JOURNAL OF CIVIL ENGINEERING AND MANAGEMENT
2010
16(3): 418–427

AN INTEGRATED FRAMEWORK FOR REDUCING PRECAST FABRICATION INVENTORY

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Received 15 Mar. 2010; accepted 31 May 2010

Abstract. Precast fabricators strive for business success on delivering products on time. To achieve this goal, fabricators start fabrication once they receive design information. However, this practice results in finished goods inventory which is regarded as waste. The objective of this study is to develop a framework for precast fabricators to reduce the inventory. The framework consists of three components. The first time buffer evaluation is used to avoid fabricators losing capacity by considering demand variability. The second component, due date adjustment, shifts production curve closer to erection dates to reduce inventory. The third scheduling component arranges production sequences to achieve multi-objectives using genetic algorithms. One real case is experimented to demonstrate the effectiveness of the proposed framework. The application results show that the developed framework can reduce the level of finished goods inventory without changing production resources.

Keywords: Precast fabrication, demand variability, inventory, scheduling.

1. Introduction

Precast concrete construction is a method where the building is built up by components or elements that are prefabricated in factory, and then shipped directly to the construction site and assembled (Bennett 2005). To support a construction schedule, precast fabricators deliver elements to a site according to its erection schedule. Building up constructions using precast elements can reduce uncertainty more efficiently than those cast in the construction site, since these elements are prefabricated in the factory (Polat 2010). In addition, precast method conforms to the needs of the industrial process.

For precast fabricators, customer satisfaction is measured by on-time delivery (Bilec *et al*. 2006). Late delivery can interrupt erection progress and thereby induce delays. Moreover, the consequences of late delivery include a penalty for contract infringement and deterioration of business reputation. To deliver products on time or whenever customers need them, fabricators start fabrication upon receipt of design information (Bull 2009). Unfortunately, since a construction site may not have enough space to store elements before they are assembled, customers often change delivery dates in accordance with erection progress. As a result, numerous finished goods are stored in yards waiting to be delivered, a practice considered wasteful (Ohno 1988).

Precast fabricators face numerous challenges as they strive for business success. Among them, demand variability is arguably the biggest headache (Ballard and Arbulu 2004; Ko and Ballard 2005). One of the ways to protect fabricators against the impact of demand variability is to finish products later relative to delivery dates. Thus, risks of changes in delivery schedules and manufacturing a product that is either not yet needed or falling victim to design changes can be reduced (Ko and Ballard 2004). However, how much later relative to the required delivery date fabricators can still deliver products on time but reduce the level of finished goods inventory is a question. Construction projects are complex, full of uncertainty, and vary with the environment. Production managers must consider uncertain information using their knowledge and experience while making production plans. In addition, an on-time delivery cannot be achieved without a supportive production plan which is difficult to be manually arranged for satisfying multiple objectives (Gosling *et al*. 2010).

According to the buffering law, systems with variability must be sheltered by some combination of inventory, capacity, and time (Hopp and Spearman 2000). The root method for solving problems induced by variability is to eliminate it (Khan 2003). Precast fabricators thus should constantly endeavor to reduce variability. Meanwhile, before variability has been totally removed, proper buffers are necessary to protect fabricators from the impact of changeability in demand. To deliver products on time (or Just-In-Time), a time buffer with a smaller inventory is needed. Otherwise, precast fabricators lose capacity due to overtime vicious cycles induced by variability.

Making appropriate production plan is one of the most important tasks in manufacturing (Pinedo 2008).

ISSN 1392–3730 print / ISSN 1822–3605 online
doi: 10.3846/jcem.2010.48

Throughput, makespan, and waiting time are dominated by production sequence. To enhance the competitiveness of a fabricator, production schedulers face the challenges of satisfying multiple objectives since one objective may conflict with the others (Chan and Hu 2002). The current practice of making precast production schedules depends on scheduler's experience. Due to inaccurate planning methods, inefficient resource utilization and overstocking are common sights in the precast industry (Chan and Hu 2002; Dawood 1993; Low and Choong 2001). Researchers have begun using computational techniques to manage scheduling issues (Chan and Hu 2002; Dawood and Neale 1993; Leu and Hwang 2001, 2002; Benjaoran *et al*. 2005).

The objective of this study is to develop a framework for precast fabricators to reduce the level of finished goods inventory. Fuzzy logic and multi-objective genetic algorithm are adapted to achieve this goal. This paper first introduces the process of precast fabrication. A production strategy is then proposed to reduce the inventory level. To carry out the production strategy, a framework is developed. Three components of the framework are discussed. Finally, application of the developed framework is explained using a real precast production project.

2. Precast production process

Precast fabrication can be divided into six steps: namely 1) mold assembly, 2) placement of reinforcement and all embedded parts, 3) concrete casting, 4) curing, 5) mold stripping, and 6) product finishing, as depicted in Fig. 1. Unlike regular production systems, precast elements are produced stationary as opposed to conveying by belts due to their huge volume and heavy weights. Therefore, fabrication jobs are completed by mobile crews. The mold assembly activity provides a specific dimension. In general, fabricators use steel molds for the purpose of reuse. Precast element primarily contains two kinds of materials, i.e., concrete and steel bars. Reinforcements and embedded parts are placed in their positions after the mold is formed. Embedded parts are used to connect and fix with other elements or with the structure when the precast elements are erected. The concrete is cast when the embedded parts are in their positions. To enhance the chemistry solidifying concrete, steam curing is implemented; otherwise, the concrete requires weeks to reach its legal strength. Moving or erecting elements before reaching the legal strength may cause damage. The molds can be stripped after the concrete solidifies. Due to the cost of developing steel molds, fabricators reuse them once they are stripped. The final step in production is finishing. Minor defects such as scratches, peel-offs, and uneven surfaces are treated in this step. Afterwards, precast elements are stored in the yard awaiting delivery to construction site.

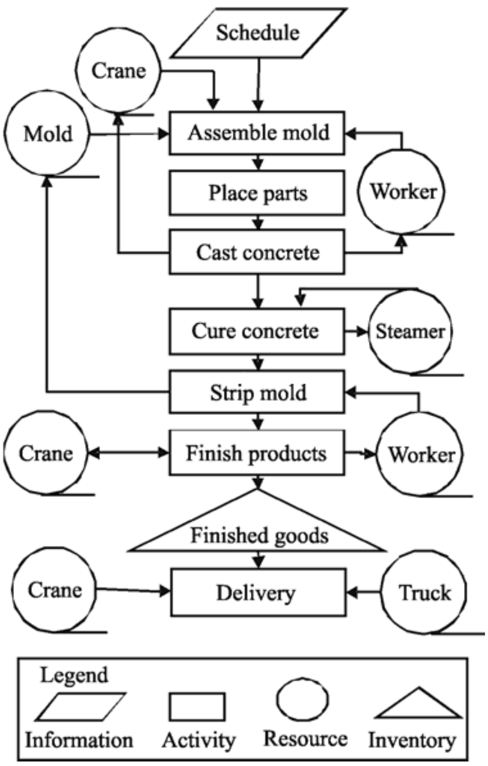

Fig. 1. Precast production process

Unlike the traditional flowshop sequencing problems, precast production features both interruptible and uninterruptible activities. The interruptible ones can be interrupted if the job cannot be completed within the working hours but can be continued by the next working day. Uninterruptible activities cannot be interrupted until the job is completed. Precast production activities including mold assembly, placement of reinforcement and all embedded parts, mold stripping, and product finishing can be done by the next day if they cannot be completed within working hours. These kinds of activities are categorized as interruptible. Concrete casting is an uninterruptible activity. It must be postponed to the next working day if it cannot be completed within the working hours or overtime. Curing is also an uninterruptible activity. A fast cure can be completed in a few hours after casting. However, stream curing generally takes 12 to 16 hours, no-workers being needed. Thus, this activity is frequently executed overnight. Durations for completing interruptible and uninterruptible activities are demonstrated in Fig. 2.

A steel mold is an essential and expensive resource for precast fabrication. Jobs must wait for their molds before fabrication can be commenced. When arranging production schedules, molds are assigned according to the job sequence. Waiting time occurs when jobs wait for

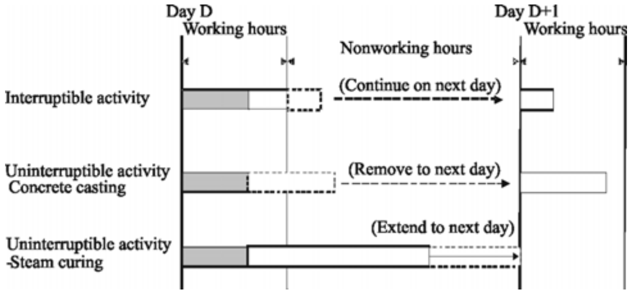

Fig. 2. Duration for completing production activities

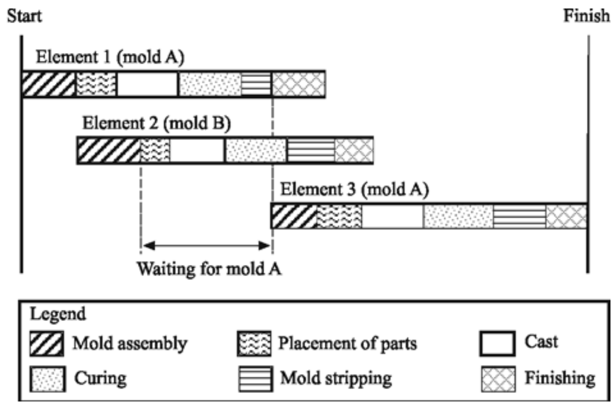

Fig. 3. Gantt chart of precast production

molds. For example, in Fig. 3, due to a limited number of mold "A," fabrication of element "3" with mold "A" cannot be begun until element "1" releases that mold "A." This example demonstrates a situation in which the fabrication waits for a mold, a frequent occurrence in actual practice.

3. Production strategy

To fulfill an erection schedule, precast fabricators start manufacturing as soon as they receive design information. However, this practice results in accumulated inventory considered as "the root of all evil" (Spearman 2002; Pulat and Pulat 1992). Change orders, categorized as demand variability, are among the largest sources of cost inflation on construction projects (Riley *et al*. 2005). Elements fabricated before they are needed frequently falls victim to change orders, such as modifications in size, quantity, and delivery date.

A strategy used to reduce inventory and protect fabricators against the impact of demand variability is to finish production later relative to required delivery dates, as illustrated in Fig. 4, where the adjusted production curve is "pulled" relatively close to the erection curve. To avoid out-of-capacity fabrication, the production curve is cushioned with a time buffer. For the time t shown in Fig. 4, an inventory level is decreased from i to i_a. The time of finished goods inventory awaiting delivery is shortened from b to a time buffer designated b_a. By adopting this strategy, both the inventory level and the impact of demand variability can be reduced without neither increasing production rate nor number of molds.

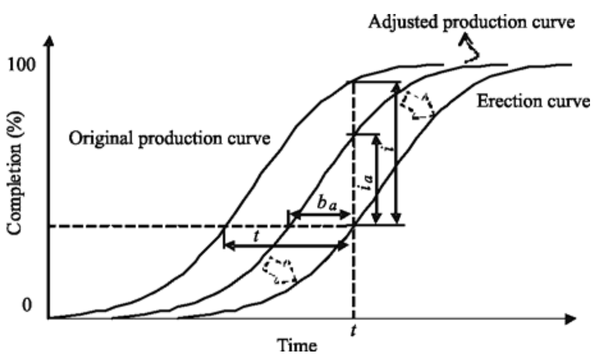

Fig. 4. Production strategy used to reduce inventory level

4. Framework of reducing inventory

This study proposes a framework to reduce level of finished goods inventory using three steps, as shown in Fig. 5. The first step is to evaluate a time buffer using fuzzy logic. Fabrication due dates are then adjusted using the inferred buffer according to the production strategy. Finally, production sequences are arranged using a multi-objective genetic algorithm. The details for each step are explained as follows.

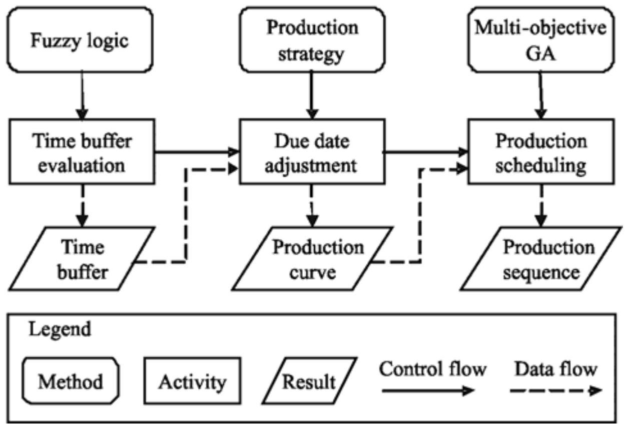

Fig. 5. Framework of reducing inventory

4.1. Time buffer evaluation

Applying a production strategy that finishes production later relative to the delivery date can ideally reduce the finished goods inventory. Unfortunately, variability such as late material supply, lost productivity, unplanned machine down time, and variation in setup times (molds) exists everywhere in the precast production system. Fabricators may be pushed out of capacity if every element is fabricated just-in-time. A proper time buffer between the delivery date and production due date is therefore necessary, just-in-case (Chen 2005). Demand variability is arguably the biggest headache when fabricators strive for business success. To avoid producing products that succumb to demand variability, elements should be fabricated later relative to the delivery dates. In contrast, for a situation in which the demand variability is relatively less, production loading can be mitigated if elements are fabricated relatively earlier. This allows fabricators to have more capacity for prior jobs. Demand variability, so called because it originates with the customer, causes fabricators to risk capacity loss or increased inventory costs (Ballard and Arbulu 2004). The reasons for demand variability are complex and situation dependent. However, some features of a project have greater chance to induce demand variability. Through interviews with experts, three factors were identified: 1) the building function, 2) ownership, and 3) type of precast elements. The factors that induce variability are difficult to quantify. The development of a mathematical model for buffer evaluation is complex and time consuming. Accordingly, this study adopts fuzzy logic that has been proven effective in processing uncertain information and complex systems (Chang 1999; Tsourveloudis and Phillis 1998;

Adenso-Diaz *et al*. 2004; Hui *et al*. 2002; Feng 2006; Plebankiewicz 2009). The time buffer is evaluated by considering these three factors. A general fuzzy logic system contains four major components: a fuzzifier, an inference engine, a rule base and a defuzzifier, discussed as follows.

1. Fuzzifier: A fuzzifier is a process for converting input values into degrees of linguistic variables. Distributions for input variables are defined using expert knowledge and experience. The membership function distribution for ownership is illustrated in Fig. 6. Since demand variability originates with the customer, the more ownerships the higher possibility the demand variability may occur. In the figure, three linguistic variables, i.e., little ownership, some ownership, and much ownership are used to describe the ownership degree. Each linguistic variable is represented using a distribution.

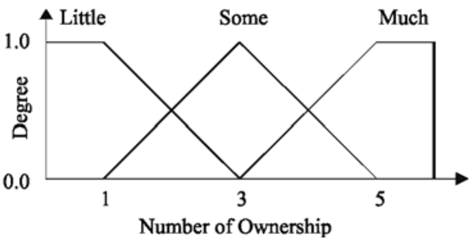

Fig. 6. Ownership membership function

2. Fuzzy rules: Fuzzy rules are relations between input and output fuzzy sets. These rules are representations of expert knowledge and often expressed using syntax forms. Fuzzy rules for shopping mall buildings are identified through interviewing experts, as summarized in Table 1. For example, the first rule primarily concerns the situation when the ownership is by many (such as 5 owners) with structural precast elements (beams or columns). In this case, the structural element dimensions are revised relatively fewer times, as a result, the demand variability is low and elements can be fabricated easier to mitigate the production load.

Table 1. Fuzzy rules for shopping mall building

No.	Fuzzy Rules
1	If Ownership is Many AND elements are Structure then time buffer is Long.
2	If Ownership is Many AND elements are Walls then time buffer is Short.
3	If Ownership is Many AND elements are Curtain Walls then time buffer is Long.
4	If Ownership is Some AND elements are Structure then time buffer is Long.
5	If Ownership is Some AND elements are Walls then time buffer is Medium.
6	If Ownership is Some AND elements are Curtain Walls then time buffer is Long.
7	If Ownership is Few AND elements are Structure then time buffer is Long.
8	If Ownership is Few AND elements are Walls then time buffer is Long.
9	If Ownership is Few AND elements are Curtain Walls then time buffer is Long.

3. Inference engine: The fuzzy inference engine, simulating the human decision-making process, has the capacity to infer results using fuzzy implication and fuzzy rules. For a given set of fuzzy rules, the fuzzy results are inferred from both fuzzy input sets and fuzzy relations using a composition operator. This study employs the Min-Max composition operator that takes the minimum membership of if part and maximum results of then part (Mamdani and Assilian 1975).

4. Defuzzifier: It is a reversal fuzzifier process, which produces a crisp output from the fuzzy inference. This research uses the most popular defuzzification method, namely center of gravity, to defuzzify an aggregative result. The operator identifies the required time buffer for demand variability. The larger the demand variability, the later the fabrication should be, thus reducing the risk of producing a product that succumbs to demand variability such as design changes. The output membership function is displayed in Fig. 7.

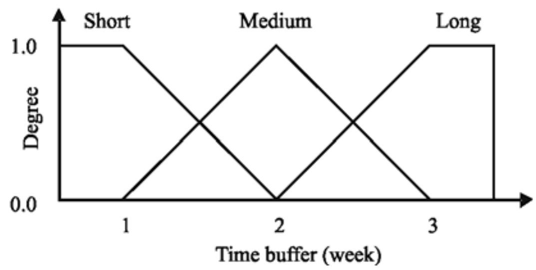

Fig. 7. Time buffer membership function

4.2. Due date adjustment

A time buffer evaluated in the previous section is regarded as a cushion to avoid having the fabricator becoming out of capacity. To support the erection schedule with less inventory, production due dates are pulled with the evaluated buffer. The derived adjusted production curve thus shifts closer to the erection curve.

4.3. Production scheduling

Once the production due dates have been determined, the next issue is how to finish products according to the due dates. This goal cannot be achieved without production schedules. Applying computational methods in recast production scheduling evolves from computer simulation to genetic algorithms (Dawood 1993, 1996; Dawood and Neale 1993). Previous studies showed that production resources have a crucial impact on throughput. In addition, precast production is a flowshop sequencing problem that can be solved using computational methods. Genetic algorithms have been proven a promising method for arranging precast production schedules (Chan and Hu 2002; Leu and Hwang 2001, 2002; Benjaoran *et al*. 2005; Vern, Gunal 1998).

4.3.1. Multi-objective genetic algorithms

Multi-Objective Genetic Algorithms (MOGAs) were first suggested and worked out in 1984 by David Schaffer (Schaffer 1984). Several algorithms were proposed after

Schaffer's work. One of the most popular algorithms was established by Murata and Ishibuchi (1995). This algorithm was developed based on evolutionary process searching for multi-objective optimization for Pareto solutions. An optimal Pareto solution is defined as a solution that is not dominated by any other solutions for the multi-objective optimization problem. Ishibuchi and Murata (1998) proposed a Multi-Objective Genetic Local Search Algorithm (MOGLS) based on MOGA by involving a local search. The MOGLS has been validated using multi-objective scheduling problems i.e. to minimize makespan and minimize schedule delays. The validation results show that MOGLS can find a better Pareto solution than those using other methods (Mohamad *et al.* 2009). This study therefore adopts MOGLS proposed by Ishibuchi and Murata (1998) as a prototype algorithm to search for optimum production schedules.

4.3.2. Precast production modeling

The traditional flowshop sequencing problem regards production as a continuous flow. The typical equation used to calculate the completion time is shown in Eq. (1) (Wang 2005):

$$C\left(J_j, M_k\right) = \text{Max}\left\{C(J_{j-1}, M_k), C(J_j, M_{k-1})\right\} + P_{jk}, \quad (1)$$

where $C\left(J_j, M_k\right)$ denotes the completion time for the jth element in k machine and P_{jk} is an operation time for that element ($P_{jk} \geq 0$).

Eq. (1) assumes an infinite buffer size between stations so that the production flow can be continuous. In practice, due to the large size of the precast elements, the buffer size between stations is limited. The regular flowshop sequencing model derived in Eq. (1) cannot meet the needs of precast production. This formula is therefore reformulated as Eq. (2):

$$C\left(J_j, M_k\right) = \text{Max}\left\{C(J_{j-1}, M_k) + WT_{j-1,k}, C(J_j, M_{k-1})\right\} + P_{jk}, \quad (2)$$

where $WT_{j-1,k}$ is the time for the (j-1)th element in k machine waiting to be sent to buffer, which can be represented using Eq. (3):

$$WT_{j,k} = \left\{\begin{array}{l} C\left(J_{j-B_k}, M_{k+1}\right) - P_{j-B_k,k+1} - C\left(J_j, M_k\right) \\ \quad .if \;\; C\left(J_j, M_k\right) < C\left(J_{j-B_k}, M_{k+1}\right) - P_{j-B_k,k+1} \\ 0 \\ \quad if \;\; C\left(J_j, M_k\right) \geq C\left(J_{j-B_k}, M_{k+1}\right) - P_{j-B_k,k+1} \end{array}\right\}. \quad (3)$$

In Eq. (3), B_k is the buffer size between the k th and the ($k+1$)th machines. When the completion time of the B_k th element at machine k is later than the beginning time of machine ($k+1$), buffer size B_k is not fully filled; otherwise, a waiting time occurs.

Unlike the general flowshop sequencing problems, precast production features both interruptible and uninterruptible activities. This situation is formulated in Eq. (4):

$$C(J_j, M_k) = \left\{\begin{array}{lll} T & if & T < 24D + H_W \\ T + H_N & if & T \geq 24D + H_W \end{array}\right\}, \quad (4)$$

where k denotes the interruptible stations ($k = 1, 2, 5, 6$); T, the accumulated completion time calculated by Eq. (5); and D, the working days represented when using Eq. (6).

$$T = \text{Max}\left\{C(J_{j-1}, M_k), C(J_j, M_{k-1})\right\} + P_{jk}, \quad (5)$$

$$D = \text{integer}(T / 24). \quad (6)$$

The concrete casting is an uninterruptible activity. Jobs must be postponed to the next working day if it cannot be completed within the working hours or overtime. The completion time for concrete casting can be calculated using Eq. (7).

$$C(J_j, M_3) = \left\{\begin{array}{lll} T & if & T \leq 24D + H_W + H_E \\ 24(D+1) + P_{jk} .. & if & T > 24D + H_W + H_E \end{array}\right\}. \quad (7)$$

Curing is also an uninterruptible activity. The completion time of the *j*th element in the curing process is formulated by Eq. (8):

$$C(J_j, M_4) = \left\{\begin{array}{lll} T^* & if & T^* < 24D + H_W \\ 24(D+1) & if & 24D + H_W \leq T^* < 24(D+1) \\ T^* & if & 24(D+1) \leq T^* \end{array}\right\}, \quad (8)$$

where T^* is a curing time that can be calculated using the following equation:

$$T^* = C(J_j, M_3) + P_{j4}. \quad (9)$$

The time that the jth element waits for a type \$ mold is calculated in Eq. (10):

$$C\left(J_{j,\$}, M_0\right) = \text{Min X}_\$ \left\{\forall y \left\{C\left(J_{y,\$}, M_5\right)\right\}\right\}, \quad (10)$$

where $X_\$$ denotes number of type \$ mold.

4.3.3. Scheduling evaluation criteria

A decision maker faces challenges in achieving multi-objectives while devising production schedules. Generally, the goal is to simultaneously minimize cost and production duration. The purpose of employing production scheduling in the study is to arrange production sequences that finish products on the due dates. Schedule performance therefore is evaluated by its makespan and on-time penalty. Makespan, also called maximum completion time (C), denoting the period needed to complete all jobs, can be calculated using formula (11):

$$f_1(\sigma) = C_{\max} = C\left(J_n, M_m\right). \quad (11)$$

Another index is the tardiness and earliness penalties. To achieve the goal of finishing products on due dates, tardiness and earliness are considered as costs when arranging production schedules. Finishing products earlier increases the level of finished goods inventory and risks subjecting fabricators to the impact of demand variability. Conversely, finishing products later risks pushing fabricators beyond their capacity. Total penalty costs are represented in Eq. (12):

$$f_2(\sigma) = \sum_{j=1}^{n} \tau_j \cdot \mathrm{Max}\left(0, C_j - d_j\right) + \sum_{j=1}^{n} \varepsilon_j \cdot \mathrm{Max}\left(0, d_j - C_j\right), \tag{12}$$

where d_j denotes production due date for job j; τ_j, the unit cost of tardiness for job j; and ε_j, the unit inventory cost for job j.

4.3.4. Evolutionary process

This research proposes a multi-objective genetic algorithm to search for optimum production schedules. The algorithm is developed on the basis of the schema of the MOGLS. The evolutionary process of the developed algorithm is represented in Fig. 8. Each step is discussed below.

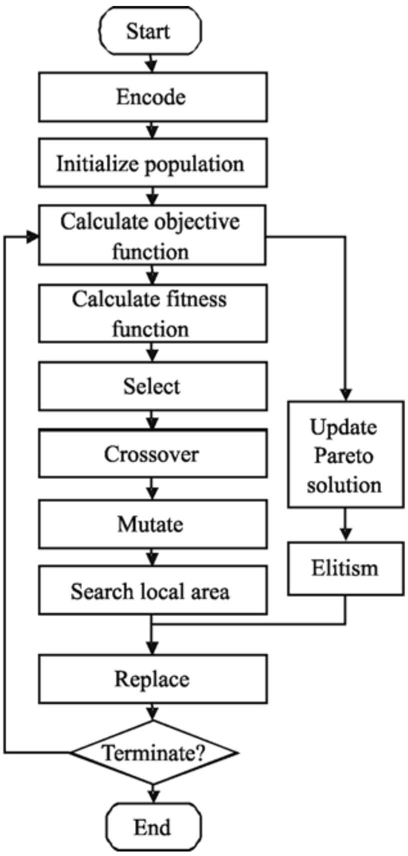

Fig. 8. Evolutionary process of multi-objective genetic algorithms

1. Encode: The factors affecting production makespan including both the resources and the sequence of production. Certain resources such as the number of cranes and the size of the factory cannot be changed by the schedulers. Others such as buffer size between stations, number of molds, and working hours can be determined. This study encodes production schedules by job sequence. The codification scheme is shown in Fig. 9. Buffer sizes and number of molds are treated as production constraints while scheduling.

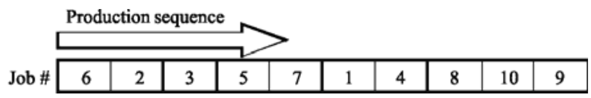

Fig. 9. Encoding scheme

2. Initialize population: A variation in an initial solution with higher fitness values can improve the searching efficiency (Šešok *et al.* 2010). To provide an equal opportunity for every state space, a set of initial solutions is randomly generated. The chromosomes obtained provide a base for further evolutionary processing.

3. Calculate objective function: In this step, the chromosomes corresponding with the precast production model are decoded. To evaluate production schedule, multi-objectives are transferred to a single objective by a weighted sum approach. A single objective after transformation is obtained in Eq. (13):

$$f(x) = \omega_1\left(f_1(x)\right) + \omega_2\left(f_2(x)\right), \tag{13}$$

where ω_1 and ω_2 are positive weights ($\omega_1 + \omega_2 = 1$); $f_1(x)$, the makespan function shown in Eq. (11); and $f_2(x)$, the penalty function calculated by Eq. (12).

4. Update Pareto solution: To be sure that the derived solutions conform to Pareto's definition, every generation should be updated to this solution pool, a task accomplished by putting the chromosomes conforming to the definition of this solution into the pool. Chromosomes in the pool which dissatisfy Pareto's are removed.

5. Calculate fitness function: Eq. (13) is used to evaluate the fitness of each chromosome.

6. Select: A selection operator is used to choose chromosomes according to their fitness. A chromosome with a higher fitness value has a greater chance for survival. The purpose of this operator is to choose fitter chromosomes for evolving better generations. This study adopts a roulette-wheel method for selection (Goldberg 1989) instead of tournament method, since an elitism strategy is used.

7. Crossover: A genetic algorithm extends the searching space by a crossover operator, which produces the next generation by exchanging partial information from parents. Precast production sequence is subjected to two constraints: every job has to be processed on all stations and is processed on one station at a time. Therefore, regular crossover methods cannot be applied due to those constraints. A two-cut-point crossover developed based on position-based is used in this study.

8. Mutate: The mutation operator produces spontaneous random changes in various chromosomes and protects against premature loss of important notations. This study uses shift mutation that randomly selects two points. The rear point is inserted ahead of the front point.

9. Elitism: Elitism has been proven successful in enhancing genetic algorithms searches (Ko and Cheng 2007), surviving a certain number of Pareto solutions to the next generation. Thus, every generation contains elite solutions for better evolution. By applying this strategy, the fitness increases from one generation to the next.

10. Search local area: A local search can explore the area that a global search stochastically skips. Moreover, it improves the convergence speed for the Pareto solution. This study searches the local area using a mutation operator.

11. Replace: Replacement is a process in which the offspring eliminate the parent chromosomes. In this process, the previous population is renewed by the generated offspring. Therefore, the next generation can continuously include new solutions for evolution.

12. Terminate conditions: The terminate conditions provide the criterion for stopping the evolutionary process, which, this study, evolutionary process is terminated by specified iterations.

5. Case study

One real case, a furniture mall constructed from precast components, is used to demonstrate the applicability of the proposed framework. This four-story, one-basement shopping mall has a construction budget of US$ 5.7 million. The precast elements required for each story are summarized in Table 2. In the table, B1F has 195 major and 290 minor beams but no precast columns. The mall also has a mezzanine, denoted as M1F, between the first and the second floors. The studied precast factory manufactures concrete elements eight hours a day, five days a week. The allowable overtime is two hours per day. The unit cost of inventory is assumed 1 whereas tardiness is 10.

Table 2. Required precast elements

Story	Column	Major beam	Minor beam
B1F	0	195	290
1F	51	31	7
M1F	35	120	165
2F	72	113	143
3F	72	118	158
4F	72	122	179
RF	15	13	17

5.1. Time buffer evaluation

The time buffer is evaluated by considering the demand variability using fuzzy logic. This studied case is a shopping mall with single ownership, constructed using precast columns and beams (structural elements). To represent the vagueness of each input, the original status for each variable is represented using crisp values. Crisp values are transferred into fuzzy values through membership functions. Applying fuzzy values to nine fuzzy rules illustrated in Table 1, the time buffers for each story can be obtained using the center of gravity method. The inference results are summarized in Table 3. Observing the table, the buffers for each story are 14 days because input values are the same for every story.

Table 3. Time buffer for each story

Story	Time buffer
B1F	14 days
1F	14 days
M1F	14 days
2F	14 days
3F	14 days
4F	14 days
RF	14 days

5.2. Due date adjustment

Production due dates are adjusted closer to the delivery dates. To avoid the fabricator being out of capacity, the time buffers inferred in the previous section are regarded as a cushion between the delivery dates and production due dates. The original production due date, adjusted production due date, and erection dates are compared in Table 4.

Table 4. Due date adjustment

Story	Original production due date (mm/dd)	Adjusted production due date (mm/dd)	Erection date (mm/dd)
B1F	08/31	09/06	09/20
1F	09/08	09/30	10/14
M1F	09/22	10/09	10/23
2F	10/04	10/20	11/03
3F	10/20	10/31	11/14
4F	11/05	11/10	11/24
RF	11/19	11/20	12/04

5.3. Production scheduling

This project includes 1988 precast elements, which is difficult to manually arrange the optimum production sequences. This study thus arranges the production sequences using multi-objective genetic algorithms. The production resources and constraints are listed in Table 5. The molds are categorized into three types, i.e., column, major, and minor beams. The required duration, shown in hours, for each activity is investigated through analyzing historical data. The parameters for the genetic algorithms used to search for production sequences are displayed in Table 6. A production sequence analyzed using genetic algorithms is visualized using Gantt chart instanced in Fig. 10.

Table 5. Production resources and constraints

Mold type	Amount of mold	Mold assembly	Placement of parts	Casting	Curing	Mold stripping	finishing
Column	6	2.6	2.7	2.0	12	0.7	1.0
Major beam	16	2.0	2.6	2.0	12	0.6	1.0
Minor beam	20	1.7	1.7	1.5	12	0.5	1.0

Table 6. Parameters of genetic algorithms

Parameter	Value
Elitism number	4
Local search number	2
Population size	40
Iterations	500
Crossover rate	0.9
Mutation rate	0.03

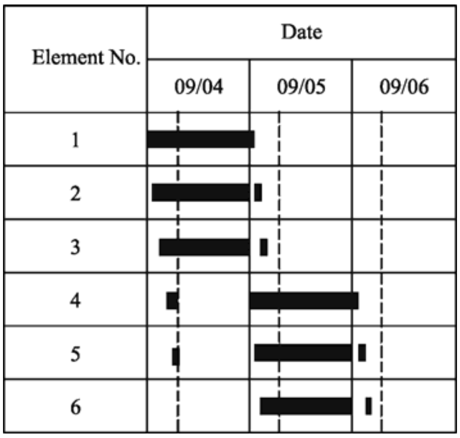

Fig. 10. Simplified production sequence

5.4. Discussion

The original production due dates, adjusted production due dates, and actual erection dates are graphically compared in Fig. 11. Observing this figure, the evaluated fabrication due dates are much closer to the erection progress, which provides a better result for the current practice. An average of 16% finished goods inventory is reduced using the proposed framework. In addition, due to relatively late production due dates, fabricators can reduce the risk of succumbing to demand variability. By applying multi-objective genetic algorithms, production sequences can be identified to fulfill the adjusted production due dates with both production resources and constraints.

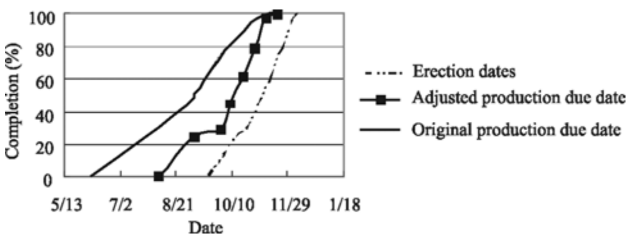

Fig. 11. Comparisons of original production due date, adjusted production due date, and erection dates

6. Conclusions

This paper has presented a framework to reduce the level of finished goods inventory by integrating artificial intelligence techniques. A production strategy that finishes products later relative to the erection dates is proposed to reduce the inventory level. To avoid having the fabricators becoming out of capacity due to late production due dates, a time buffer was evaluated by considering the demand variability. A multi-objective genetic algorithm was then used to search for production sequences to fulfill the production goal. The studied case validates that the analyzed production sequences can fit with the precast fabrication requirement, thereby providing a set of production plans to assist in decision making.

Most precast fabricators generate a substantial finished goods inventory to satisfy the customer's demand. The proposed framework can significantly reduce the finished goods inventory level using a supportive production plan. Moreover, the framework used to shift the production curve closer to the erection dates can reduce the risk of fabricator exposure to the impact of demand variability. The proposed research work is one of the first studies that evaluate production time buffer by considering demand variability and arrange production sequence using multi-objective genetic algorithms in the construction industry. This research has not considered the overtime wages. Future study may investigate the impact of overtime wage on production sequences.

Acknowledgments

This research was funded by grants NSC 94-2218-E-212-011, NSC 95-2221-E-212-051, NSC 96-2221-E-212-020, and NSC 97-2221-E-020-036-MY2 from the National Science Council (Taiwan), whose support is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in the paper are those of the author and do not reflect the views of the National Science Council. The author would like to thank the investigated precast fabricator for supporting this study. Partial analyses are carried out through the assistance of Yu-Chun Chen and Shu-Fan Wang for which the author is grateful.

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INTEGRUOTOJI SISTEMA GAMYBINĖMS SURENKAMOSIOS STATYBOS ATSARGOMS MAŽINTI

Chien-Ho Ko

Santrauka

Surenkamosios statybos sektorius siekia didinti verslo struktūrų gebėjimą produktus tiekti laiku. Tokia gamyba pradedama vos gavus projektinę informaciją. Tačiau taip gaminant susikaupia daug gaminių atsargų, apsunkinančių įmonės veiklą. Šio tyrimo tikslas – sukurti sistemą, kuri leistų tokias atsargas sumažinti. Sistemą sudaro trys komponentai. Pirmasis komponentas padeda atsižvelgti į paklausos kitimą ir išvengti per didelio gamybos pajėgumų mažinimo. Šis komponentas vadinamas pirmojo pareikalavimo įtakos sušvelninimu. Antrasis komponentas leidžia mažinti gamybines atsargas, gamybą priderinant prie statybos ir montavimo laiko. Trečiasis sistemos komponentas skirtas planuoti darbus, išdėstant gamybos operacijų sekas pagal daugiatikslius kriterijus ir taikant genetinius algoritmus. Aprašomas praktinis pavyzdys, iliustruojantis pasiūlytosios sistemos efektyvumą. Taikymo rezultatai rodo, kad įgyvendinta sistema leis sumažinti pagamintos produkcijos atsargas, nemažinant gamybos sąnaudų.

Reikšminiai žodžiai: surenkamoji statyba, paklausos kitimas, gamybinės atsargos, darbų planavimas.

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