EVALUATING PRODUCTION TIME BUFFER FOR DEMAND VARIABILITY

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Abstract

Precast fabricators face numerous challenges as they strive for business success. Among them, demand variability is arguably the biggest headache. The objective of this research is to develop a Buffer Evaluation Model (BEM) to protect fabricators against the impact of demand variability. Laws of forecasting are considered when developing the model. A pulling strategy of finishing production later relative to erection dates is established thereafter. To avoid fabricators losing capacity due to the relatively later fabrication, a time buffer is analyzed using Fuzzy Logic (FL). FL, in the BEM, is primarily used to deal with uncertain information encountered while evaluating time buffer. This study validates performance of the proposed method using a real precast project. Application results show that the proposed method can effectively reduce level of the inventory as well as reduce the risk of producing product falling victim to design changes.

Keywords: Fuzzy logic, Precast fabrication, Finished goods inventory, Buffer management, Demand variability.

1. INTRODUCTION

Precast fabricators of engineered-to-order products face numerous challenges as they strive for business success. Among them, changes in required delivery dates (demand variability) are arguably the biggest headache (Ko and Ballard 2005, Ballard and Arbulu 2004). In the precast industry, customer satisfaction is measured by on-time delivery. Late delivery can interrupt erection progress and therefore induces delays (Ko and Chen 2012). Besides, consequences of late delivery include penalty of contract breaking and deterioration of business reputation (Ko and Wang 2011). To delivery products on time or to delivery products whenever customers need them, fabricators start to production once they received design information. Unfortunately, since construction site may not have enough space to pre-store precast elements, customers often change delivery dates corresponding to erection/construction progress. As a result, numerous finished goods are stored in the yard waiting to be delivered (finished goods inventory) (Shiau et al. 2012).

One of the ways to protect fabricators against the impact of demand variability is to finish production later relative to required delivery dates, thus reducing the risk of changes in delivery dates, and reducing the risk of producing product that is either not yet needed or falls victim to design changes (Ko and Ballard 2004). However, how later relative to required

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delivery dates is appropriate for fabricators to delivery products on time and to reduce the level of finished goods inventory? Under an invariable environment, the answer is certain. Unfortunately, variability such as material supply not on time, productivity lose, unplanned machine down time, variation of setup times (molds), etc. is everywhere in the precast production system. The answer is different when circumstances change.

According to buffering law, systems with variability must be buffered by some combination of inventory, capacity, and time (Hopp and Spearman 2000). The root method to solve problems induced by variability is to remove variability. Nevertheless, totally removing variability may take forever. Toyota took 25 years (from the 1940s to the late 1960s) of constant attention to reduce setups from three hours to three minutes (Monden 2012). Precast fabricators could constantly pay attention to reduce variability. In the meanwhile, before variability is totally been removed, proper buffers are necessary for fabricators to protect themselves from the impact of demand variability. To deliver products on time (or Just-In-Time), a time buffer with relatively less inventory is needed. Otherwise, precast fabricators lose capacity due to overtime vicious cycle induced by variability.

Uncertain and imprecise information are encountered while evaluating time buffer. In practice, factors inducing variability are difficult to be quantified. As a result, the development of mathematical model for buffer evaluation is complex and time consuming. Fuzzy Logic (FL) has been proven as an effective method to process uncertain information and complex systems. Chang (1999) and Kristianto et al. (2012) considered production inventory in a fuzzy sense. The investigators represented uncertain product quantity using a triangular fuzzy number. In One-of-a-Kind Product (OKP) manufacturing systems, customers usually have different degrees of satisfaction with the due date. To clearly describe the problem, Wang et al. (1999) developed an algorithm for Just-In-Time (JIT) production planning with a fuzzy due date. To considering the characteristics of an environment with imprecise information, a fuzzy-based model was developed and implemented in a real environment by Adenso-Diaz et al. (2004). The model considering imprecise information allows the simulation of expert behavior. Value stream mapping is frequently used to analyze value in a production system. However, selecting detailed mapping tools for identification of waste is complex and full of uncertain information. Singh et al. (2006) developed a decision support system using FL to select value stream mapping tools.

To evaluate appropriate buffer against demand variability, this research develops a Buffer Evaluation Model (BEM) using FL. Basic considerations of developing the BEM are firstly discussed by laws of forecasting. FL concepts adopted in the research are then explained. Finally, a description of model implementation in a real project is reported.

2. LAWS OF FORECASTING

There is simply no way to sensibly make decisions of how much time buffer is proper without any evaluation. Evaluation by definition of Webster's dictionary (1987) is to determine the significance, worth, or condition of usually by careful appraisal and study. According to the context, if the evaluation such as time buffer is made for the future, the function of evaluation is the same with prediction. In fact, no matter how sophisticated the model, to perfectly evaluate a time buffer for the future status is simply not possible. Buffer evaluation in this research is the same with buffer prediction. To make appropriate decisions, laws of forecasting (Armstrong 1985 and Hanke and Reitsch 1995) are seriously considered when developing the BEM.

- First law of forecasting: Forecasts are always wrong.
- Second law of forecasting: Detailed forecasts are worse than aggregate forecast.
- Third law of forecasting: The further into the future, the less reliable the forecast will be.

By considering the first law, this research estimates reasonable time buffers ranging from one to three weeks as opposed to long periods. The strategy provides flexibility for tolerating inevitable prediction errors. The production system therefore will not lose capacity due to wrong estimations. By the contrast, inventory level can be reduced and demand variability can be buffered by the likely correct estimations. For the second law, this research estimates the trends of the buffer, which will be addressed in Buffer Evaluation Model section. For the third law, a one-month time frame is used in the research. In general, precast fabricators need seven to ten days to fabricate products. The one-month time frame allows fabricators to either start producing products earlier or later relative to delivery dates.

3. FUZZY LOGIC

This research adopts FL to develop the BEM. FL was first developed by Zadeh in 1960s for representing uncertain and imprecise information. In a wide sense, fuzzy logic is synonymous with fuzzy set theory; that is, the theory of classes with unclear boundaries. In a narrow sense, fuzzy logic is a logic system that intends to serve as a logic of approximate reasoning (Zadeh 1994). Classical logic (two-valued logic) assumes that every proposition is either true or false. This basic assumption has been questioned. Unlike classical logic, fuzzy logic is viewed as an extension of multi-valued conventional logic.

FL simulates the high-level human decision-making process, which aims at modelling the imprecise modes of reasoning to make rational decisions in an environment of uncertainty and imprecision. It provides approximate but effective descriptions for highly complex, ill-defined, or difficult-to-analyze mathematical systems. A general Fuzzy Logic System (FLS) contains four major components: fuzzifier, inference engine, rule base, and defuzzifier, as shown in Figure 1. Details about each component are discussed in BEM section.

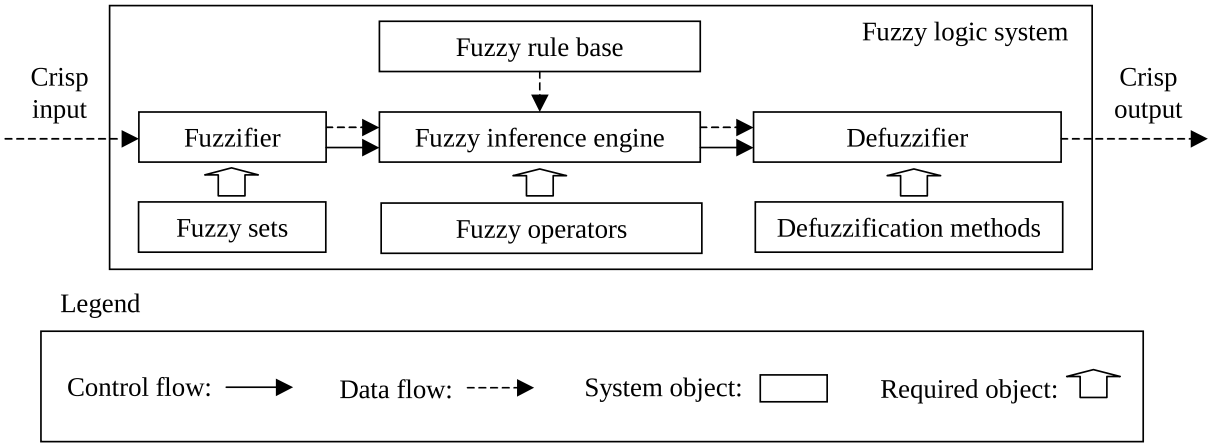

Figure 1: General schema of a typical fuzzy logic system.

4. BUFFER EVALUATION MODEL (BEM)

The BEM is developed using fuzzy logic. This study explains the development of BEM by its components.

4.1 Fuzzifier

Fuzzifier is a process of converting input values into degrees of linguistic variables. During this scale mapping, membership functions are used to define the relationships between input variables and linguistic variables. Demand variability, so called because it originates with the customer, causes fabricators to risk the loss of capacity or increases inventory costs (Ballard and Arbulu 2004). Reasons inducing demand variability are complex and situation depended. However, some features of a project indeed have more chances inducing demand variability. Through interviewing with the experts, three factors are identified: 1) function of the building, 2) ownership, and 3) type of used precast element. The distribution of membership function for ownership is illustrated in Figure 2. In the figure, three linguistic variables i.e. few ownerships, some ownerships, and many ownerships are used to describe the input variable ownership. Each linguistic variable is represented using a distribution. For example, the meaning for “few ownerships” can be described using a trapezoid. The degree for one ownership of the distribution is 1.0. Three ownerships for the few ownership distribution are 0.0. Another linguistic variable “some ownerships” is described using a distribution of triangle. For the distribution, the degrees of one ownership and five ownerships are 0, whereas three is 1.0. Distributions for all input variables are defined through experts according to their knowledge and experience.

Table 1: Fuzzy rules for shopping mall building.

No.	Fuzzy Rules
1	If Ownership is Many AND elements are Structure then demand variability is Low.
2	If Ownership is Many AND elements are Walls then demand variability is High.
3	If Ownership is Many AND elements are Curtain Walls then demand variability is Low.
4	If Ownership is Some AND elements are Structure then demand variability is Low.
5	If Ownership is Some AND elements are Walls then demand variability is Medium.
6	If Ownership is Some AND elements are Curtain Walls then demand variability is Low.
7	If Ownership is Few AND elements are Structure then demand variability is Low.
8	If Ownership is Few AND elements are Walls then demand variability is Low.
9	If Ownership is Few AND elements are Curtain Walls then demand variability is Low.

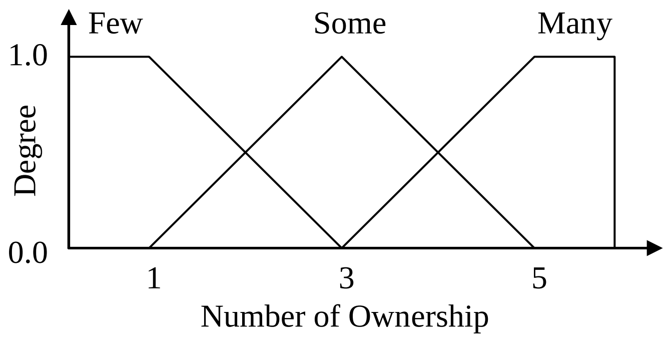

Figure 2: Ownership membership function**.**

4.2 Fuzzy Rules

Fuzzy rules are relations between input and output fuzzy sets. These rules are representations of expert knowledge and are often expressed using syntax forms. Fuzzy rules for shopping mall buildings are identified through interviewing with experts, as summarized in Table 1. For example, for the first rule, it primarily concerns the situation when ownerships is many (such as 5 ownerships) with structural precast elements (beams and/or columns). For the case, dimensions of structural elements are relatively less being revised, as a result, demand variability is low. Those rules are operated in the inference engine, which is discussed in the following section.

4.3 Inference Engine

The fuzzy inference engine, simulating the human decision-making process, has the capacity of inferring 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 by a composition operator. This study employs the Min-Max composition operator proposed by Mamdani (1976) that takes minimum membership of if part and maximum of then part. The composition process is schematically shown in Figure 3. It is applied to each rule displayed in Table 1. For instance, for if part of the rule 1 shown in Figure 3, degree of “many ownerships” is smaller than the one of structure, therefore, the smaller degree is taken (Min). Mapping the smallest degree of if part to the than part, the degree of than part can be obtained. The largest degree of then part is then selected as the reprehensive result (Max).

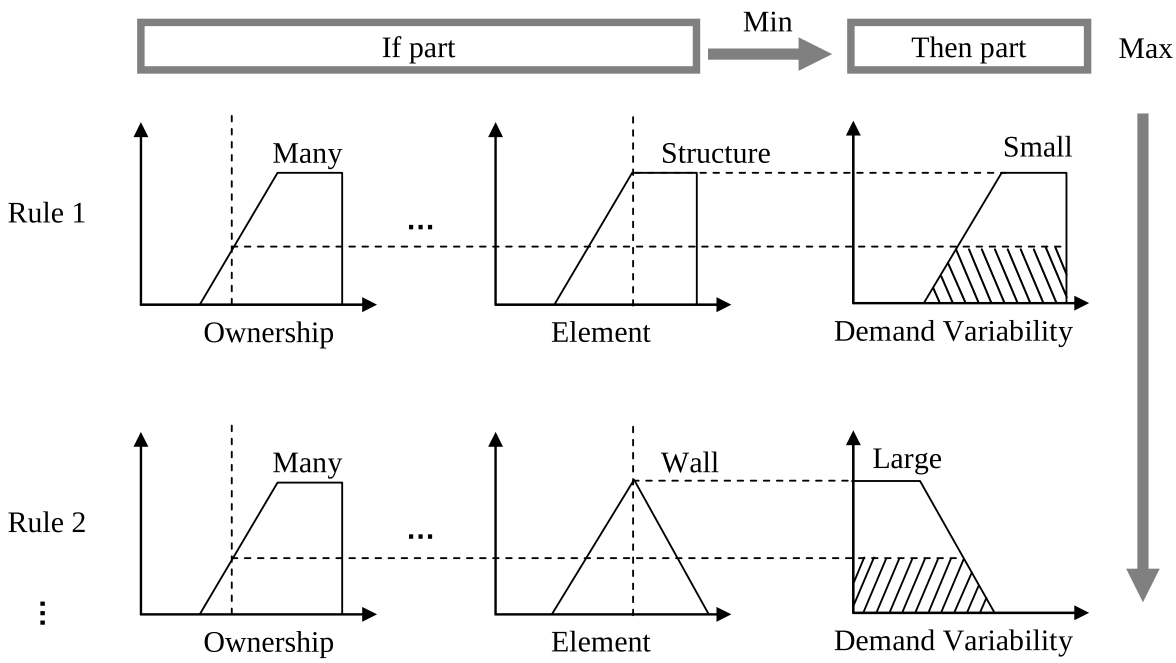

Figure 3: Min-Max composition.

4.4 Defuzzifier

Defuzzifier is a reversing process of fuzzifier, which produces a crisp output from fuzzy inference. This research uses the most common defuzzification namely center of area to defuzzify an aggregative result. The method is demonstrated in Figure 4. It identifies required time buffer for demand variability. The larger the demand variability, the later the fabrication should be. Thus reducing the risk of producing product falls victim to demand variability such as design changes. Suppose fuzzy inference engine concludes two results from two fuzzy rules. Area A shown in Figure 4 denotes medium demand variability whereas B denotes large demand variability. To conclude a result from those two distributions, the center of areas A and B (shown as c) is calculated. Note that overlapped region of A and B is only counted for once. The center is used to represent an inference result for all fuzzy rules. In the figure, a time buffer for delivering products on time with relatively less finished goods inventory is about 1.5 weeks.

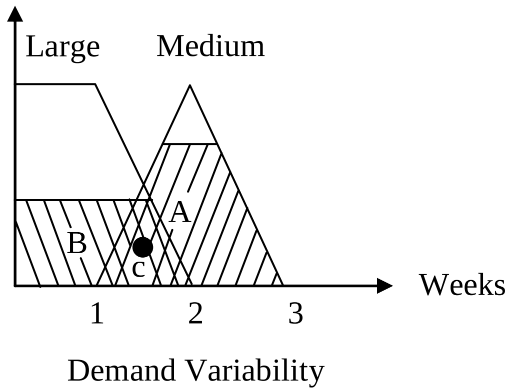

Figure 4: Center of area defuzzification.

5. APPLICATION

One real case in Taiwan is used to demonstrate the performance of BEM. The project is a furniture shopping mall whose structural system is constructed using precast elements. The shopping mall has four stories and one basement all belonging to a single owner. Construction budget for the project is 1.7 hundred million NTD (about 5.7 million USD). Precast elements required for each story is summarized in Table 2. For instance, B1F has no precast column, 195 major beams, and 290 minor beams.

Table 2: Required precast elements.

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

[1]M1F is a story between first floor and second floor.

Three inputs of BEM (i.e. function of the building, ownership, and type of precast element) are displayed in Table 3. In the table, original inputs denote statuses of input variables. The studied case is a shopping mall with single ownership and constructed using precast columns and beams (structure elements). To represent the vagueness of each input, original statuses are represented using crisp values. For example, in Figure 2, single ownership is directly represented as “one” in the x-axis of the membership function ownership. Shopping mall and structure elements are represented as one and five in the building function membership function and element type membership function respectively. Crisp values are transferred into fuzzy values using membership functions. Using single ownership as an example, as shown in Figure 2, the degree of “few ownerships” for one (single ownership) is 1; the degree of “some ownerships” for one is 0; and the degree of “many ownerships” for one is 0. The crisp value is therefore represented as (1,0,0). Some numbers of ownerships, e.g. two, falling between one and three can be represented as (0.5,0.5,0).

Table 3: Inputs of buffer evaluation model.

Values	Building Function	Ownership	Element Type
Original Input	Shopping Mall	1	Structure
Crisp value	1	1	5
Fuzzy values	(1,0,0)	(1,0,0)	(0,0,1)

Applying fuzzy values shown in Table 3 to nine fuzzy rules illustrated in Table 1, buffers for each story can be obtained. Inference results are summarized in Table 4. Observing the table, buffers for each story are 14 days since input values are the same for every story. According to the results, fabrication due dates can be obtained.

Table 4: Buffer for each story.

Story	Buffer
B1F	14 Days
1F	14 Days
M1F	14 Days
2F	14 Days
3F	14 Days
4F	14 Days
RF	14 Days

The estimated fabrication due dates, actual erection dates, and actual fabrication finished dates are compared in Figure 5. Observing the figure, the evaluated fabrication due dates are much closer to erection dates, which provides a better result to the current practice. An average 16% finished goods inventory is reduced by the proposed method.

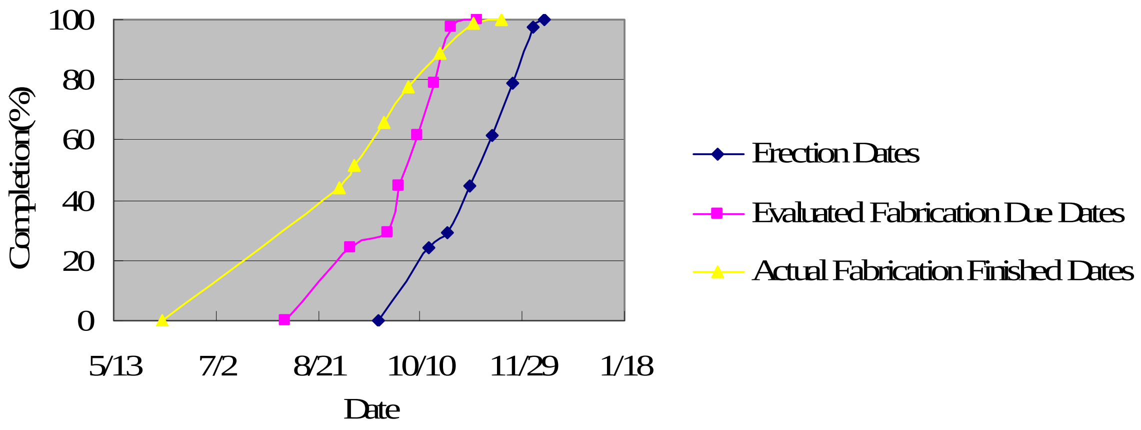

Figure 5: Comparisons of erection dates and fabrication due dates.

6. CONCLUSIONS

This paper has briefly introduced concepts of developing the Buffer Evaluation Model (BEM). To protect precast fabricators against the impact of demand variability, fabrication due dates are pulled later relative to required delivery dates. A time buffer is then analyzed using fuzzy logic to avoid fabricators losing capacity.

Most precast fabricators produce products using a mass production way. The application case shows that the proposed method pulling the fabrication due dates later relative to required delivery dates can significantly reduce inventory level. In addition, the impact induced by the demand variability can be decreased, due to a relatively certain erection dates and a relatively clear construction status.

To improve the performance of precast production systems, a synthesis approach is needed. Removing the root of demand variability is as important as protecting fabricators from its impact. Future research could focus on reducing fabrication lead times, customer relationship management, and agile manufacturing. Simulation technique would also be a promising tool to validate the scenario driven by BEM. The current BEM is a prototype. Numerous experiments are underway verifying the proposed method including influencing factors, membership functions, fuzzy rules, and basic ideas. More research results will be reported in the future.

For those factories that can fabricate precast elements in one day could directly apply this model. However, for those that need more than one day to fabricate precast elements has to consider the minimum duration for fabrication and re-evaluate the latest fabrication due dates. Although the proposed model can suggest later fabrication due dates, it might run higher risk of not finishing in time, resulting in customer dissatisfaction (which is outside the model). Future studies may consider the performance measure such as service level or probability of satisfying the project by due date to verify that the later fabrication due dates are in fact a better solution.

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