AN APPLICATION OF ARTIFICIAL INTELLIGENCE PLANNER FOR BESPOKE PRECAST CONCRETE PRODUCTION PLANNING: A CASE STUDY

Vacharapoom Benjaoran[1] and Nashwan Dawood[2]

ABSTRACT

Precast concrete manufacturers are highly involved in the construction industry through the supply of bespoke products. Their workload is a complex combination of different and unique designed products, which have various delivery dates. The production process from design to manufacturing is complicated and contains uncertainties due to many factors such as: multi-disciplinary design, progress on construction sites, and costly purpose-built moulds. Lean construction concepts aim to identify and reduce all forms of wastes in the construction process including its supply chains. An integrated, comprehensive planning system called Artificial Intelligence Planner (AIP) has been proposed to improve the efficiency of the process by targeting on the production planning as a significant impact to the success of the business. Artificial intelligent techniques are used in AIP to enhance data analyses and decision supports for production planning. A case study for the implementation was conducted on a real bespoke precast concrete manufacturer. The difference between AIP and this factory setting was attended. Data from the studied were reformatted and the AIP configuration was customized. Finally, the successful implementation has showed the adaptability and flexibility of AIP to the real production conditions, and it has given the improvement of the resulted production schedules. The anticipated outcomes are the shortened customer lead-time and the optimum factory's resource utilization. These consequently make the construction process lean.

KEY WORDS

Bespoke precast concrete products, Production planning, Genetic algorithm, Neural network.

INTRODUCTION

The precast concrete industry is a major supplier of off-site prefabricated components to the construction industry. The construction of a building can be regarded as an assembly of hundreds of bespoke precast concrete components, some of which have different and unique designs and delivery dates. 'Bespoke' precast concrete production has a major distinction from ordinary 'mass' production that is, it constantly requires new product design. Variations in the demand of precast components also create a complexity in the planning of concrete production in terms of efficient resources utilization (Ballard et al., 2002). Since the production is less uniformity, the 'learning curve' is hard to establish and the automation is hardly implemented to assist the process. Therefore, the production planning process requires sophisticated managerial skills and becomes a key of the success of the delivery program, customer lead-time competitiveness, and the effective utilization of purpose-built moulds.

Many research studies consider the way to achieve lean in construction not only need the effort on the construction site but also the supply chain of construction projects. This includes precast concrete manufacturers who typically have a major role of supplying precast concrete components. Ballard and Arbulu (2004) revealed close relationships and effects between the prefabrication and construction processes. Sacks (2004)

1 Researcher, Centre for Construction Innovation and Research, University of Teesside, Middlesbrough, TS1 3BA, UK, +44 (0) 1642-342406, FAX +44 (0) 1642-342401, b. vacharapoom@tees.ac.uk

2 Professor, Centre for Construction Innovation and Research, University of Teesside, Middlesbrough, TS1 3BA, UK, +44 (0) 1642-342405, n.n.dawood@tees.ac.uk

suggested that a global benefit across multi-parties of construction projects should be focused as a goal rather than aggregate benefit.

The aim of this research is to develop an innovative (semi-automatic) planning system to manage bespoke precast concrete production called the '*Artificial Intelligence Planner*' (AIP) (Benjaoran et al., 2004). The AIP system and the operations of its components are briefly described in the next section of this paper. This paper is mainly focused on the application of the proposed system to a real case study, which is the bespoke precast concrete production of a UK leading manufacturer.

ARTIFICIAL INTELLIGENCE PLANNER (AIP) APPROACH

AIP's operations start from preparing input data and finally arranging production schedules. The system adopted artificial intelligence technologies (neural network (NN) and genetic algorithm (GA)) to assist the process of production planning. Figure 1 shows the main components of the system, which are: information inputs, main production processes and information outputs.

Primary information inputs of the proposed system are generated from external sources (project designers and contractors of construction projects). This can be project drawings, product specifications, and construction schedules. The main production process includes product design, productivity estimation, production planning, and manufacturing. Three main AIP components have been developed namely: '*Graphic data Extractor*' (GDE) to assist the product design; '*Processing-Time Estimator*' (PTE) for the productivity estimation; and '*Production Scheduler*' (PS) for the production scheduling. Also, the AIP system implements data integration technology through the central database to manage historical and current project data. The ultimate outputs of the system can be a high quality production schedule that satisfies short customer lead-time, effective factory resource utilization, and satisfaction of delivery requirements.

PRODUCT DESIGN WITH GDE

The product design is a key task of the bespoke production. It generates unique designs of products. This crucial information then is used by the downstream production process. The quantity taking-off task is considered as an intermediate process that transfers product information from designs to production planning and the task itself is time consuming (Ogunlana and Thrope, 1991). There are some researchers who recognized this problem and developed a system for automating this quantity taking-off task. A study has applied AutoCAD features of organization of drawing elements to retrieve the product information from

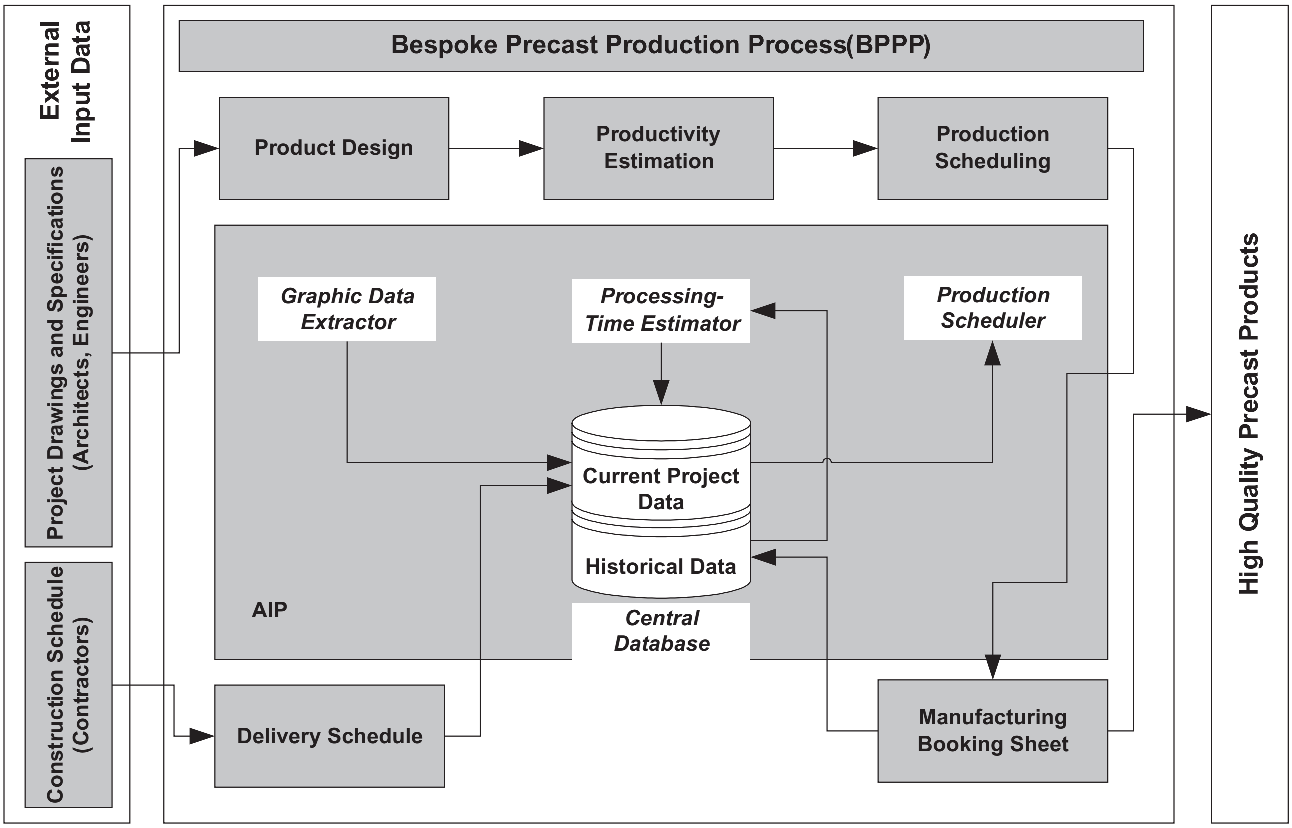

Figure 1: An Overview Flowchart of the 'Artificial Intelligence Planner' System

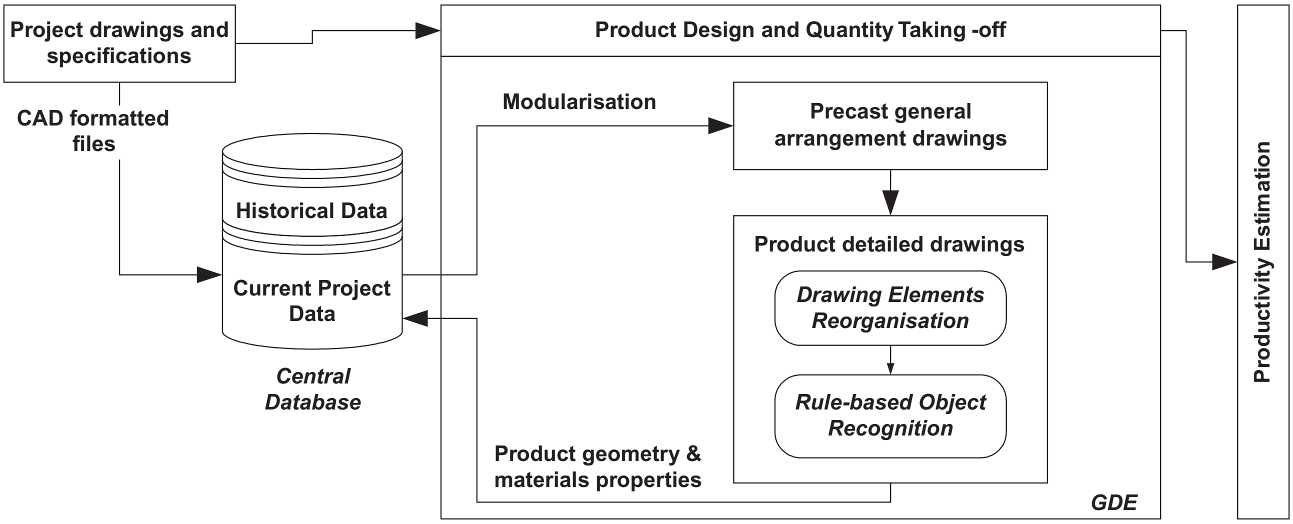

Figure 2: An operation procedure of 'Graphic Data Extractor'

2D drawings (Eben Saleh, 1999). Another proposed a new method of modeling 3D CAD product data from horizontal and vertical viewpoint 2D drawings for the purpose of material quantity taking-off (Kim et al., 2002).

GDE is initiated to automatically extract targeted product information regarding products' geometry and material properties from their drawings. Figure 2 shows the operation procedure of GDE. GDE draws on the CAD objects identification technology of AutoCAD and rule-based object recognition that was assimilated from the quantity surveyors' professional knowledge and experience. The methodology is to reorganize all CAD *drawing elements* into referable categories, which the object recognition rules can be applied. This extracted information will be used for the productivity estimation.

PRODUCTIVITY ESTIMATION WITH PTE

The productivity estimation of precast concrete manufacturing routines is a necessary task before being able to arrange production schedules. A large variety of bespoke product designs results in requiring their own different manufacturing time. The current practice of this task relies on estimators' implicit knowledge which is experience and intuition based. It is difficult to share this valuable knowledge within the company. Within PTE, a neural network (NN) has been adopted to formulate a productivity estimation model. The model is used to map the obscure mathematical relationships between the productivity of manufacturing tasks and their own influential factors. These relationships are built upon historical project data and are used to estimate productivity values of the new project. Figure 3 shows the operation procedure of PTE. It is difficult to exhaustively determine all factors affecting labor productivity. Many productivity models that have been proposed by previous literature have different sets of these factors. Previous studies (Sonmez and Rowings, 1998; AbouRizk et al., 2001; Thomas et al., 2003) have proposed their models for the on-site construction tasks considering influential

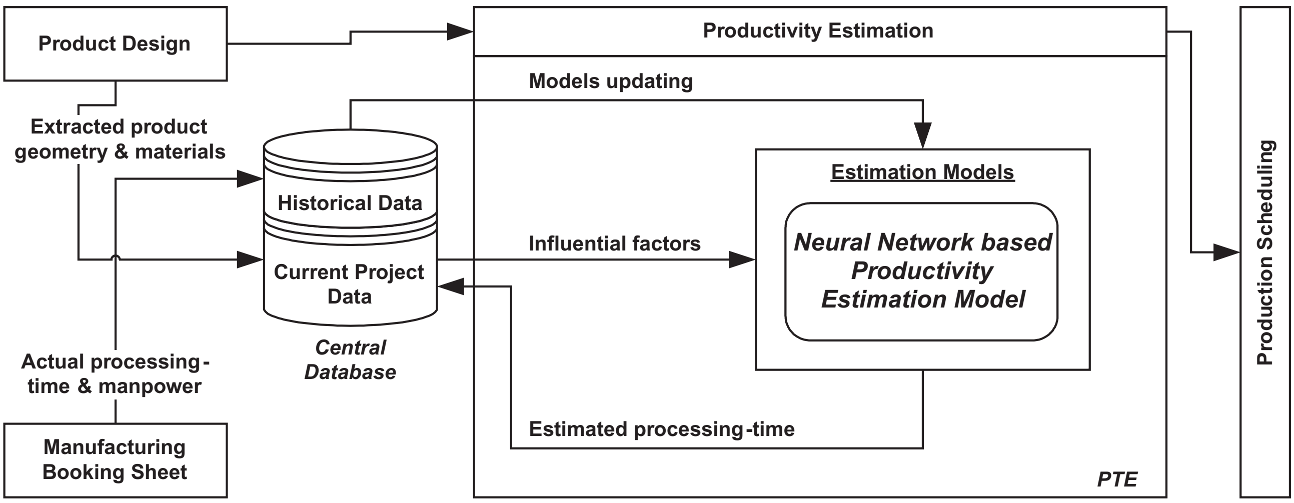

Figure 3: An operation procedure of 'Processing Time Estimator'

factors largely based on the variation of the working environment regardless building designs.

However, bespoke precast concrete manufacturing is executed in a more controlled working environment but it has a very large variation of product designs. The difficulties in product designs should contribute important influences. This research study identified influential factors mostly based on the difficulty and variation in their custom designs regarding product geometry, materials, and manpower. The values of these influential factors are already extracted and prepared by GDE as stated before. The outputs are the estimated processing-time values for accomplishing the manufacturing tasks.

PRODUCTION SCHEDULING WITH PS

The production planning is very complicated and has a high impact on time and cost of the production program. However, the current practice of production scheduling is much simplified by applying the earliest due-date sequencing rule. Precast concrete manufacturing consists of many repetitive routines and each product is independent without obvious logical precedence. Pioneering researchers (Chan and Hu, 2002; Leu and Hwang, 2001) have proposed scheduling methods for the precast concrete manufacturing using the '*flowshop scheduling model*' and the GA approach for the optimization.

The principle of the flowshop scheduling (Johnson, 1954) has been adopted to formulate a scheduling model particularly for '*bespoke*' precast concrete manufacturing and using a genetic algorithm for the optimization. Figure 4 shows the operation procedure of PS. This model has included mould reuse considerations since types and available numbers of moulds have impacts to the production cost and time. The moulds are costly and purpose-built in a limited number. Bespoke precast concrete products are tied to specific delivery dates which usually correspond to the construction progress on sites. It is important that the production schedule must be attempted to satisfy all product delivery dates.

The directive routines of bespoke precast concrete manufacturing process which are activities associated with the casting procedure are included into the flowshop scheduling model. They are namely mould modification, mould preparation, concrete pouring, curing, mould stripping, and finishing. These routines have their own special characteristics and work logics which are modeled accordingly with a set of complicated mathematic equations (Benjaoran and Dawood, 2004). The GA-based optimization then randomly arranges job sequences and evaluates them with the multi-objective function. This procedure is repeated numerous times until optimum solutions (or near) are found. The optimum job sequences are allocated into a factory's timetable with regard to the existing workload. The outputs of PS are efficient production schedules and a decision support for utilizing factory's resources such as moulds and manpower.

A CASE STUDY OF AIP APPLICATION

A case study was conducted on a bespoke precast concrete company in the UK referred as 'X'. The objective of the case study is to evaluate the possibility of the implementation of the proposed AIP system on this company and to benchmark the system results. The difference between the model assumptions and the real implementation is expected on any development. Therefore, this trial implementation is needed to be conducted. AIP is put to the test here.

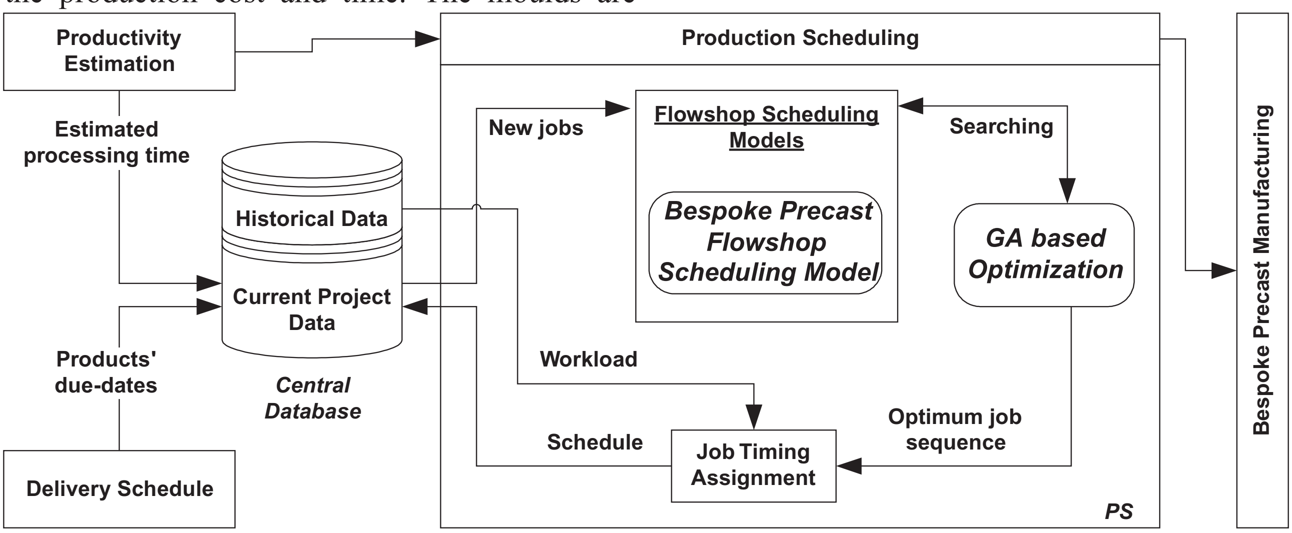

Figure 4: An operation procedure of 'Production Scheduler'

BACKGROUND OF THE COMPANY

Real life production data was collected from company 'X' for being the system inputs. Some adjustments for this case study have been made and described as follows. Company 'X' uses semi-dry cement mix in the casting and therefore moulds can be stripped off their side forms immediately after the final compaction. The cast-units can support their own weight and maintain their shapes. The finishing or surface repairing process will be proceeded straight away. Therefore, the side forms of the moulds can be reused on the next unit and the new casting cycle begins. The manufacturing model of AIP was formulated from the traditional casting process which is using ordinary concrete and requires concrete hardening time. Moulds reuse consideration in the scheduling logic is not applied on this case study because of the advantage of immediately mould stripping. The mould availabilities of all types were set as infinite numbers in PS. The waiting time due to mould occupation is eliminated.

Another area of the differences, the manufacturing model of AIP includes three crews working together to complete the whole manufacturing process. There are six consecutive manufacturing routines that form scheduling logics of the model. In this case study of 'X', these manufacturing routines are reduced to two: mould preparation and casting. They are executed by two crews: joiners and casting workers. These two routines form a working cycle that complies with the flowshop scheduling concept. PS input for the other four routines was left blank. None or simple reinforcement can be inserted in between of the pouring routine so that there is no reinforcement cage installment before pouring. The curing routine which could have taken a long time in the middle of the manufacturing process is not applied in the scheduling logics because moulds are not occupied during the curing routine.

Also, 'X' records their casting crew productivity in term of man-days while PS requires this in term of hours. there is no detail record of each casting routine because any worker completes all the routines individually and continuously. The productivity rates of manufacturing routines are estimated by experience using constant factors to covert job quantities (tons) into required man-day unit. Given their product designs are in general simple shapes, the difference and difficulty of designs which could affect the productivity rate is not concerned. From the historical data analysis (two months period of actual production), the error from this estimation is small (less than 5%). PTE is considered as unnecessary for this case study.

APPLICATION OF AIP

The production data are prepared in a two-week period (collected from historical records from 30 August to 13 September 2004). There were 46 bespoke jobs released in this period. After the system customization and data preparation, all data input are fed into PS to start the scheduling optimization. There are three sets of schedules to be compared as shown in Figure 5 and 6. The first schedule is arranged from the Earliest Due Date (EDD) rule which is the current standard scheduling technique. The second schedule is from the actual production record and the last one is the optimum from the AIP result.

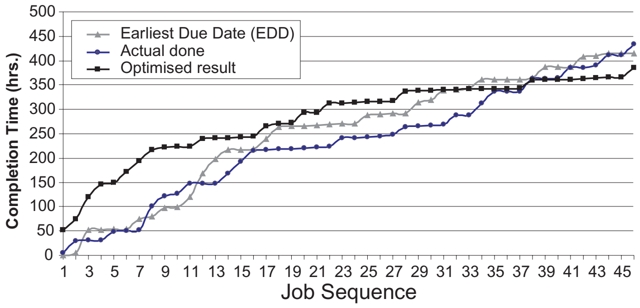

Figure 5: Completion Time Comparison of Scheduling Results

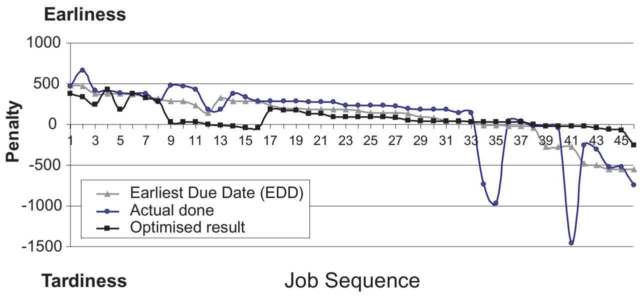

Figure 6: Earliness and Tardiness Penalty Comparison of Scheduling Results

Six objective functions are used to evaluate and compare the three schedules. Total-flowtime is a summary of all product completion time. It can show how well the factory resources have been utilized. Machine-idle-time is a total waiting time of all working stations. Total-penalty of earliness and tardiness is a total penalty of early or late completion of products from their due dates. Makespan is the length of production to complete all released jobs. The others are the number of products which are early and late finished, respectively. All the objective functions are subjected to the minimization which means the less values of the multi-objective function the better the schedule is. However, some of these objective functions are in reverse relationships. It is impossible that any schedule will achieve all function values at minimum. The result graphs (Figure 5 and 6) show that the optimized schedule has the least makespan and total-penalty but it has a slightly higher total-flowtime. These result values are opposite to the values of the actual-done schedule.

Table 1: A Summary of Scheduling Results

Objective functions	EDD	Actual done	Optimised
Total Flowtime	11673	10626	12990
Machine Idle Time	584	604	555
Total Penalty	11156	15683	5003
Makespan	415	435	386
No. of early finish	33	35	32
No. of late finish	13	11	14

The summary of three scheduling results is shown in Table 1. The EDD schedule does not give the best results as the values of objective functions are in-between values of the other two schedules. It also does not guarantee the lowest number of late finish units because this value is still high as 13. It reveals that to execute the jobs in EDD sequence may result in a high total-penalty (even not the highest) with many early or late jobs. In addition, many jobs are executed too early and unnecessarily waiting in the stockyard.

In comparison, the actual-done gives relatively poor schedule result. The actual-done schedule tends to execute easy jobs (without waiting and required less processing time) first. This results in the smallest total-flowtime value but a very high (the highest) total-penalty value. In addition, its makespan is the highest. The actual-done schedule is considered a less effective one. The optimized schedule gives a considerably low and the least total-penalty. It tends to execute most jobs just slightly earlier than their due dates but some of them are still late finish. This results in a slightly higher total-flowtime. Although the optimized schedule gives the highest number of late finish units, it can still give very low and the least the total penalty. On average this optimized schedule is the best result out of the three because its all objective function values are relatively low to the lowest.

This successful AIP application on 'X' has shown the adaptability and flexibility of AIP and its possibility of real implementation. Benefits of AIP still can be seen on this case study. The important backbone part of the AIP is the data integration through the central database. That helps to automate the production planning process. Interoperability between the coordinated departments that involved in the production process can be achieved. Improved schedules result with more efficiency in term of time resource.

CONCLUSIONS

The paper proposes an innovative production planning system for bespoke precast concrete products. The proposed AIP is a decision support system, which adopts artificial intelligence techniques: genetic algorithm (GA) and neural network (NN) to alleviate the complexity in bespoke precast concrete production. The system consists of three components for assisting different tasks namely: GDE for the product design, PTE for the productivity estimation, and PS for the production scheduling. They are integrated together through the central database.

After AIP has been developed, a bespoke precast concrete company (referred as 'X') was selected to be a case study of the trial implementation. This company has different details of production process from the configurations of AIP model but they are sharing the same bespoke production style. The differences of them were described and attended. General comparison concluded that this company is a simplified version of AIP. The collected actual production data were reformatted before being input of AIP. The result showed that GDE can extract the targeted product information well from the reorganized product drawings as it has been designed and developed for. Schedule results from PS (or the optimized schedule) were compared with the EDD and the actual-done schedules. The result from PS showed relatively better than the other two. This case study shows the successful AIP application on another company settings and it helps evidence the generalization of the AIP for the real implementation.

AIP is an add-in program that is developed with widely-used application software such as MS EXCEL, MS ACCESS and AUTOCAD. Prospective users can easily familiarize themselves with the AIP program interface combined with the existing features of those software applications. It helps convince precast companies to actually adopt AIP systems.

The optimum production schedules that are resulted from AIP can increase the reliability of delivery services of precast concrete manufacturers and shorten the lead-time of bespoke products. Consequently, construction operations which require offsite-components can reduce their wasting or buffer time and progress more efficiently, and the construction process can be kept lean.

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