Lu *et al*., 2021). However, the construction industry is still struggling with several tough issues including, but not limited to, high costs, poor on-site safety performance, decreased productivity, lack of professional expertise, resource scarcity, etc. (Project Strategy and Governance Office [PSGO], 2018).

Modular construction can serve as a remedy to alleviate the above torments. It does so by splitting the building into blocks, moving the manufacturing of these blocks offsite, and finally transporting them to the construction site for assembly (Innella *et al*., 2019; Lou and Lu, 2022). Outsourcing 80-95% of the construction work to offsite factories, allows it to alleviate some of its local problems, e.g., poor safety performance, labor and resource shortages, and high costs (Li *et al*., 2022). Moreover, leveraging the well-controlled manufacturing environment within factories, modular construction makes itself tempting by realizing better quality and higher productivity (Yang and Lu, 2023). Such a way of making building a house as easy as building LEGO has earned modular construction a huge potential market. In Hong Kong, according to Construction Industry Council (CIC), the estimated demand for modular construction modules will reach 50,300 (approximately 596,000 m^2) by 2024 and 241,100 (approximately 2,821,600 m^2) by 2029 (CIC, 2021).

When implementing modular construction, design is one of the most burdensome tasks. Modular construction involves numerous processes and stakeholders. Each process has specific constraints, and each stakeholder has their own interests. This requires the design phase to fully consider the various process constraints and stakeholder requirements (Lou *et al*., 2022). More and more decisions are expected to be made at an early design stage. One of the important decisions is how to modularize the floorplan design (Building and Construction Authority [BCA], 2018). Figure 1 shows a real-world example of modularized design. Taken as a whole, the overall design does not change much. Looking at it locally, the designer has made some detail adjustments to accommodate the requirements of other processes and stakeholders. Before making these detail adjustments, the designer needs to prepare a general modularization solution. In a typical modularization solution, the designer usually has to determine the type of module, the area of each module type, and the number of each module type. With these major decisions in mind, the designer can then adjust local details accordingly.

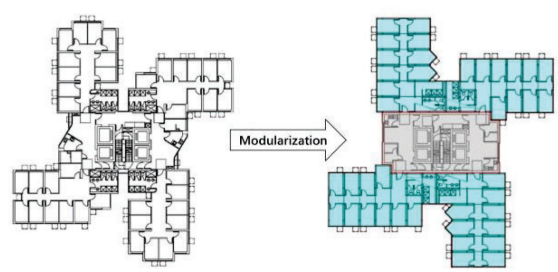

Figure 1: An example of floor plan modularization

However, designers are often overwhelmed when making these decisions and have difficulty in determining an optimal modular solution. Because modularization, as a critical step in design, can result in a significant impact on all the downstream phases of manufacturing, transport, and assembly. Designers need to consider numerous factors during modularization. Design for manufacturing and assembly (DfMA) has been coined as an innovative design paradigm (Gao *et al*., 2018). It fits right in with the above discussion of placing decisions in the early design phase. The strengths of modular construction can be maximized using DfMA. In recent years, DfMA has gradually evolved into DfX (Wuni *et al*., 2021), where "X" represents any excellence criteria, e.g., transportation, sustainability, resilience, and so on. In this paper, the manufacturing criteria are taken as the focus of our consideration. In other words, we will explore the optimal modularization solution, while considering the manufacturing operations.

The influence of modularization solutions on manufacturing operations is manifested in many ways. For example, it is desirable to have as many of the same modules as possible in order to obtain economies of scale in the manufacturing process. In addition, the size of the module also has an impact on the difficulty of manufacturing. Unlike product modules from other industries, building modules are often bulky and heavy (Piller, 2010). Oversized building blocks have a negative impact on manufacturing operations, e.g., adding to costs for lifting and transport, and increasing the number of components and interactions among them.

Many studies have been carried out in the area of optimizing manufacturing operations. A common research stream is the optimization of manufacturing schedules. For example, Hammad *et al*. (2020) proposed a novel mixed integer non-linear programming model to optimize the schedule of manufacturing activities. Lee and Hyun (2019) used genetic algorithms (GA) to solve a multiple modular construction scheduling problem. Moreover, other studies have been conducted to optimize the factory facility layout (Yang and Lu, 2023), resource allocation (Hyun *et al*., 2021), and energy consumption (Xie *et al*., 2018) within the manufacturing stage. However, to the best of our knowledge, very few studies, if any, have been conducted to consider the influence of modularization solutions on manufacturing operations when optimizing.

The aim of this paper is to propose an optimization model to obtain the near-optimal modularization solution considering manufacturing operations and solve the model by adopting GA. Near-optimal in this context means good enough but not globally optimal. With GA it is possible to obtain near-optimal results very quickly, balancing computational efficiency with accuracy. The rest of this paper is written as follows. The following section will introduce the proposed model. Then, a case study will be described. Finally, conclusions and future directions will be drawn.

Model formulation

Problem statement

The problems to be solved in this paper are described as follows. In modular construction, given a building floor plan that is to be modularized, the primary decision variables include the number of types of modules n, the area of each type of module s_i, and the number of each type of module m_i, where i denotes the i-th type of module. All these decision variables carry important effects on manufacturing operations. For example, a larger n requires more frequent adjustments to the manufacturing settings and increases the complexity of manufacturing (Khalili & Chua, 2014). Unlike products in other industries, building products are usually large and bulky, resulting in additional manufacturing costs that cannot be ignored (Piller, 2010). Generally speaking, the larger the s_i, the greater the manufacturing costs incurred along with the production lines during the manufacturing process. In addition, if the number of modules with the same type is larger, i.e., the larger the m_i, the benefits of economies of scale are likely to be reaped (Lawson *et al*., 2012).

The roles of these variables are usually not completely concerted, but more often conflicting and need to be traded off. In the early design stage, designers often need to consider various aspects of the manufacturing process, weighing different decision variables to choose the best modularization solution. However, the sophisticated interactions between decision variables make identifying the best modularization solution a challenging task. Thus, an optimization model that abstracts the real-world problem is proposed in the following sections for designers to provide assistance in decision-making when implementing modularization.

Mathematical notations

The mathematical notations used in the proposed model include subscripts, parameters, and decision variables. They are summarized with detailed explanations in Table 1.

Table 1: Notations for the optimization model

Notations	Explanations
Subscripts	
i	1, 2, …, n, module type index
m	Items related to manufacturing
c	Items related to set-up changes
Parameters	
c_m	Total cost of manufacturing
c_{mi}	Unit area manufacturing cost of the modules of type i
a	Linear increasing rate of unit area manufacturing cost with area growth
t_m	Total time of manufacturing
t_{mi}	Unit area manufacturing time of the modules of type i
b	Linear increasing rate of unit area manufacturing time with area growth
c_c	Total cost for set-up changes to manufacturing different modules

c_{ci}	Cost for set-up changes to manufacturing the modules of type *i*
t_c	Total time for set-up changes to manufacturing different modules
t_{ci}	Time for set-up changes to manufacturing the modules of type *i*
T	Time constraints for manufacturing completion of all modules
f	Unit time fines to be paid for exceeding time constraints
S	Total area of the floor plan
Decision variables	
n	Number of module types
s_i	Area of modules of type *i*
m_i	Number of modules of type *i*

The proposed optimization model

The proposed optimization model is introduced in two parts, i.e., objective function and constraints. The objective function of this model primarily takes into account the requirements of cost and time, which are spent for manufacturing and set-up changes. We propose the following model with the production of a typical floor as a scope.

The cost and time spent on manufacturing are related to the module area, number of modules, and module type. In practice, the cost and time of individual modules, are usually calculated as the cost and time per unit area multiplied by the area. Therefore, the larger the module area, the higher the cost and time spent. The number of modules is also linearly and positively related to the cost and time of manufacturing. The module type also has a significant impact on manufacturing costs and time. Different types of modules are manufactured at different speeds and unit costs. For simplicity, the distinction between module types is deemed here to be made by the size of the area. Moreover, it is assumed that the larger the area, the higher the cost and time per unit area for manufacturing. This assumption is based on two considerations. Firstly, in general, the larger the module area, the more building components it contains. Therefore, it may take more cost and time to coordinate the interaction between these building components to form a complete module (Ramaji *et al*., 2017). Secondly, due to the characteristics of bulky and heavy building products, when the area increases, the need for lifting and transportation per unit area may also increase (BCA, 2018). To be more specific, the effect of module type, namely, the relationship between cost and time per unit area and module area, is assumed to be as shown in Equation (1) and Equation (2):

$$c_{mi} = as_i \tag{1}$$

$$t_{mi} = bs_i \tag{2}$$

where *a* and *b* are the coefficients of these linear relationships. The specific values of a and b can be obtained by collecting data on unit area costs and time, and regressing them against area data. The total manufacturing cost and time can be obtained by multiplying the cost and time per unit area, module area, and number of modules. The calculations are specified in Equation (3) and Equation (4):

$$c_m = \sum_{i=1}^{n} c_{mi} s_i m_i = \sum_{i=1}^{n} a s_i^2 m_i \tag{3}$$

$$t_m = \sum_{i=1}^{n} t_{mi} s_i m_i = \sum_{i=1}^{n} b s_i^2 m_i \tag{4}$$

The cost and time spent on set-up changes are often required in the factory manufacturing environment. Set-up changes refer to the changes in factory settings to enable the manufacturing of other different types of modules. For example, for modules made of reinforced concrete, custom molds of specific sizes are commonly needed to shape the concrete into desired dimensions (Khalili & Chua, 2014). For steel frame modules, specific jigs need to be set up or adjusted to accommodate different module manufacturing (CIC, 2021). The total cost and time for set-up changes are simply the sum of the cost and time of each change. In this paper, the cost and time of each change are considered to be the same for simplicity. Their calculations are illustrated in Equation (5) and Equation (6):

$$c_c = nc_{ci} \tag{5}$$

$$t_c = nt_{ci} \tag{6}$$

The proposed model also considers the time constraint in modular construction projects. Manufacturers are usually required to deliver a specific number of modules within a certain time frame, and fines are imposed for late delivery. According to Equation (4) and Equation (6), the real-time consumed by the manufacturing of modules can be calculated using the following formula:

$$T_r = t_m + t_c \tag{7}$$

The difference between the time consumed and the time constraint is ΔT, as calculated in Equation (8):

$$\Delta T = T_r - T \tag{8}$$

If the time difference ΔT is greater than 0, it will result in a loss or a corresponding fine due to the schedule delay. Thus, the objective function can be written as Equation (9):

$$\varphi = c_m + c_c + \max\left(\Delta T, 0\right) \cdot f \tag{9}$$

The constraint of the optimization model is derived from an assumption that the area of the floor plan remains constant before and after modularization. In other words, the individual modules add up to an area equal to the area of the original floor plan, as shown in Equation (10):

$$\sum_{i=1}^{n} s_i m_i = S \tag{10}$$

To summarize, the final model can be written in the following standard form:

$$\begin{aligned} &\min \varphi \\ &s.t. \sum_{i=1}^{n} s_i m_i = S \\ &n, s_i, m_i > 0 \end{aligned} \tag{11}$$

The adopted solving algorithm

In this model, there are three main types of decision variables, i.e., the number of module types (n), the area of modules of type i (s_i), and the number of modules of type i (m_i). A unique characteristic of this model is that the value of n affects the number of other decision variables (s_i and m_i), which in turn generates different models. To deal with this dilemma, we control the variable n as different discrete values (e.g., 1, 2, …, 10), each discrete value corresponding to a separate model. By doing so the number of decision variables in each separate model is fixed, and each separate model is then optimized individually.

Mathematical programming algorithms try to obtain exact analytical solutions, but they are time-consuming and ineffective in the face of complex nonlinear problems. Typically, construction problems are complex, and their modelling is consequently non-linear. In the proposed model, both the constraints and objective functions are highly nonlinear, thus making it difficult to yield an exact analytical solution by traditional programming methods. The metaheuristic algorithm, on the other hand, can come to a balance between effectiveness and accuracy in handling such nonlinear problems (Civera *et al*., 2021; Lee and Hyun, 2018). The genetic algorithm (GA), as one of the most powerful metaheuristic algorithms, is adopted to solve the proposed optimization model. The detailed flowchart of the adopted solving algorithm in this study is shown in Figure 2.

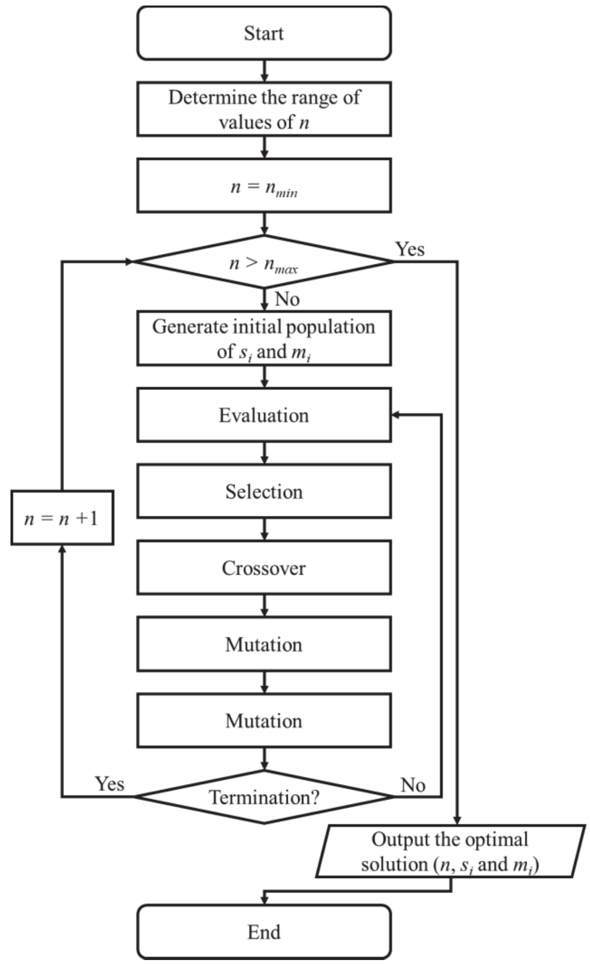

Figure 2: Flowchart of the adopted solving algorithm

Case study

We present a hypothetical case study to demonstrate the application of the proposed optimization model and validate the solving algorithm. The values of each process parameter are displayed in Table 2. These values are estimated by the authors from interviews and surveys with module manufacturers. In this case, it is assumed that the cost and time for set-up changes are the same for all module types.

The control parameters of GA include the size of the population, the maximum number of genetic generations, the probability of performing crossover, and the probability of mutation. Their values are shown in Table 3.

Table 2: Values of process parameters in the case study

Parameters	Values	Units
a	0.01	10^4 \$/m^4
b	0.05	day/m^4
c_{ci}	0.2	10^4 \$
t_{ci}	2	day
T	80	day
f	5000	\$
S	120	m^2

Table 3: Values of control parameters of GA

Parameters	Values
Size of the population	50
Maximum number of genetic generations	10000
Probability of performing crossover	0.5
Probability of mutation	0.5

According to the flowchart in Figure 2, the value range of module type n is set to 2 to 10. Each n corresponds to a separate optimization model, meaning that a total of 9 optimization models are required to be solved. Figure 3 illustrates typical records of optimizing an objective function with a GA. In the population, the average objective value keeps converging to the best objective value. Eventually, they become identical and stabilize.

Figure 3: Decrease of the objective values with the generation number

Table 4: Near-optimal modularization solutions

n	Modularization solutions (s_i and m_i)	
	s_i	m_i
2	9.2, 9.2	6, 7
3	4.3, 7.9, 9.9	8, 2, 7
4	8.8, 9.1, 9.5, 10.2	1, 10, 1, 1
5	4.0, 16.7, 5.2, 4.0, 4.0	6, 4, 1, 5, 1
6	18.8, 4.0, 4.3, 5.2, 5.0, 13.0	2, 1, 2, 8, 3, 1
7	15.9, 18.2, 19.4, 4.0, 4.0, 14.5, 4.0	1, 1, 1, 4, 3, 1, 6
8	5.0, 6.1, 23.4, 9.6, 5.0, 20.0, 4.0, 4.0	8, 1, 1, 1, 1, 1, 3, 1
9	4.1, 10.6, 8.6, 5.8, 4.6, 7.7, 4.0, 28.0, 4.0	1, 1, 2, 4, 2, 1, 3, 1, 2
10	16.4, 12.4, 2.0, 16.1, 3.3, 2.8, 2.0, 2.0, 2.0, 2.1	3, 1, 10, 1, 1, 1, 2, 2, 3, 1

Table 4 shows the near-optimal modularization solutions for each n (number of module types). The objective function values for each option are shown in Figure 4. It follows that the total cost of the modularization solution is lowest when n is 3. More specifically, the lowest total cost is achieved when there are three module types, each with an area of 4.3 m^2, 7.9 m^2, and 9.9 m^2, and when the number of modules of the three types is 8, 2, and 7 respectively. The lowest cost of the modularization solution is \$ 10.30×10^4. As can be seen from the Figure, the general trend of the objective function values decreases first and then increases as n increases. But within this general trend, there are also small fluctuations. For example, when n increases from 5 to 6, there is a decline in the value of the objective function. This may be because when n is 5, the objective function value is near-optimal, but not sufficiently optimal. If a more optimal result is desired, the number of iterations or genetic generations needs to be extended.

Figure 5 shows the time consumed for solving the optimization model. The computing device is "Intel(R) Core(TM) i7-10700 CPU @ 2.90GHz". All the models are solved within the range from 3.011s to 3.834s. It can be seen that the solving algorithm can yield a near-optimal solution that is sufficiently satisfying in a very short time.

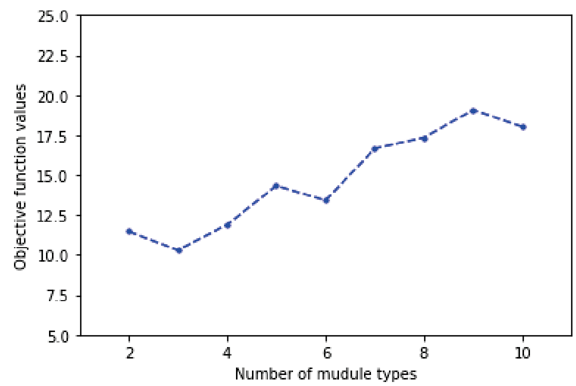

Figure 4: Decrease of the objective values with the generation number

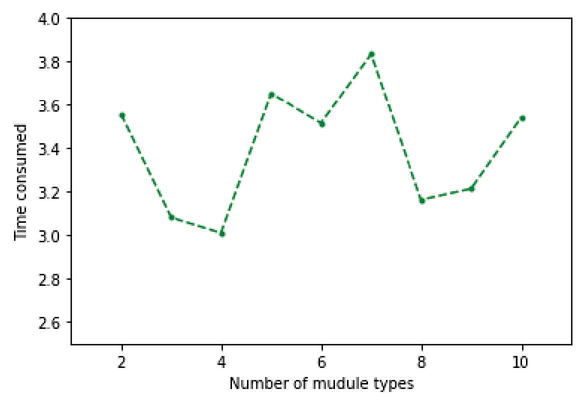

Figure 5: Decrease of the objective values with the generation number

Discussion

Modularization is a very complex issue. On one hand, it requires consideration of the details on drawings, such as building axes and internal wall divisions. These factors come from the requirements of the product. However, in practice, considering only these factors is not sufficient to generate a good modularized solution. On the other hand, it also needs to consider some requirements related to business processes (e.g., manufacturing, transportation, and installation). Designers usually need to consider many factors in these two aspects to make the final decision, which is a very difficult process.

To solve this problem, we start with the requirements of the business process, and only consider the manufacturing stage (i.e., DfM) for now. After making some simplifying assumptions, we transform this problem into solving the proposed model. We conducted interviews with two modular construction designers. We showed them our model, assumptions, and calculation results. The feedback we received indicates that the model can preliminarily consider the designer's logic of DfM in decision-making. But at the same time, it is pointed out that there is still a lot of room for improvement for the model in the future.

Just as this paper is only a preliminary exploration in the area of modularization issues, further research is still needed to improve it in the following aspects. Firstly, it is necessary to include more business process stages such as transportation and installation stages to establish a more comprehensive model. Secondly, future studies should consider the requirements of both business processes and product development, that is to say, segmentation and modularization should be based on building axis and interior wall positions. Thirdly, more specific constraints, such as requiring a module to have an area of no less than 15 square meters, need to be taken into consideration.

Conclusions

Different modular solutions for floor plans have a considerable impact on manufacturing operations. But few studies have explored the optimal modularization solution in consideration of manufacturing operations. This paper proposed a newly developed optimization model. The model mainly considered manufacturing costs, set-up change costs, manufacturing time, and set-up change time. A modified genetic algorithm (GA) was adopted to obtain near-optimal solutions. A case study has been conducted to demonstrate the efficiency and effectiveness of the solving algorithm.

Future studies are suggested as follows. Firstly, more detailed constraints (e.g., the area of a specific module) should be added to the model. Secondly, the transportation and installation stages should be integrated into the model and considered collectively with the manufacturing stage. Thirdly, uncertainty should be addressed using techniques, e.g., stochastic programming.

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