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Schedule risk modeling in prefabrication housing production

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Abstract

Every country is dealing with its own housing problems; however, none compares with Hong Kong where housing has always been a major concern as a result of low supply over the past decades. Against the constraints in delivering sufficient houses, prefabrication as a sustainable solution for housing has been increasingly advocated for its potential merits of better quality, construction safety and cleaner built environment. However, schedule delay caused by various risks affected the prefabrication housing production (PHP) in Hong Kong. This problem can be further worsened when the manufacturing sector of PHP has entirely moved to offshore areas in the Pearl River Delta region. This study applies system dynamics to recognize and investigate the potential effect of various risks on the scheduling of prefabrication housing construction projects through the employment of Vensim software package. The simulation results show that schedule risks, namely low information interoperability between different enterprise resource planning systems (LIIBDERPS), logistics information inconsistency due to human errors probability (LIIHEP), Delay of delivery of precast element to site (DDPES), and Design information gap between designer and manufacturer (DIGDM) significantly contribute to the schedule delay in PHP. However, schedule is more sensitive toward LIIBDERPS than for the other three risks, indicating that LIIBDERPS should be monitored and given priority. The system dynamic model serves as an effective tool for quantitatively evaluating the effect of various risks on the schedule of PHP, offering valuable references for managers though comparing simulation results under different risk scenarios, so that potential risks that might lead to schedule delay could be identified and handled in advance.

1. Introduction

Every country is dealing with its own housing problems, but none compares with Hong Kong where houses have always been a concern to most local citizens for the past serval decades. A number of 2,671,900 permanent residential flats were in stock as of the end of 2014, of which 1,496,500 (56%) were private flats, 781,500 (29%) were public rental housing and 393,900 (15%) were subsidized housing (Department, 2015). On the demand side, as of end of December 2015, public rental housing has about 147,000 general applications, and the average waiting time for general applicants was 3.7 years (Authority, 2016). The Hong Kong Housing Authority reiterated an ambitious housing plan to supply 93,400 public housing rental units until 2020 (Authority, 2016). However, Hong Kong is suffering from a series of constraints including safety, time, environmental protection and labor shortages to deliver housing plans. Against this background, prefabricated construction as a solution is envisioned to be increasingly accepted as main construction method in Hong Kong.

Potential benefits cannot be supported without overcoming its inherent drawbacks of fragmentation, discontinuity, and poor interoperability, which raise a range of risks that have adverse influence on the schedule performance of prefabrication housing production (PHP). To help address encountered schedule delay problem in PHP, many excellent researchers have looked into riskrelated issues and contributed to the body of knowledge of the management of PHP (Wang et al., 2014, 2015; Li et al., 2016a,b). However, these studies only consider risks from static and isolated perspectives, despite that these risks are coherently interrelated with each other and might vary along with time. Moreover, most previous research also does not take sufficient consideration into their quantified influence on the schedule of PHP and fail to predict potential delays through simulations (Li et al., 2014a,b; Tam et al. 2007, 2014; Uttam and Le Lann Roos, 2015). To fill the research gap and meet with the practical industry need, this study proposes a dynamic model to assess and simulate potential risks found in four major prefabrication construction processes, employing the system dynamics (SD) method. The objectives of establishing this evaluation model include (1) exploring interactional, interdependent, and complicated relationships underlying the risk factors that have significant influence on the schedule performance of PHP; (2) evaluating and simulating the effect of identified risks on the schedule of PHP; (3) comparing and analyzing the potential effect on the schedule of PHP under different risk scenarios.

2. Research background

2.1. Prefabrication housing production (PHP) in Hong Kong

Most house construction in Hong Kong still applies traditional construction technologies characterized by bamboo scaffolding, cast-in-situ, wet trades, falsework and formwork, fixed jobsites and labor intensive. Though conventionally construction technologies like wet trades and cast in-situ may have their own benefits such as high flexibility to design changes, they have received extensive criticisms. The Construction Industry Review Committee (CIRC) systematically reviews current development in the construction industry in Hong Kong and recommends enhancement measures to raise the quality and performance of local construction. The report, named construct for excellence, critically pointed out the problems surrounding the construction industry of Hong Kong, including but not limited to: disappointing environmental performance, incompetently trained labor force, and poor record of construction site safety. As a result, the wider use of precast components was proposed as a prime measure to enhance the performance of the construction industry in

Hong Kong. In comparison with traditional housing production technologies, prefabrication construction has the following benefits: (1) Better on-site construction environment as a result of reductions dust and noise, construction waste (Tam et al., 2015), water and air pollution, (Hong et al., 2016); (2) Compressed construction schedules as the change of the sort of work flow, for instance, allowing foundations being poured on-site for while the precast components are assembled offsite at the same time (Tam and Hao, 2014); (3) Easier for quality control, labor supervision and fewer material deliveries (Li et al., 2016a,b); (4) Fewer losses as a result of misplacement of materials and less requirements for on-site material storage (Lu et al., 2011); and (5) Safer working environment for worker through reducing dangerous operations, e.g., components traditionally constructed on-site at heights or in confined spaces can be fabricated offsite and then hoisted into place using cranes(Ingrao et al., 2014).

2.2. Literature review on prefabrication

Existing research on the management of prefabricated construction (MPC) can be categorized into four parts, namely, vertical relations, benefits, challenges and promoting approaches. Vertical relations are analysed based on the characteristics of MPC: 1) relationships, where buyer-supplier relationships have received wide attention (e.g., Bildsten, 2014; Doran and Giannakis, 2011; Hofman et al., 2009) because of the significant role of suppliers in guaranteeing stable and high-quality supply for production, while clientcontractor relationships are also claimed to be important for improving the efficiency of MPC by reducing variations in the onsite installation stage (Doran and Giannakis, 2011); 2) structure, where make-to-order and engineer-to-order are the major strategies adopted in supplying prefabricated products. Make-to-order is usually used for supplying standard or configurable components for production (Cheng et al., 2010) and can provide effective support for the management of logistics chains (Court et al., 2009), while engineer-to-order provides clients with diverse products which are developed according to completely new designs (Gosling and Naim, 2009) and the management process is relatively more difficult due to the complex information flows (Ergen et al., 2007); 3) results, referring to mass customization of the housing sector as a consequence of long-term and efficient development of MPC. Regarding the benefits, the literature points out that effective MPC can help increase the productivity (Demiralp et al., 2012; Sungkon et al., 2015), enhance quality management (Ikonen et al., 2013) and reduce waste generation (Lu and Yuan, 2013). MPC, however, presents significant challenges due to lack of experienced stakeholders (Mao et al., 2014), lack of prefabrication-related skills and knowledge and limited supply capability (Blismas and Wakefield, 2009), indicating the fragmentation of the supply chains. Some approaches are proposed in order to promote SCM for prefabricated construction, such as information technologies (Cu s-Babic et al., 2014), technological innovation (Chiang et al., 2008), planning systems (Bergstrom and Stehn, 2005€), and coordination mechanism (Cu s-Babic et al., 2014; Xue et al., 2005).However, although previous studies have contributed to the knowledge base on the management of prefabricated construction, studies on schedule risk-related issues in the implementation of prefabrication are limited. While various risks occur along the whole process of PHP processes and have vital influence on the successful delivery of prefabrication housing projects. Moreover, a consensus on the complexity of risks in prefabrication construction exists because of its characteristics including dynamics, uncertainty, and mutual interaction, while previous research regarding risk management considers risks from a static and isolated perspective. For example, Luu et al. (2009) explored major cause-effect relationships among identified schedule risks through expert interviews;

DavisMcDaniel et al. (2013) applied event-fault tree for risk assessment of bridge failure; Kim et al. (2009) described how Bayesian belief network is applied to quantify schedule risks. They considered little about the dynamic changes during the construction period. Moreover, they neglect the fact that interactions between risks are increasing and strengthening along with the prefabrication construction, which increases the difficulty of risk management and leads to project delays (Li et al., 2016a,b). From this aspect, systematic analysis can help managers gain a better understanding of system essence, function, and behavior, as well as interaction with the environment. Therefore, this research adopts the SD method for analyzing and evaluating the potential effect of various risks on the schedule of PHP from the dynamic and mutual interaction perspective, to fill the current research gap and provide a practical tool for simulating schedule variation in prefabrication housing projects.

3. Methodology

Originated by Forrester in the 1960s, SD is a science that emphases on the structure of complex systems and the relationship between dynamic behaviors and function based on computer simulation technology and the theory of feedback control (Forrester, 1968). SD has been applied in a wide variety of research fields for macro analysis and management, such as economic development (Meadows et al., 1972; Tauheed and Wray, 2006), military system management (Fan et al., 2010; Moffat, 1996), energy and resources management (Ansari and Seifi, 2013; Aslani et al., 2014; Ford, 1996), and urban planning (Fong et al., 2009; Shen et al., 2009; Xu and Coors, 2012). Construction project management mainly includes two levels: strategic project management from macro level and operational project management from micro level. (Lee et al., 2006; Pena-Mora et al., 2008~). Strategic project management focuses on scheduling, budgeting, and resource allocation, and contains a significant number of feedbacks. Take schedule delay for example, schedule delay tends to increase pressure to workers; pressure exceeding a certain level could reduce work efficiency; with continuous decrease in work efficiency, the construction rate would decline, and finally increase schedule delays. SD methodology specializes in handling with these strategic level relationships in a complex system because it can simplify these feedback relationships into operable units through the use of causal loop diagrams and stock flow diagrams from a multi-dimensional and dynamic perspective. Compared with static method, such as fault tree analysis, bayesian belief network, influence diagram and analytic hierarchy process, SD can not only deal with complexities and interactions inherent in construction system, but also can reflect the uncertainty of schedule risks. Therefore, this study uses SD as the main method to investigate the influence of risk on the schedule of prefabrication construction from a strategic perspective.

Generally, five steps are needed for developing an SD model as shown in Fig. 1, which includes: (1) Determining the boundary of system; (2) Mapping casual loop diagram to depict relationships underlying identified variables; (3) Transforming casual loop diagram into stock flow diagram to build model for quantitative analysis; (4) Implementing tests direct structure test and structureoriented behavior test to build up confidence for the developed model prior to simulation analysis; (5) risk scenario analysis that comprises a base run simulation and scenario simulation will be performed to investigate possible impact on the schedule of PHP under various risk scenarios.

4. Model development

4.1. System boundary

Different system boundaries will generate different system structures and behaviors. System boundaries should be defined clearly to facilitate the system modeling process as well as meet research objectives. This research divides the SD model into three subsystems: prefabrication supply chain subsystem, schedule risks subsystem, and schedule performance subsystem. The relationship between the three subsystems is shown in Fig. 2.

(1) Prefabrication housing production subsystem

Prefabrication housing construction is known as off-site construction, which refers to structures built at a different location than the construction site (Gibb, 1999). Therefore, prefabrication housing construction has a unique supply chain, which includes design, manufacture, storage, transportation, buffer, and assembly on site. Specifically, in the design process, the client will hire an architect, a structure engineer, and a services engineer to do the design, with special considerations to structure safety, buildability, and even transportation convenience. Then, the design information will be transmitted to the manufacturing company to produce precast components before storage. Once the transportation order is received, the logistics company would transport the components from storage to the buffer of the construction site. In the end, these components will be installed by an assembly company. As can be seen, the prefabrication supply chain is significant in the prefabrication housing construction.

(2) Schedule performance subsystem

Schedule performance subsystem mainly includes two parts, namely, planned schedule and actual schedule. Comparing them would make it easy to determine whether schedule delay occurred or not. If the actual schedule is consistent with the planned schedule, the project will have good performance; otherwise, the project will have poor schedule performance.

(3) Schedule risks subsystem

Based on literature review and expert interviews, schedule risks influence schedule mainly from three aspects, namely, project scale, resources, and management (Lee et al., 2009; Nguyen and Ogunlana, 2005; Wang and Yuan, 2016). Resources refer to all labor, materials, and machinery, which are needed in the whole supply chain. A housing construction can only be carried out easily with adequate resources. Restriction in resources would affect the project schedule. Resources can be directly affected by schedule performance subsystem and influence prefabrication supply chain subsystem. For example, the schedule performance subsystem encounters a schedule delay; it needs to increase the number of resources to finish the job faster. In return, increase in resources will accelerate construction rate and reduce schedule delay. Project scale indicates special quantities of housing construction. Project scale changes are common in the construction market. Owner's demand changes, design drawing changes, and changes in specific construction conditions would lead to project scale changes. Project scale changes would cause the change in resource demand, and may lead to schedule delay. Management is mainly associated with quality problems. Quality problems would entail rework, which could lead to schedule delays. Therefore, management is interrelated with schedule performance subsystem. In addition, completing the job faster may increase the occurrence of project quality problems and installation error rate; hence, management can also be interrelated with prefabrication supply chain subsystem.

4.2. Causal loop diagram

Based on the analyses above, the causal-loop diagram, which depicts the interrelations underlying various variables, can be drawn, as shown in Fig. 3. Four positive feedbacks and three negative feedbacks are defined within the diagram.

Feedback 1. An increase in the number of precast elements to be installed will raise the number of installed precast elements; and subsequently, the number of inspected precast elements increases, which leads to increase in the number of defective precast elements to be reinstalled. The more work completed, the more mistakes will be found. Finally, more defective precast elements to be reinstalled will lead to an increased number of precast elements to be installed. Feedback 1 has four positive correlations, and is considered positive feedback. If feedback 1 is not controlled, its variables will continuously increase, which will cause serious schedule delay.

Feedback 2. Feedback 1 and Feedback 2 have almost the same framework apart from one variable, quality problem. The more precast elements inspected, the more quality problems are found, which will raise the number of precast elements to be installed. Feedback 2 also has also four positive correlations, and is considered positive feedback.

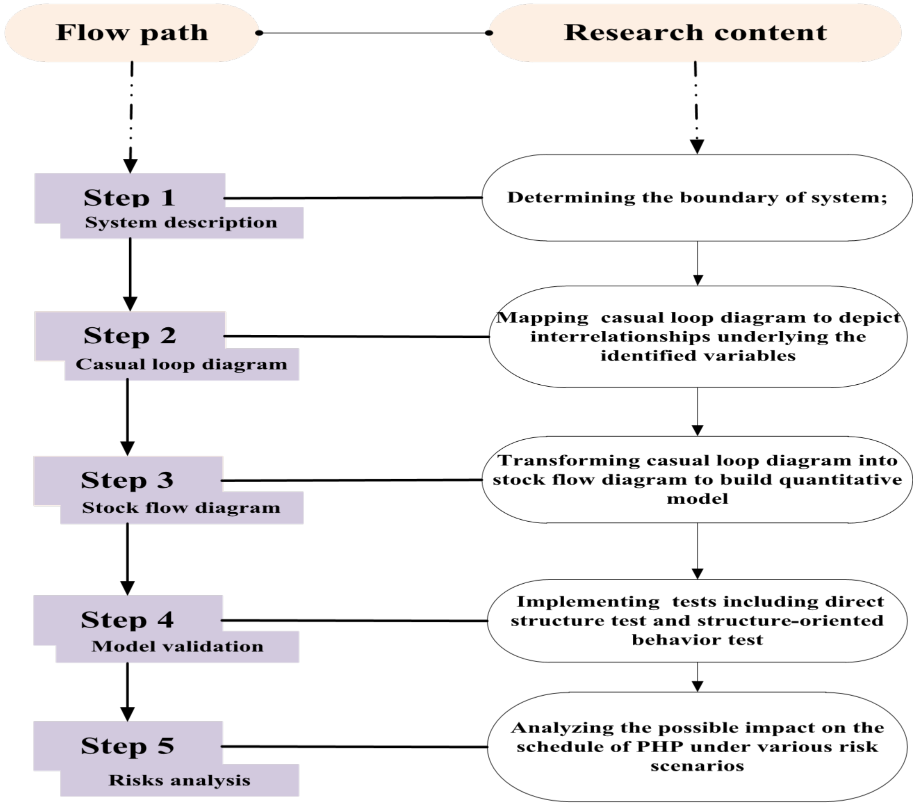

Fig. 1. Research flow.

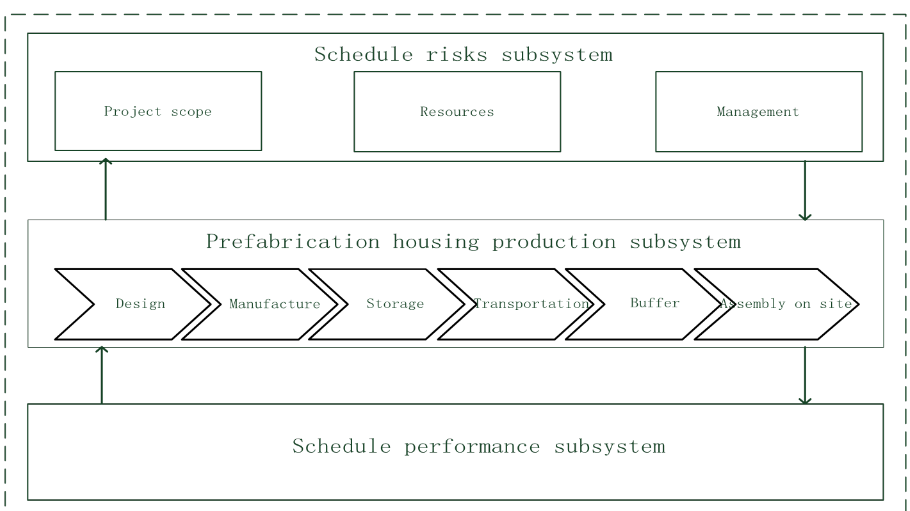

Fig. 2. The relationship between the three subsystems.

Feedback 3. The increase in the number of inspected precast elements increases will contribute to the installation percentage. If the installation percentage is in line with the planned installation percentage, a good schedule performance is expected. Otherwise, it will lead to schedule delay, which results in more pressure. According to the related study, the relationship between pressure and efficiency could be described as an inverted U-shaped curve, which shows that proper pressure will increase work efficiency. However, if pressure exceeds a certain level, construction efficiency will decrease; and subsequently, the number of precast elements to be installed will decrease, which will finally reduce the number of inspected precast elements. Feedback 1 has four positive correlations and two negative correlations, which are considered positive feedback.

Feedback 4. Apart from resulting in more pressure, bad schedule performance can also change the management strategies of project managers. As the schedule delay increases, the project manager will input more resources (including labor, material, and mechanical resources),

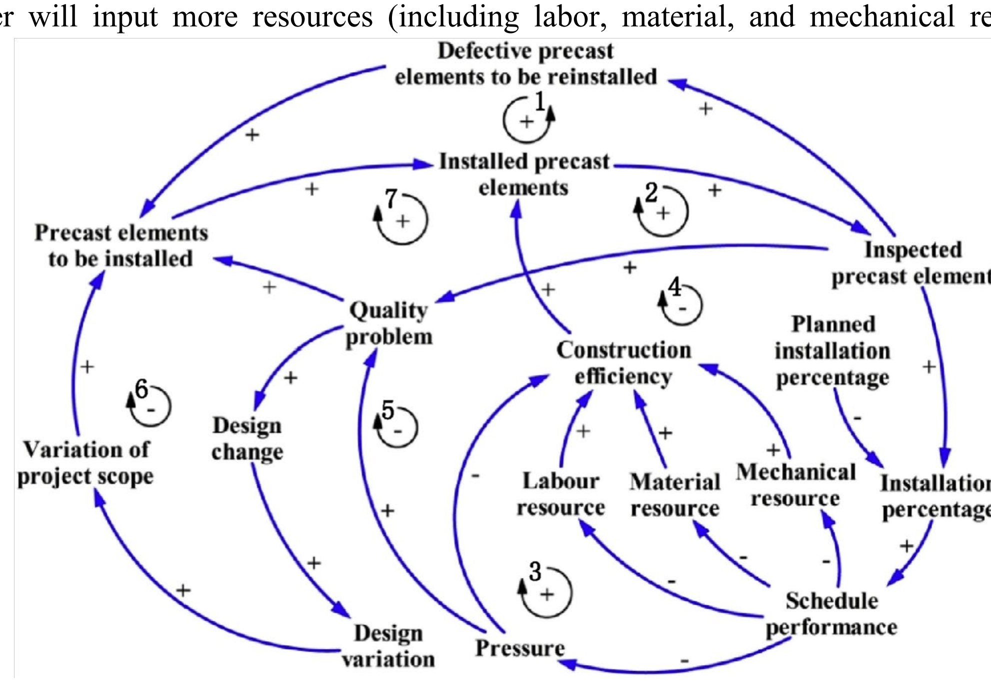

Fig. 3. The causal-loop diagram of system dynamics.

which can rapidly improve construction efficiency. The rest of feedback 4 (from construction efficiency to schedule performance) is the same as that in Feedback 3 so that feedback 4 has five positive correlations and one negative correlation, and is considered negative feedback.

Feedback 5. Supposing an increase in the amount of pressure, then the possibility of quality problem in construction will increase, which would also increase the number of precast elements to be installed and installed precast elements accordingly. The correlations from installed precast elements to pressure in feedback 5 are the same as that in Feedback 3. Therefore, Feedback 4 has six positive correlations and one negative correlation, and is considered negative feedback.

Feedback 6. The increase in the number of quality problems will cause design variations; and subsequently project scope variation will expand, which leads to increase in the number of precast elements to be installed. The rest of feedback 6 (from precast elements to be installed to quality problems) is the same as that in Feedback 2. Feedback 6 has six positive correlations; thus, feedback 6 is a positive feedback.

Feedback 7. The correlations from installed precast elements to quality problems in feedback 7 are the same as Feedback 5 and the correlations from quality problem to installed precast elements are the same as Feedback 6. In general, Feedback 6 has eight positive correlations and one negative correlation so that Feedback 6 is a negative feedback.

4.3. Stock-flow diagram

After interpreting interrelationships among variables through the causal loop diagram, stock-flow diagram will be developed with the use Anylogic software to quantitatively evaluate their potential impact of the Schedule of PHP, as shown in Fig. 4. Basically, compared with the casual loop diagram, stock-flow diagram is another form of model with more detailed information regarding system behavious to be modelled (Yuan, 2012; Yuan et al., 2012). Previously defined relationships in the causal loop diagram will be converted in the stock-flow diagram for quantitative evaluation through adding back auxiliary variables. The developed stock-flow diagram is presented along with brief definitions of variables in the model, as shown in Table 1.

Data collection was carried out mainly through two sources. One is by referring to various literature, internet web page, and reports from government departments. The other is by conducting on-site surveys toward a practical project located at Tuen Mun in Hong Kong, as shown in Fig. 5. The Tuen Mun project proposes to build five 34e38 storey buildings, providing about 5000 units with the expectation of holding more than 14,000 people. The construction practice of Block 5 is taken as a case study for the developed model. The studied building has a construction area of 15815 m^2, consisting of 37-story residential buildings, with the expected project duration period of 509 days. Moreover, to determine the values of some qualitative variables influencing the prefabrication construction process, serval around of interviews are conducted with designed questionnaire.

4.4. Model validation

Prior to further analysis, testing the validation of SD model, which contains model structure test and model behavior test, is crucial. Model structure test includes direct structure test and structure-oriented behavior test (Barlas, 1996; Barlas and Kanar, 2000). Direct structure test, including structure confirmation test, parameter confirmation test, boundary adequacy test, and dimensional consistency test, checks the validity of the SD model by comparing the model structure with real system structure to help calibrate the model to fit real world situations (Barlas,1996; Lee and Pena-Mora, 2007~). The structure-oriented

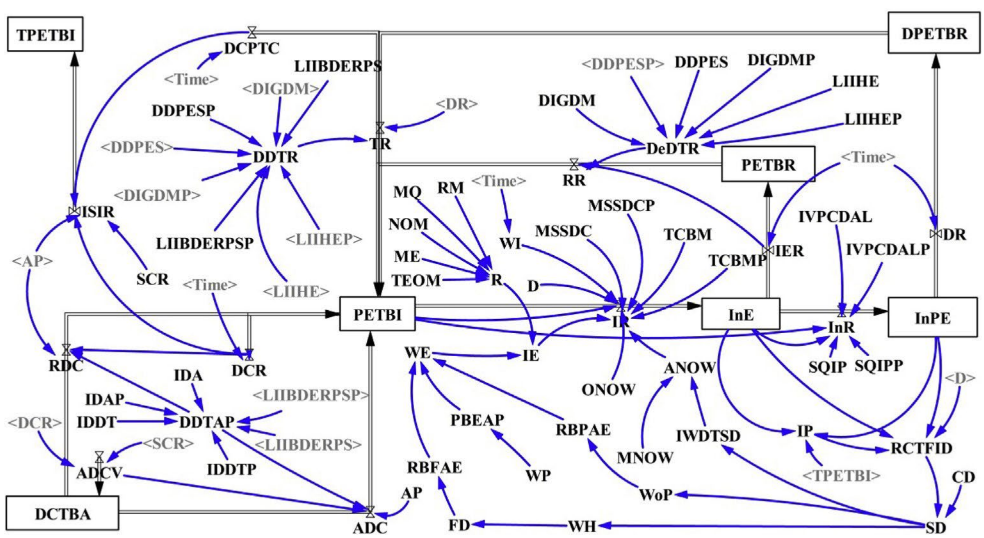

Fig. 4. Stock-flow diagram of schedule risk simulation system.

behavior test combines the advantages of structure test and quantitative test, with the aim of making the model more convincing. It includes an extremecondition test, behavior sensitivity test, and integral error test (Barlas, 1996). In general, major testing includes: (1) structure confirmation test, wherein the model structure should be in line with relative descriptive cognition; (2) parameter confirmation test, wherein the parameter should have specific meaning in the actual project; (3) boundary adequacy test, wherein the model should contain all important variables corresponding to research purpose; (4) dimensional consistency test, wherein the model should have no meaningless parameters; (5) extreme-condition test, wherein the model should be reasonable even under extreme conditions; (6) behavior sensitivity test, wherein all sensitive parameters should have high accuracy; (7) integral error test, wherein the model outcomes should slightly change with different integrals; and (8) model behavior test, wherein the model outcomes should be in line with the actual data;

Test 1 involves whether all cause-and-effect chains and feedback loops in the model are in line with the experience of actual system and professional knowledge. The causal-loop diagram in this research is based on mature studies (Ford and Sterman, 1998; Lee et al., 2005; Wang, 2011) that contain a multitude of cases and practical basis. In addition, an on-site survey toward a practical project had been conducted before model construction. Obviously, all cause-and-effect chains and feedback loops reflect the recognized knowledge and objective fact.

Test 2 is the process of conceptual evaluation and quantitative evaluation for constants in the actual system. All constants in this research are obtained from literature review, government reports, information from the internet, and a practical project with semi structure interviews (Lee and Pena-Mora, 2007~). Therefore, all constants meet the requirements of test 2. Test 3 requires that all important variables should correspond to research purpose. It is performed by checking whether all related variables have been embodied in the causal-loop diagram (Yuan and Wang, 2014). Through multi-round expert interviews, final variables in the stockflow diagram are closely related to the research purpose. Test 4 is performed through "units check" by manual inspection (Barlas, 1996; Yuan and Wang, 2014) and all variables should pass the test, meaning that all variables involved in the model no unit inconformity problem and all equations are dimensionally consistent.

In test 5, the model behavior is inspected under extreme conditions (Barlas, 1996). Design change and installation error are widely acknowledged to have a strong effect on schedule (Wang, 2011) to achieve 100% design change and 100% installation error. In other words, the risks of design and installation are supposed to occur with the probability of 100% and have the largest influence on the schedule of PHP, are taken as extreme conditions. Besides, a project without any schedule risks is also taken as an extreme condition. By simulation, the corresponding model behaviors (duration) are 839.85, 814.4, and 508.64 days under the three extreme scenarios, complying with practical experience of average schedule of 850, 820 and 509 days according to the interviews toward senior managers.

Test 6 is performed by observing the change in model behavior by changing the variables in a reasonable range to determine which variables are sensitive and which are not. A sensitive variable is the focus for model correction given that its change would have an assignable effect on the schedule. In contrast, an insensitive variable does not require high accuracy because of the minor change in schedule caused by its change (Wang, 2011). Considering that demonstrating all variables in test 6 is not practical because of limited space in the paper, the variables "defect rate,""installation error rate,""design change prior to commencement,""scale change rate," "delay due to approval procedures," and "delay due to reinstallation" are taken herein as examples for illustration. The five variables are assigned with three possible values, namely, the minimum value, most likely to occur value, and the maximum value, to test their potential effect on the schedule of PHP (Table 2). The minimum value stands for the most optimistic value, while the maximum indicates the most pessimistic value. Take the defect rate as an example, the most optimistic scenario is that no defect exists; thus, the defect rate has the minimum value of 0. In contrast, the most pessimistic scenario is that the number of defects is the highest, in effect the defect rate has the maximum value of 0.1.

After simulation, three kinds of indicators are attained, namely, duration, variety degree, and range of variation, as shown in Table 3. Variety degree involves two values, one is variety range of the minimum duration with respect to the most likely duration (the minimum value minus the most likely value and divide the most likely value); the other is the variety range of the maximum duration with respect to the most likely duration (the maximum value minus the most likely value and divide the most likely value). The sum of their absolute values is the range of variable. Twenty percent is set as the boundary (if the range of variation of a parameter exceeds 20%, it means that the parameter is a sensitive variable; otherwise, the parameter is an insensitive variable) (Wang, 2011) and the scale change rate is found to be a sensitive variable. Based on the above process, all sensitive variables, including scale change rate and design change request, are found and assigned with relatively accurate values.

In test 7, the original integration step of the model is set at 1 day/

Table 1

Variables in the mode.

No.	Abbrev.	Significant	Variable type
1	TPETBI	Total precast elements to be installed	Stock
2	DCPTC	Design change prior to commencement	Flow
3	ISIR	Installation scope increase rate	Flow
4	TR	Treatment rate	Flow

5	DDTR	Delay due to reproduction	Auxiliary variable
6	PETBI	Precast elements to be installed	Stock
7	RDC	Rejected design change	Flow
8	DDTAP	Delay due to approval procedures	Auxiliary variable
9	DCR	Design change request	Flow
10	SCR	Scale change rate	Auxiliary variable
11	AP	Approval percentage	Auxiliary variable
12	ADCV	Actual design change variation	Flow
13	DCTBA	Design change to be approved	Stock
14	ADC	Approved design change	Flow
15	WE	Worker efficiency	Auxiliary variable
16	TEOM	Theoretical efficiency of machine	Constant
17	ME	Mechanical efficiency	Auxiliary variable
18	NOM	Number of machine	Auxiliary variable

19	MQ	Material quality	Auxiliary variable
20	RR	Reinstallation rate	Flow
21	IR	Installation rate	Flow
22	RM	Required material	Constant
23	WI	Weather impact	Auxiliary variable
24	D	Duration	Constant
25	InE	Installed elements	Stock
26	InR	Inspection rate	Flow
27	PETBR	Precast elements to be reinstalled	Stock
28	DPETBR	Defective precast elements to be reinstalled	Stock
29	DR	Defect rate	Flow
30	InPE	Inspected precast elements	Stock
31	IP	Installation percentage	Auxiliary variable
32	IER	Installation error rate	Flow
33	DeDTR	Delay due to reinstallation	Auxiliary variable
34	R	Resource	Auxiliary variable

35	IE	Installation efficiency	Auxiliary variable
36	PBEAP	Relationship between efficiency and proficiency	Auxiliary variable
37	RBFAE	Relationship between fatigue and efficiency	Auxiliary variable
38	FD	Fatigue degree	Auxiliary variable
39	WP	Workers proficiency	Auxiliary variable
40	WH	Working hours	Auxiliary variable
41	RBPAE	Relationship between pressure and efficiency	Auxiliary variable
42	WoP	Working pressure	Auxiliary variable
43	MNOW	Maximum number of workers	Constant
44	ONOW	Original number of workers	Constant
45	ANOW	Actual number of workers	Auxiliary variable
46	IWDTSD	Increased workers due to schedule delay	Auxiliary variable

47	SD	Schedule delay	Auxiliary variable
48	RCTFID	Required current time for initial duration	Auxiliary variable
49	CD	Current duration	Auxiliary variable
50	IDA	Inefficiency of design approval	Auxiliary variable
51	IDAP	Inefficiency of design approval probability	Auxiliary variable
52	IDDT	Inefficiency design data transition	Auxiliary variable
53	IDDTP	Inefficiency design data transition probability	Auxiliary variable
54	LIIHE	Logistics information inconsistency due to human errors	Auxiliary variable
55	LIIHEP	Logistics information inconsistency due to human errors probability	Auxiliary variable
56	LIIBDERPS	Low information interoperability between different enterprise resource planning systems	Auxiliary variable
57	LIIBDERPSP	Low information interoperability between different enterprise resource planning systems probability	Auxiliary variable

58	DIGDM	Design information gap between designer and manufacturer	Auxiliary variable
59	DIGDMP	Design information gap between designer and manufacturer probability	Auxiliary variable
60	DDPES	Delay of delivery of precast element to site	Auxiliary variable
61	DDPESP	Delay of delivery of precast element to site probability	Auxiliary variable
62	MSSDC	Misplacement on the storage site due to carelessness	Auxiliary variable
63	MSSDCP	Misplacement on the storage site due to carelessness probability	Auxiliary variable
64	TCBM	Tower crane breakdown and maintenance	Auxiliary variable
65	TCBMP	Tower crane breakdown and maintenance probability	Auxiliary variable
66	IVPCDAL	Inefficient verification of precast as a result of ambiguous labels	Auxiliary variable
67	IVPCDALP	Inefficient verification of precast as a result of ambiguous labels probability	Auxiliary variable
68	SQIP	Slow quality inspection procedures	Auxiliary variable

69	SQIPP	Slow quality inspection procedures probability	Auxiliary variable

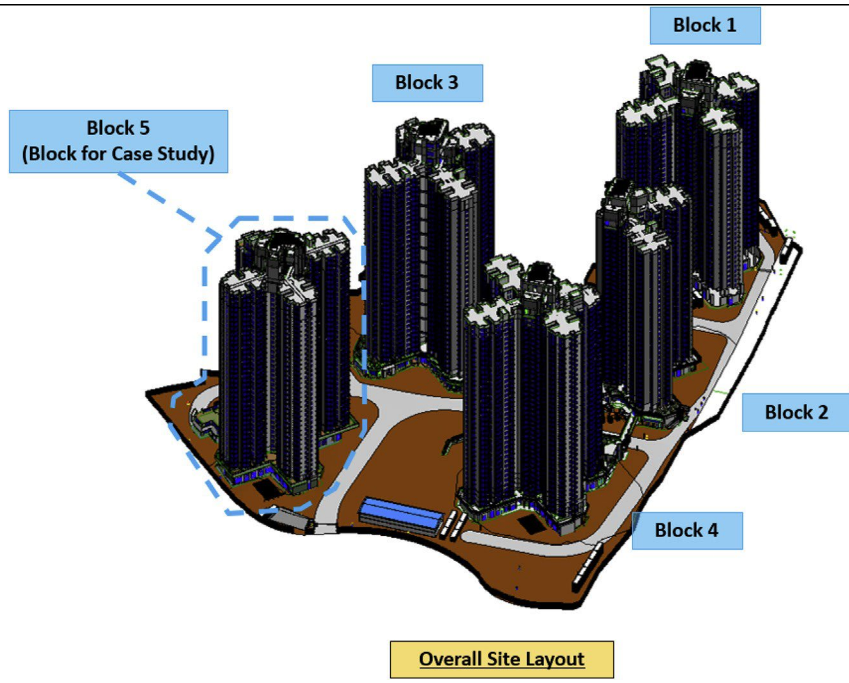

Fig. 5. Surveyed case in Hong Kong.

Table 2

Parameter setting in sensitive text.

Parameter	Min	Most	max
Defect rate	0	0.01	0.1
Installation error rate	0	0.05	0.15
Scale change rate	1	1.1	1.3
Delay due to approval procedures	0	3	7
Delay due to reinstallation	0	5	10
Design change prior to commencement	0	0.05	0.2

per time. Through the change in the integration step to 0.5, 0.25, 0.125, and 0.0625 day/time, the corresponding model behaviors with duration of PHP in this research are 508.64, 508.01, 507.64, and 507.43 days, indicating that the model is in line with the requirement of the integral error test (Sterman, 2000). In test 8, a comparison analysis of historical data is applied for the model behavior test. The test is to detect to what extend the results simulated from the model are consistent with the corresponding historical data (Li et al., 2014a,b). In the practical project, the actual schedule is 578 days, which was caused by inefficiency of design approval (IDA), inefficiency design data transition (IDDT), logistics information inconsistency due to human errors (LIIHEP), low information interoperability between different enterprise resource planning systems (LIIBDERPS), design information gap between designer and manufacturer (DIGDM), delay of delivery of precast

Table 3 Result of sensitive test.

Parameter	Duration (min/max)	Variety degree (min/max)	Range of variety
Defect rate	508.64/554.32	0%/8.90%	8.9%
Installation error rate	508.64/579.35	3.82%/8.90%	12.72%
Scale change rate	508.64/653.7	8.84%/17.94%	26.78%
Delay due to approval procedures	508.64/509.53	0%/0.2%	0.2%
Delay due to reinstallation	508.64/513.78	0%/0.79%	0.79%
Design change prior to commencement	508.64/604.87	3.78%/14.46%	18.24%

element to site (DDPES), misplacement on the storage site due to carelessness (MSSDC), tower crane breakdown and maintenance (TCBM), inefficient verification of precast due to ambiguous labels (IVPCDAL), and slow quality inspection procedures (SQIP). All risks that occurred in the actual construction are entered into the model and the output is 578.56, with error of 0.1%, which demonstrate the satisfied matching effect of the model.

5. Scenario analysis

5.1. Base run simulation

Based on the research conducted by (Li et al., 2016a,b), ten critical schedule risks that have significant influence on the schedule of PHP are identified, namely, IDA, IDDT, LIIHEP, LIIBDERPS, DIGDM, DDPES, MSSDC, TCBM, IVPCDAL, and SQIP, which caused 69 days schedule delay. One of the most significant characteristics of schedule risk is uncertainty. Therefore, analysing the uncertainty nature of risks based on single data is difficult, e.g., 69 days schedule delay in this project. Based on the study of Bekr (1990) and Touran and Wiser, (1992), triangular distribution, is especially suitable for schedule risks when information of most likely value is available. Therefore, triangular distribution is chosen to describe the uncertainty of schedule risks. For a deeper research, this study obtains the triangular distribution of ten schedule risks via in-depth interviews as indicated in Table 4. Then, the ten schedule risks will be placed into the SD model for Monte Carlo simulation.

In this research, R is used to produce the curve of density function of project duration under different schedule risks. After 200 simulations, we can attain the curve of density function of all risks, as shown in Fig. 6, which is similar to a normal distribution but not statistically normal distribution according to curve fittings and statistical analysis. For this kind of curve, a median can be used to reflect the average duration under all risks (Lu et al., 2015). The worst scenario is postponed for 110.9 days while the most optimistic scenario is delayed for 18.6 days. The median of 59 days should not be overlooked. According to statistics, the duration has about 50% possibility to be between 558.2 and 580.

To determine which risk contributes most to the schedule delay, each schedule risk will be placed into the SD model separately. The results are divided into three parts according to their influence degree for better analysis, as shown in Figs. 7e9. Fig. 7 shows the curves of density functions of duration under IDDT and IDA. According to curve fittings and statistical analysis, neither the distribution of duration under IDDT nor that under IDA is an actual normal distribution. However, both are similar to a normal distribution. Therefore, using the median of durations to reflect the average duration under risks is reasonable (Lu et al., 2015). Clearly, little difference can be observed between IDDT and IDA apart from the ranges as indicated in Table 5.

The curves of density function of duration under IVPCDAL, SQIP, MSSDC, and TCBM are created and shown in Fig. 8. The mean and median under the same risk are the same; hence, both can be used to reflect the average of durations. The curves of density functions of duration under MSSDC and TCBM have two curve peaks and both of the smaller ones are located at 509, which is the planned schedule. The smaller peak is caused by acceleration. When the probability distribution of a risk obeys the triangular distribution and the “most” is closer to the “max”, the “smaller peak” is more likely to appear.

Fig. 9 shows the curves of density function of the duration under DIGDM, DDPES, LIIHEP, and LIIBDERPS. All the curves are similar to a normal distribution but are not statistically normal distributions. Based on the discussion above, using a median to reflect the average duration under these risks is reasonable. In general, the delay caused by LIIBDERPS is an average of 42.4 days, which makes it the risk that generates the maximum effect on the schedule. Another risk due to information issue, LIIHEP, comes second in Fig. 9, while DDPES, followed by DIGDM, are ranked at number three, postponing for an average of 39.3 days. The delay caused by IDA is approximately the same duration as that by IDDT, which is an average of 10.1 days. MSSDC, SQIP, and IVPCDAL postpone for an average of 5.8, 6.8, and 8.1 days respectively. With an average of 4.5 days, TCBM is placed at the bottom among the risks.

Table 5 shows the risk ranking according to mean, range,

Table 4

No.	Schedule risk	Min	Most	Max
1	Inefficiency of design approval	1	8	10
2	Inefficiency design data transition	0	6	8
3	Low information interoperability between different enterprise resource planning systems	0	5	10
4	Design information gap between designer and manufacturer	1	5	8
5	Delay of delivery of precast element to site	0	7	12
6	Logistics information inconsistency due to human errors	0	6	9
7	Misplacement on the storage site due to carelessness	1	6	9
8	Tower crane breakdown and maintenance	1	8	10

9	Inefficient verification of precast due to ambiguous labels	0	4	6
10	Slow quality inspection procedures	0	4	8

Risks and their probability distribution.

median, and standard deviations. In general, schedule risks in prefabrication housing construction can be divided into three categories according to their effect on the schedule, as shown in Table 5. The first category contains TCBM, MSSDC, SQIP, and IVPCDAL; and the average schedule delays caused by them are less than 10 days. The second category includes IDA and IDDT; and the average schedule delays caused by them are less than 20 days and greater than 10 days. LIIBDERPS, LIIHEP, DDPES, and DIGDM, belonging to the third category, are the top four risks contributing most to the schedule delay; and the average schedule delays caused by them are more than 30 days. In the next section, the top four schedule risks, namely, IVPCDAL, SQIP, MSSDC, and TCBM, are chosen for further scenario analysis.

5.2. Scenario analysis

To understand the effect of high influencing risks, four risks, namely IVPCDAL, SQIP, MSSDC, TCBM, and their combined effect are selected for scenario analysis. The scenario analysis involves a base case scenario and two modified scenarios, i.e., risk decreased by 50% and risks increased by 50% as shown in Fig.10. As the system dynamics model has passed model structure testing and model behavior testing. The confidence of model structure is built up, indicating that the model behavior is in line with practical experience. The outputs of scenario analysis are correct and can reflect practical situation of prefabrication housing production.

5.2.1. Scenario A

In the scenario, the value of LIIHE is initially set as shown in Table 4 (A1). The value is decreased by 50% (A2) and increased by 50% (A3). Simulation results are shown in Fig. 11 and Table 6. The width of the range (32.6) in A2 decreased by 54.08%, while the width of the range (98.6) in A3 increased by 38.87%, which indicates that the width of range is more sensitive to the decrease of LIIHE than that to the increase of LIIHE. In contrast, the average delay (increased by 63.43%) in A3 shows a greater sensitive than that (decreased by 54.71%) in A2.

5.2.2. Scenario B

In scenario B, the width of range (30.4) in B2 decreased by 52.28%, while the width of range (92.9) in B3 increased by 45.84%, in which the trend of sensitive is almost the same as scenario A. Besides, average delay decreased by 47.06% in B2 and increased by 50.15% in B3 (Fig. 12 and Table 6).

5.2.3. Scenario C

The width of range (33.1) in C2 decreased by 49.62%, while the width of range (94.9) in C3 increased by 44.44%. The average delay decreased by 45.71% (17.1) in C2 and increased by 46.98% (46.3) in C3. DDPES and DIGDM have almost the same variation trend, because they have the same prerequisites to some degree, e.g.,

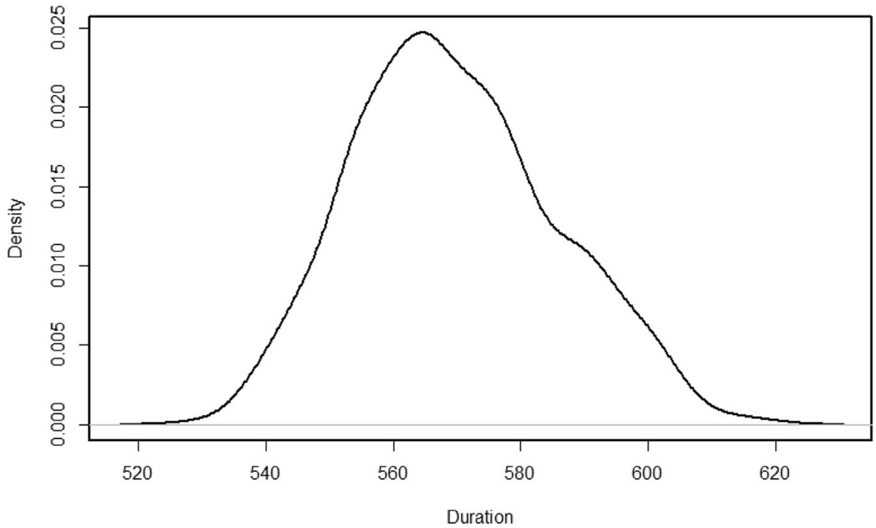

Fig. 6. Curve of density functions of all risks.

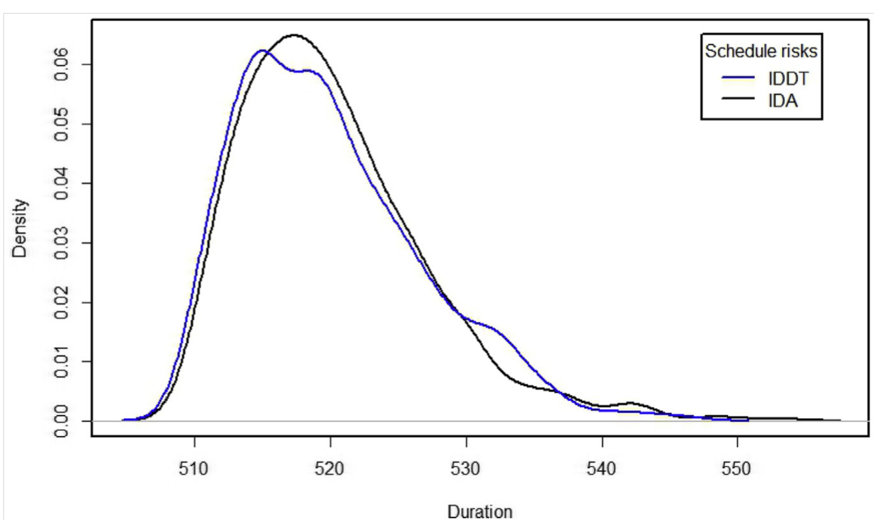

Fig. 7. Curves of density functions of IDDT and IDA.

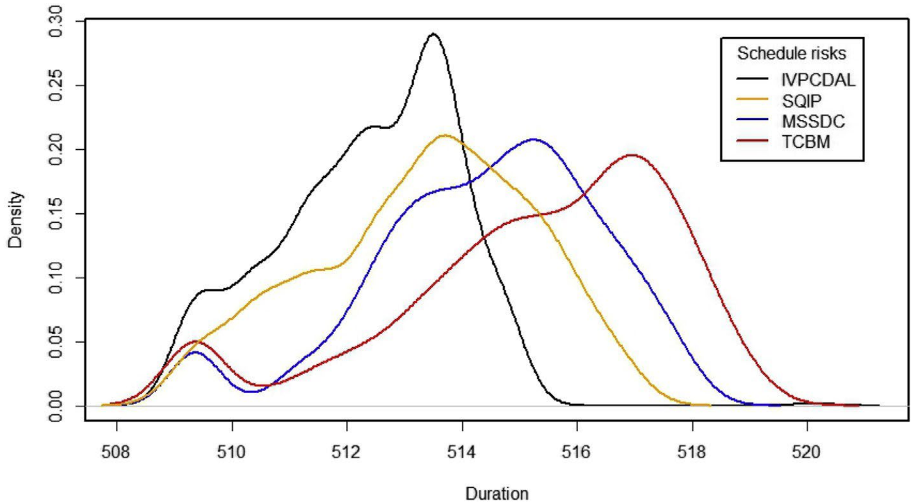

Fig. 8. Curves of density functions of IVPCDAL, SQIP, MSSDC, and TCBM.

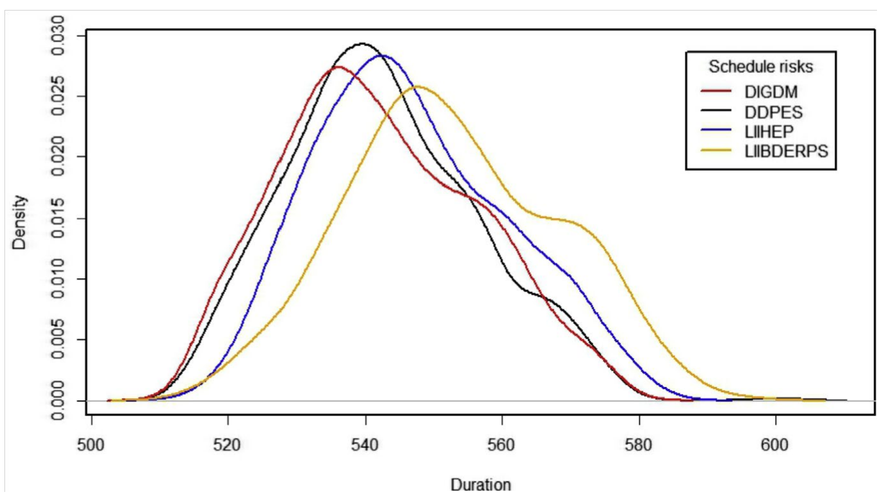

Fig. 9. Curves of density functions of DIGDM, DDPES, LIIHEP, and LIIBDERPS.

Table 5

Statistical information of duration under different risks.

Category	Mean	Range	Median	Standard deviation
LIIBDERPS	552.6	514.8e595.2	551.4	15.4
LIIHEP	546.8	513.1e584.1	545.1	14.0
DDPES	542.5	513.8e577.5	541.3	13.8

DIGDM	542	512.2e577.9	540.5	14.2
IDA	520.2	509.3e552.9	519.1	6.8
IDDT	520	509.5e546.1	518.9	6.8
TCBM	515.7	509.4e519.3	515.7	2.4
MSSDC	514.4	509.4e518.2	514.6	2.0
SQIP	513.3	509.1e516.9	513.5	1.9
IVPCDAL	512.4	509.1e515	512.5	1.5

defect and installation error. Therefore, the best way to reduce DDPES and DIGDM is to reduce the occurrence of defect and installation errors (Fig. 13 and Table 6).

5.2.4. Scenario D

The width of range (29.3 days) in D2 decreased by 63.56%, while the width of range (187 days) in D3 increased by 132.59%, which is totally different from the first three scenarios. The average delay decreased by 75% in D2 and increased by 150.24% in D3, as shown in Fig. 14 and Table 6. Therefore, controlling LIIBDERPS is important. Once LIIBDERPS increases, the duration would substantially increase.

5.2.5. Scenario E

The width of range (37.1) in E2 decreased by 53.39%, while the width of range (202.6) in E3 increased by 154.52%. The average delay decreased by 74.73% in E2 and increased by 146.90% in E3, as shown in Fig. 15 and Table 6. Based on the previous analysis, LIIBDERPS contributes most to the combination. Therefore, controlling LIIBDERPS can reduce the effect of the combination effectively.

Overall, the top four schedule risks can be divided into two categories. The first category includes DDPES, DIGDM, and LIIHE. When they decreased by 50%, the average schedule delays are between 16 and 21, and the ranges of schedule are between 510 and 550; when they are increased by 50%, the average schedule delays are between 46 and 56, and the ranges of schedule are between 512 and 620. The second category is LIIBDERPS, which makes the schedule more sensitive. When it is decreased by 50%, the average

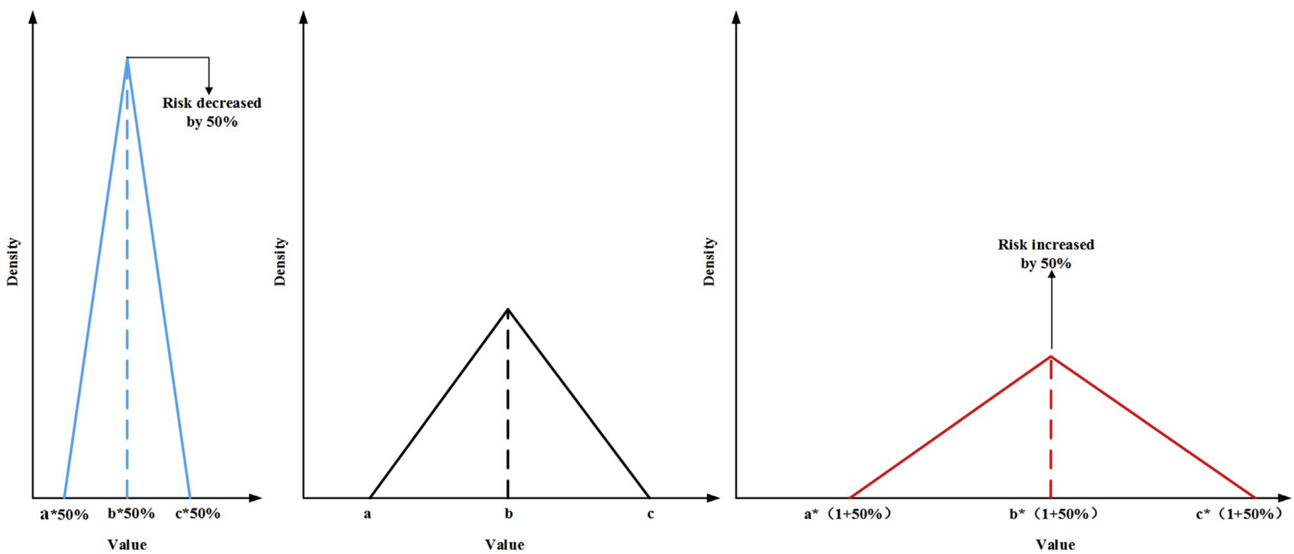

Fig. 10. An example of risk in a base scenario and two modified scenarios.

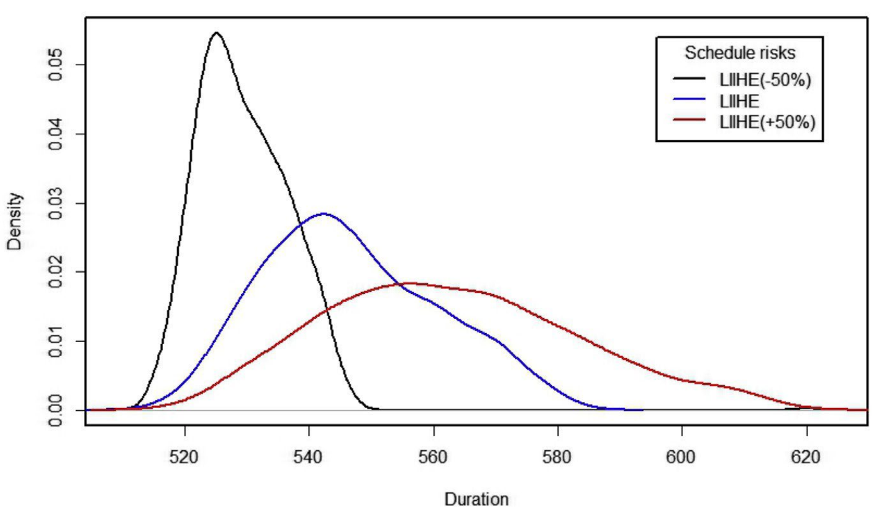

Fig. 11. Curves of density functions LIIHE (50%), LIIHE, and LIIHE (þ50%).

Table 6

Statistical information of duration under different risks.

Category	Mean	Median	Range	Standard deviation
DDPES	526.9	526.1	512.9e543.3	6.8
(50%)	558.2	557.5	514.7e607.6	20.5
DDPES	526.1	526.1	512e545.1	6.9
(þ50%)	556.9	555.3	513.1e608	21.2
DIGDM	520.2	519.6	509.1e538.4	6.6
(50%)	616.6	615.1	534.6e721.6	34.7
DIGDM	529.4	528.6	514e546.6	7.0
(þ50%)	562.8	561	518.8e617.4	20.2
LIIBDERPS	521.7	520.8	509.2e546.3	7.2
(50%)	557.2	555.7	522.7e602.3	15.8
LIIBDERPS				
(þ50%)				
LIIHE				
(50%)				
LIIHE				
(þ50%)				
Combination				
(50%)				

Combination				
Combination (þ50%)	625.8	624.3	531.9e734.5	34.1

schedule delay (11) is less than that of the risks in the first category, and the ranges of schedule (509.1e538.4) is smaller than in the risks in the first category. When it is increased by 50%, the average schedule delay is more than that of the risk in the first category, and the ranges of schedule (534.6e721.6) are much greater than in the risks in the first category.

6. Conclusion

Schedule delay caused by various risks affect the PHP in Hong Kong. To deal with this problem, a model is developed for modeling and simulating the effect of various risks on the schedule of PHP by employing an SD model and Monte Carlo simulation method, in which the feedbacks, uncertainty, and dynamics nature of schedule is well examined. The results of the simulation show that schedule risks in prefabrication housing construction can be divided into three categories according to their effect on the schedule; the category including LIIBDERPS, LIIHEP, DDPES, and DIGDM contributes most to the schedule delay. In addition, schedule is more sensitive to LIIBDERPS than LIIHEP, DDPES, and DIGDM, which means that LIIBDERPS is the major schedule risk that needs to be monitored and prevented. This study is the first attempt to conduct quantitative analysis for the risk analysis in PHP by investigating the interactions of major variables in construction schedule system and the uncertainty of each schedule risk. The system dynamic model serves as an effective tool for quantitatively evaluating the effect of various risks on the schedule of PHP, offering valuable references for managers though the comparison of simulation results under different risk scenarios, so that potential risks that might lead to schedule delay could be identified and handled in advance.

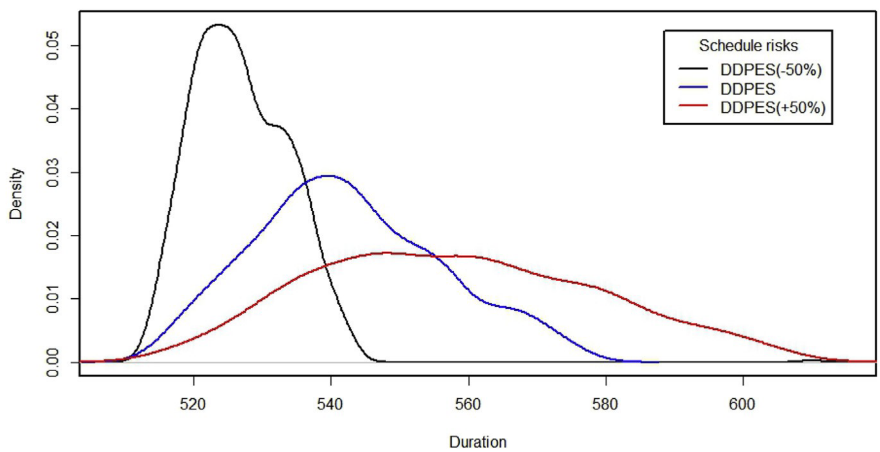

Fig. 12. Curves of density functions DDPES (50%), DDPES, and DDPES (þ50%).

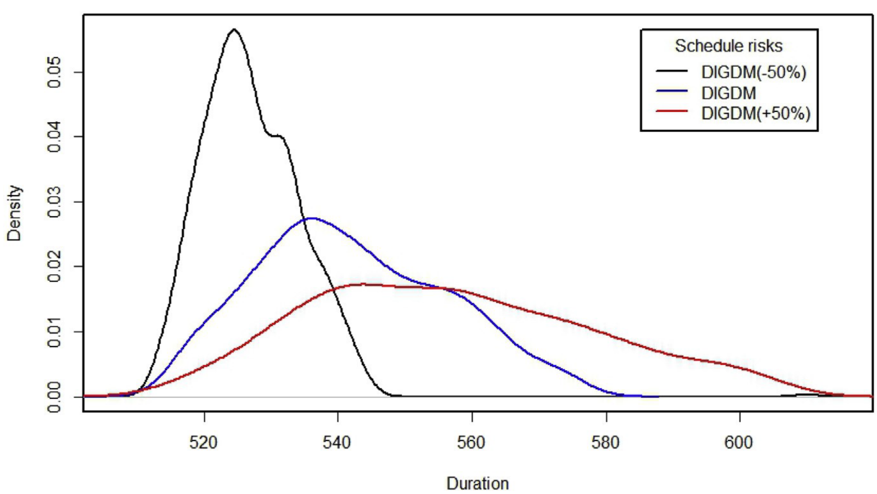

Fig. 13. Curves of density functions DIGDM (50%), DIGDM, and DIGDM (þ50%).

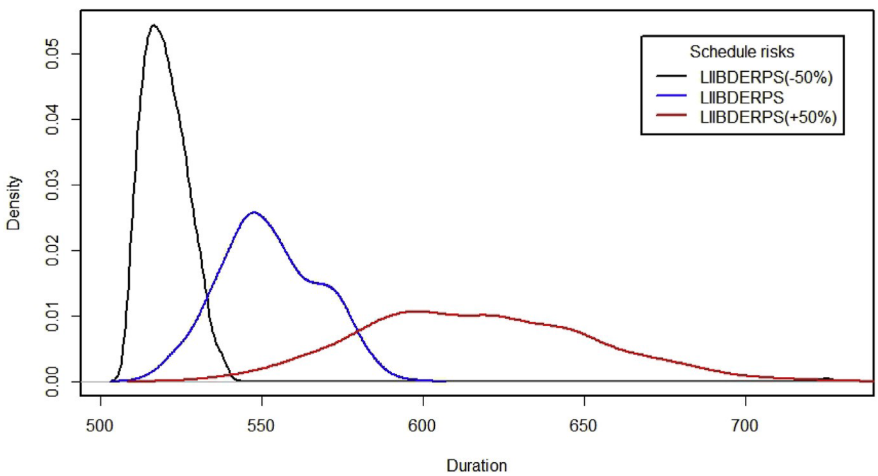

Fig. 14. Curves of density functions LIIBDERPS (50%), LIIBDERPS, and LIIBDERPS (þ50%).

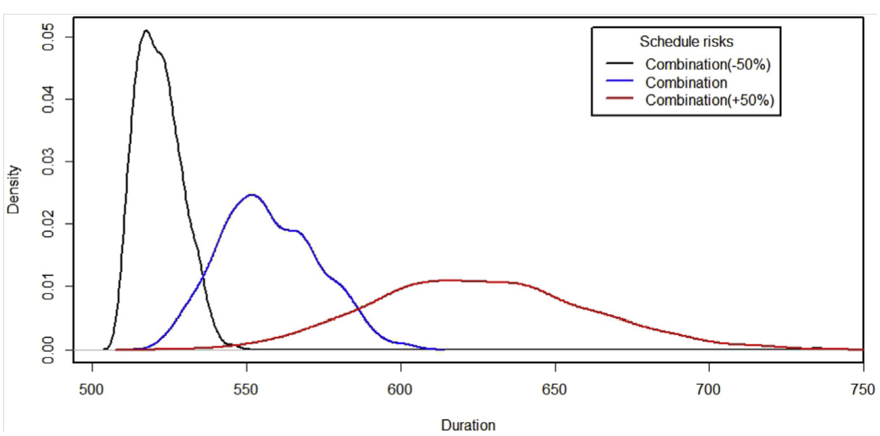

Fig. 15. Curves of density functions Combination (50%), Combination and Combination (þ50%).

Limitations of this research mainly lie in that the developed model in this study does not consider the processes of PHP from the perspective of operational project management concerning microlevel issues, such as the predecessor and successor relationship of network activity of PHP, detailed information for execution and etc.

Operational project management would be difficult by only employing SD for analysis given that it does not generally form a work breakdown structure of discrete sub-activities. Further research can be conducted by integrating the use of SD and discrete event simulation to improve the robustness and reliability of the model considering both strategic project management and operational project management.

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