IMPACT OF VARIABILITY ON CONSTRUCTION SCHEDULES

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ABSTRACT

Variability degrades project performance. Two types of variability may affect a construction schedule, namely, task duration and the availability of resource and information (RI) prerequisites. It is well known that the variability of task duration could delay project completion, however, the effect of RI availability/unavailability on construction schedule needs to be depicted. This paper presents a simulation model which allows studying the effect of RI related variability on construction schedule. Comparisons are made to illustrate the impact of each type of variability as well as the combination of both types of variability. The results suggest that both types of variability should be minimized in order to achieve reliable work plans which is important to reduce project delays and schedule changes.

KEY WORDS

Variability, Integrated Production Scheduler, Constraints, Reliable plan

INTRODUCTION

Variability causes delays and disruptions in construction processes, which accounts for problems such as time overrun and cost overrun (Aibinu and Jagboro, 2002). Variability analysis and control effect of task duration related variations. play an important role in management because Recently, there has been considerable attention on increasing variability always degrades the perfor- the effect of resource delivery related variations in mance of a product system (Hopp and Spearman, the manufacturing industry (Tan, 2001; Zimmer, 2000). Ballard and Howell (1998) reported that 2002; So and Zheng 2003). Each aspect covers a shielding production from uncertainties is essen- number of variability sources, which directly or tial, which can increase productivity up to 30% indirectly affect task durations or the availabilities when higher Percent Plan Complete (PPC) is of resource prerequisites. Specifically, the former achieved. Tommelein et al (1999) presented a is subject to the performance of labors and parade game to illustrate the impact variability machines; and the latter is dependent on the perhas on work flow in a single-line production formance of other trades in the supply chain and system, which reveals that unreliable work flow information flow. Ideally, these two types of variresults in unutilized production capacity and ability should be addressed simultaneously; othlarger intermediate buffers when high variability erwise the analysis would be incomplete. It is also prevails. Thomas et al (2002) examined the issue helpful to compare the impact of two different of variability in construction and its impact on variability sources, which allows for a better project performance and summarized that vari- understanding of the significance of variability ability caused by unreliable flows should be and, consequently, appropriate measures could be reduced to acceptable levels and the remaining taken to reduce the adverse impact. system variability should be managed using effec-

tive workforce management strategies. Accordingly, it is necessary to reduce variability to achieve stable work flow and reliable plan for better project performance.

Many variability analyses have investigated the

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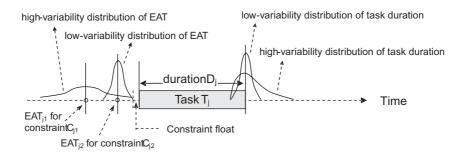


Figure 1: Schematic illustration of variability in task duration and EAT

This paper presents a simulation approach which helps analyze the effect of two independent types of variability on construction schedules. It has been implemented in the prototype of Integrated Production Scheduler (IPS), a constraintbased scheduling tool that facilitates constraint modeling and analysis to improve schedule reliability and project collaboration (Chua et al., 2003). The simulation results illustrate how the variability of task durations and resource/information (RI) availabilities may disturb a work plan and impede process performance, based on which strategies for variability control can then be devised in the future.

IDENTIFICATION OF VARIABILITY IN CONSTRUCTION SCHEDULE

At the production phase, a Critical Path Method (CPM) based schedule may turn out impractical if certain RI prerequisites are missing or delayed. Chua et al (2003) proposed an augmented CPM (ACPM) to determine more reliable plan with the incorporation of another constraint regarding the estimated available time (*EAT*) for RI prerequisite, which possibly delays the early start time (*ES*) of a task as shown in Eq. (1):

$$ES'_{j} = MAX \begin{cases} MAX \\ all i \\ all i \\ all i \end{cases} \begin{cases} INITIAL & TIME \\ EF'_{i} + FS_{ij} \\ MAX(EAT_{jl}) \end{cases} \end{cases}$$
(1)
$$EF'_{i} = ES'_{i} + D_{i} \qquad (2)$$

and

where EAT_{ji} represents the EAT for the l^{th} constraint of task T_j . EF_j ', LF_j ', LS_j ', D_j , FS_{ij} , and FS_{jk} , are the modified early finish, late finish, late start, duration, finish-to-start relationship between task T_i and T_j , and finish-to-start relationship between task T_i and T_i , respectively.

With the ACPM, two schedule parameters could become random variables. One is the task duration contributed by the time in production or non-production related activities, e.g. material handling, waiting, and rework. The other is the EAT of RI prerequisites accounting for delivery time and setup time. If setup is not required, as could be in the case of information prerequisite, EAT should be the same as delivery time. Figure 1 schematically illustrates how random variations affect task duration and EAT and hence the impact on downstream schedule. With the same mean D, a high-variability distribution (i.e. high standard deviation) may yield much longer task duration than that of a low-variability distribution (i.e., low standard deviation). Likewise, considering EAT_{il} for the l^{th} constraint, the higher the variability, the earlier the mean EAT_{ii} is required to maintain the same level of constraint float'. Both types of random variations may change the schedule of task T_i as well as the schedules of the downstream tasks. Therefore, random variations, especially those carrying high-variability distributions, should be minimized to prevent the disruptive impact on schedule.

SIMULATION MODEL

In the simulation model, it is assumed that task duration and EAT are two independent random variables. The simulation follows a two-stage cycle (i.e., planning and execution), which is repeated weekly. At the planning stage, schedule is computed with the ACPM and all time attributes are deterministic. Subsequently at the execution stage in the same week, the task durations and the EATs in the current week are replaced with random variables, which represent the execution

³ Similar to activity floats, constraint floats can be used to determine the criticalities of an RI constraint to its owner task or the project in terms of constraint total float and constraint free float.

of work assignments and the delivery of RI prerequisites. The schedule is then updated in the following week and a new cycle starts. A description of the simulation model is presented below:

- Random variation is only applicable in the current week when the work plan is executed.
- Each task or RI prerequisite has an independent variability distribution, according to which the corresponding random variable for task duration or EAT is generated.
- Predecessors should be 100% completed before their successors can start.
- Each task may have one or more RI prerequisites
- Work plan is updated weekly at the end of each week.
- The delivery of RI prerequisites is scheduled at the end of each week and remains unchanged in the coming next week till the work plan is updated.
- Unexecuted tasks in the current week will be reassigned in the next week and its RI prerequisites, if any, will be rescheduled.
- Unfinished (but already started) tasks will be continued till its completion.

During each simulation cycle, the underlying routine is followed:

- 1) Determine the starts and the ends of the current week.
- durations and EATs. This step represents making work assignments.
- 3) Generate random variables of task duration in some repeating processes (e.g., construction and EAT in the current week. This step represents execution of work assignments and delivery of RI prerequisites.
- 4) Update the schedule with the ACPM.
- If a task initially scheduled in the current a) week starts beyond the end of this week, it is considered not executed and will be rescheduled in the next week.
- If a task is partially finished by the end of b) current week, it will be continued till fully completed.
- 5) The boundary of current week advances one week forward. Go back to step (1) until the end of simulation is reached and then go to step (6).

6) Output the simulation result for this cycle. After each simulation cycle, the following data are generated and reported in the simulation output file. The first two measure time-related performance, and the latter two measure plan reliability.

- **Project duration**. This is the time from start to finish of the project.
- ber of task units completed divided by pro- completed. ject duration.

- Percent Plan Complete (PPC) for each working week. PPC is the number of completed tasks divided by the number of scheduled tasks in the current working week. The completion of a task is considered in one of two ways. First, if a task is wholly scheduled in the working buffer, it should be fully finished by the end of the week. Second, if a task is partially scheduled in the working buffer, then the task is virtually split into two portions and the first part inside the current week should be finished before it can be counted.
- Percent Plan Impacted (PPI) for each working week. PPI is the number of tasks that are rescheduled divided by the number of tasks scheduled in the current working week. Comparatively, PPI measures how many tasks are rescheduled, while PPC measures how many tasks are completed. PPI and PPC are important indicators for plan reliability. The former evaluates the impact of variability on task schedules; the latter evaluates the effectiveness of schedule execution.

SIMULATION RESULTS

The simulation case comprises 35 sequential tasks; each task takes 1 day to complete and any two adjacent tasks have a finish-to-start prece-2) Update the schedule with deterministic task dence relationship. Sequential process flow is typically represented by the assembly line in manufacturing. In construction, such flows exist cycles for standard building storey). Generally speaking, an architecture-engineering-construction (AEC) project may contain many concurrent chains of flows. The purpose of choosing a sequential process flow is to avoid the distraction of flow interaction while still being able to illustrate the impact of variability on project performance and plan reliability.

Besides the generic assumptions described previously in the simulation model, three additional assumptions are adopted. First, each task has one RI prerequisite, though more can be assigned as well. Second, the setup time for each RI prerequisite is equal to 0 so that EAT is the same as activity start, i.e., just-in-time, although the need for setup time can be easily accommodated. Third, discreet triangular probabilistic distribution is adopted assuming 4 time steps per day for practical consideration. The selection of triangular distribution is for the simplicity of illustration. Another distribution can be adopted wherever applicable. Fourth, each week contains 7 working • Average task density. This is the total num- days and therefore 35 tasks take 5 weeks to be

Simulation Case	Variation	n of Task D	uration	Variation of EAT			
	$a/t_0, c/t_0, b/t_0$	μ_T/t_0	σ_T/t_0	cv_T	$a/t_0, c/t_0, b/t_0$	μ_{RI}/t_0	σ_{RI}/t_0
Augmented CPM	1, 1, 1	1	0	0	0, 0, 0	0	0
Case 1A (Low)	0.75, 1, 1.25	1	0.102	10.2%	-	-	-
Case 1B (Mid)	0.5, 1, 1.5	1	0.204	20.4%	-	-	-
Case 1C (High)	0.25, 1, 1.75	1	0.306	30.6%	-	-	-
Case 2A (Low)	-	-	-	-	-0.25, 0, 0.25	0	0.102
Case 2B (Mid)	-	-	-	-	-0.5, 0, 0.5	0	0.204
Case 2C (High)	-	-	-	-	-0.75, 0, 0.75	0	0.306
Case 3A (Low)	0.75, 1, 1.25	1	0.102	10.2%	-0.25, 0, 0.25	0	0.102
Case 3B (Mid)	0.5, 1, 1.5	1	0.204	20.4%	-0.5, 0, 0.5	0	0.204
Case 3C (High)	0.25, 1, 1.75	1	0.306	30.6%	-0.75, 0, 0.75	0	0.306

Table 1: Three types of probabilistic distributions

Three types of variability are presented, **PROJECT DURATION** namely, random variation in task duration (case 1), random variation in EAT delay (case 2), and the combination of both (case 3). The corresponding triangular distribution parameters are shown in Table 1, where parameters a, b, and c are proportions to the duration of owner task t_0 equaling to 1 day each. Distribution types 1A, 1B, and 1C stand for low, mid, and high variability of task duration respectively, which have increasing standard deviation σ_{τ} (i.e., 0.102, 0.204, and 0.306 day) or coefficient of variation cv_{τ} (i.e., 10.2%, 20.4%, and 30.6%) with a common mean task duration μ_{τ} (1 day). Similarly, distributions 2A, 2B, and 2C stand for low, mid, and high variability of EAT, which have the same level of increasing standard deviation σ_{RI} (i.e., 0.102, 0.204, and 0.306 day) with a common mean EAT delay (0 day). Distributions 3A, 3B, and 3C stand for three combinations of the above distributions, i.e., 1A and 2A, 1B and 2B, and 1C and 2C. Each simulation is performed 1000 cycles and the results are depicted below.

Table 2 shows that the mean project duration μ_{p} increases from 3.2% to 9.3% of the original $\mu_{\ensuremath{\mathcal{D}}\xspace2}$ when probabilistic distributions 1A, 1B, and $1\overline{C}$ are applied in task duration. The coefficient of variation (cv_p) of project duration also rises from 1.2% to 2.8%. In comparison, applying probabilistic distributions 2A, 2B, and 2C to EAT results in less impact on μ_{D} (from 2.3% to 6.4%) and cv_{D} (from 0.8% to 1.2%). Finally, applying both types of probabilistic distribution simultaneously leads to the highest increase of μ_{p} (from 4.3% to 11.7%) and cv_{p} (from 1.4% to 3.0%). The graphical repre-

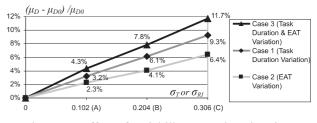


Figure 2: Effect of variability on project duration

	Project Duration								
Simulation Case	MeanIncrease μ_D (Day) $(\mu_D - \mu_{D\theta}) / \mu_{D\theta}$		Standard deviation σ_D (Day)	Coefficient of variation v_D					
Augmented CPM	35	0	0	0					
Case 1A (Low)	36.12	3.2%	0.45	1.2%					
Case 1B (Mid)	37.15	6.1%	0.77	2.1%					
Case 1C (High)	38.24	9.3%	1.06	2.8%					
Case 2A (Low)	35.82	2.3%	0.27	0.8%					
Case 2B (Mid)	36.45	4.1%	0.33	0.9%					
Case 2C (High)	37.25	6.4%	0.46	1.2%					
Case 3A (Low)	36.5	4.3%	0.51	1.4%					
Case 3B (Mid)	37.74	7.8%	0.82	2.2%					
Case 3C (High)	39.1	11.7%	1.16	3.0%					

Table 2: Effect of variability on project duration

	Average Task Density								
Simulation Case	Mean μ_{TD} (task unit /day)	Reduction $(\mu_{TD} - \mu_{TD\theta})/\mu_{TD\theta}$	Standard deviation σ_{TD} (task unit/day)	Coefficient of variation <i>CV_{TD}</i>					
Augmented CPM	1	0	0	0					
Case 1A (Low)	0.97	-3%	0.01	1.0%					
Case 1B (Mid)	0.94	-6%	0.02	2.1%					
Case 1C (High)	0.92	-8%	0.03	3.3%					
Case 2A (Low)	0.98	-2%	0.01	1.0%					
Case 2B (Mid)	0.96	-4%	0.01	1.0%					
Case 2C (High)	0.94	-6%	0.01	1.1%					
Case 3A (Low)	0.96	-4%	0.01	1.0%					
Case 3B (Mid)	0.93	-7%	0.02	2.2%					
Case 3C (High)	0.9	-10%	0.03	3.3%					

Table 3: Effect of variability on average task density



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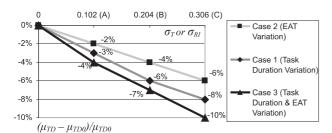


Figure 3: Effect of variability on average task density

sentation of simulation results is shown in Figure 2, which suggests that variation of task duration and EAT always increases μ_D and cv_D . The higher the variability, the more increases are found in μ_D and cv_D . It also can be observed that variation of task duration gives rise to more significant impact on μ_D and cv_D than those caused by the same level of EAT variations, while the combination of both types of variations leads to the worst situation.

AVERAGE TASK DENSITY

Meanwhile, the effect of variability can also be revealed by the reduction of average task density. The mean average task density μ_{TD} for each simulation case is computed and displayed in Table 3 and Figure 3. It can be seen that the higher the variability, the more reduction is found in μ_{TD} Comparatively, the variations of task duration bring more reduction of μ_{TD} (from -3% to -8%) than that caused by the EAT counterpart (from -2% to -6%), while the combination of both types of variations leads to the maximum reduction of μ_{TD} (from -4% to -7%). Meanwhile, the variation of task duration causes higher coefficient of variation cv_{TH} (from 1.0% to 3.3%) than that of EAT variation (from 1.0 to 1.1%). Applying both types of distribution yields slightly higher cv_{TH} (from variation of task duration.

PERCENT PLAN IMPACTED (PPI)

According to Table 4 and Figure 4, variability causes considerable rescheduling as indicated by the PPI in each working week. The higher the variability, the higher is the PPI. In Case 3, for example, the average PPIs over 5 weeks vary from 47.6% with distribution 3A to 72.6% with distribution 3C. Moreover, it is noteworthy that, variation of EAT leads to much *higher* PPI than that caused by the equivalent variation of task duration (for example, 74.0% with distribution 2C compared with 46.8% with distribution 1C). This result, interestingly, differs from the previous finding where the variation of task duration contributes more to the drop in project performance in terms of longer project duration and lower average task density. It implies that EAT variations may produce higher impact on plan reliability; its reason will be explained in the next section.

PERCENT PLAN COMPLETE (PPC)

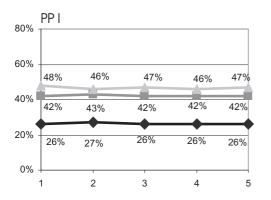
PPC is another measure for evaluating plan reliability focusing on plan implementation. It is indicated in Table 4 and Figure 4 that the higher the variability in task duration and EAT, the lower PPC is accomplished. Comparatively, variability in EAT causes relatively lower PPC than that of the task duration counterpart and the existence of both types of variability leads to the worst situation, though the difference is marginal in this sequential example.

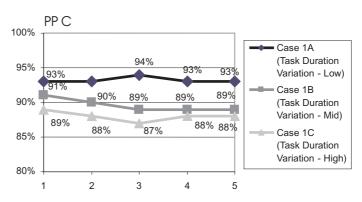
SUMMARY

of task duration causes higher coefficient of variation cv_{TH} (from 1.0% to 3.3%) than that of EAT variation (from 1.0 to 1.1%). Applying both types of distribution yields slightly higher cv_{TH} (from 1.0% to 3.3%) which is primarily attributed to the

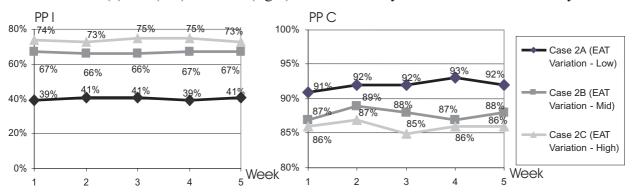
Simulation	PPI (Mean)					PPC (Mean)						
Case	1	2	3	4	5	Average	1	2	3	4	5	Average
Case 1A	26%	27%	26%	26%	26%	26.2%	93%	93%	94%	93%	93%	93.2%
Case 1B	42%	43%	42%	42%	42%	42.2%	91%	90%	89%	89%	89%	89.6%
Case 1C	48%	46%	47%	46%	47%	46.8%	89%	88%	87%	88%	88%	88.0%
Case 2A	39%	41%	41%	39%	41%	40.2%	91%	92%	92%	93%	92%	92.0%
Case 2B	67%	66%	66%	67%	67%	66.6%	87%	89%	88%	87%	88%	87.8%
Case 2C	74%	73%	75%	75%	73%	74.0%	86%	87%	85%	86%	86%	86.0%
Case 3A	47%	49%	50%	46%	46%	47.6%	91%	90%	90%	90%	90%	90.2%
Case 3B	67%	67%	66%	65%	65%	66.0%	88%	87%	87%	87%	87%	87.2%
Case 3C	73%	73%	71%	72%	74%	72.6%	86%	84%	85%	85%	84%	84.8%

Table 4: Effect of variability on PPI and PPC for the weekly plan

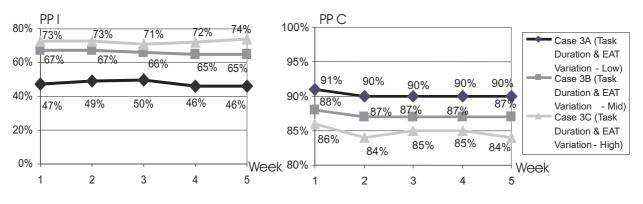




(a) PPI (left) and PPC (right) when variability exists in task duration only



(b) PPI (left) and PPC (right) when variability exists in EAT only



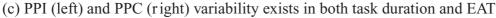


Figure 4: Effect of variability on PPI and PPC in weekly work plan

ations leads to the worst situation.

paper length, the finding cannot be elaborated illustrated in Figure 5(d). herein. These findings suggest that the EAT variability should be minimized or eliminated.

DISCUSSIONS

instance) is attributed to the increases of task compared with that in EAT variations. duration in T3, T4, and T5 cumulatively. In contrast, Figure 5(c) suggests that the effect of EAT FUTURE WORK delay in RI prerequisite is independent. Only the maximum EAT delay caused by C2 accounts for The above simulation case can be enhanced with

poorer plan reliability in terms of higher PPI and tion and decrease on average task density than lower PPC. The combination of both types of vari- those of EAT variations, as evident from the results in Tables 2 and 3. Finally, applying both Another example with non-sequential pro- types of random variations may further drive up cesses was also investigated and the same trend as project duration attributed to both task duration the above has been observed. Due to the limit of (i.e., T3, T4, and T5) and EAT (i.e., C2) as

On the other hand according to Figure 5(b), 3 ability cannot be ignored and both types of vari- out of 5 tasks (i.e., T2, T4, and T5) are rescheduled due to the delays of predecessors; while in Figure 5(c) all 5 tasks are rescheduled due to the delays in EAT. In particular, the maximum EAT delay (i.e., C2) pushes back not only its owner task but also A possible explanation for the simulation results all the downstream tasks. This shows that plan may be depicted in Figure 5. Figure 5(a) stands for reliability is independent from time related proa work plan containing 5 sequential tasks. Figures ject performance, though in general variability 5(b), (c), and (d) represent three illustrative cases reduces project performance and plan reliability where random variation exists in task duration, in the same direction. Finally, Figure 5(d) reveals EAT, and both, respectively. According to Figure that the combination of both types of variability 5(b), the project delay (i.e., 0.75 day in this causes the same or possibly higher increase of PPI

the project delay (i.e., 0.5 day), which is shorter the consideration of some practical issues. For than that of Figure 5(b). This difference implies example, the production rates of the same trade that the variations of task durations may cause over several locations or over weeks are heavily more significant increase on mean project dura- correlated. This would affect the variability distri-

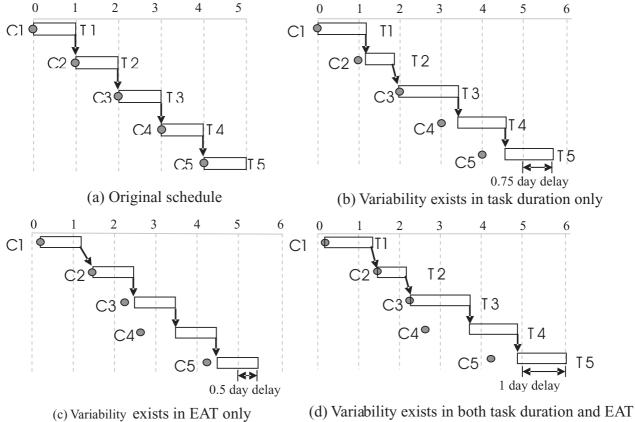


Figure 5: Illustration on delays caused by different types of variations

butions assigned to these correlated tasks, and are at about 30%. In contrast, random variations consequently the simulation results. Another is that the variability of task duration is a result of other underlying variability sources such as quantity (of work), productivity, and number of resources. Tracking these underlying variability sources should improve the determination of the variability of task duration.

The simulation results suggest that it is necessary to adopt appropriate means to reduce the impact of variability in both task duration and EAT. As one of the key measures, constraint identification and management play an important role not ignore EAT related variability but take meain production planning and control. Chua et al (2003) proposed an implementation of task buffer management with the prototype of IPS to improve plan reliability. Recently, a method called key constraint analysis has been proposed to help locate the most critical constraints in the process **REFERENCE** and resolve them iteratively to reduce project delays (Chua and Shen, 2005; Shen and Chua, 2005). With the above simulation model, the impact of variability in the plan can be analyzed which may contribute to the determination of task buffer management strategies. The future research in this aspect could be extended to ascertain the impact of differing magnitude of variability in the critical and non-critical paths, and critical and non-critical constraints. Another possible study is to determine the suitable sizes of Chua, K. H. D., Shen, L. J., and Bok, S. H. (2003). constraint floats which allow eliminating the impact of EAT delay while maintaining low inventory levels.

CONCLUSIONS

Variability degrades the performance of a construction process and impairs plan reliability. Although it looks like common sense, the effect of Hopp, W.J., and Spearman, M.L. (1996). Factory RI availability related variability on a construction weekly work plan is not very obvious and needs to be studied. A simulation model using constraint-based scheduling has been developed to analyze the impact of variability arose from task duration and/or EAT. In addition to the time related performance measures such as project duration and average task density, two other measures were employed to address plan reliability, i.e. Percent Plan Impacted (PPI) and Percent Plan Completed (PPC). The simulation results showed that both types of variability result in longer project duration, lower average task density, increased PPI, and reduced PPC. Comparatively, random variations of task duration caused longer project duration (9.3%) and lower average task density (-8%) compared with those of EAT variations, 6.4% and -6% respectively, when the coefficient of variation for both task duration and EAT

of EAT resulted in higher PPI (average 74.0%) and lower PPC (average 86.0%) suggesting poorer plan reliability compared with those of task duration related variations, average 47% and 88.0% respectively. The existing of both types of variations, which represents the common practice in project implementation, usually resulted in the worst situation, i.e., 11.7%, -10%, 72.6%, and 84.8% in project duration, average task density, average PPI, and average PPC, respectively. It is therefore advised that the project manager should sures to handle both types of variability through effective production management and flow constraint management so as to improve project performance and enhance plan reliability.

- Aibinu, A.A., and Jagboro, G.O. (2002). "The effects of construction delays on project delivery in Nigerian construction industry". International Journal of Project Management 20, 3-599.
- Ballard, G. and Howell. G. (1998). "Shielding production: essential step in production control." Journal of Construction Engineering and Management, ASCE, 124(1), 11–17.
- "Constraint-based planning with Integrated Production Scheduler over Internet." Journal of Construction Engineering and Management. 129(3), 293-301.
- Chua, K. H. D. and Shen, L. J. (2005). "Key constraint analysis with Integrated Production Scheduler." Journal of Construction Engineering and Management, July issue.
- Physics: Foundations of Manufacturing Management. Irwin/McGraw-Hill, Boston, Massachusetts.
- Shen, L. J., and Chua K. H. (2005). "Key Constraint Analysis: Achieving Lean Processes with the Application of TOC." Construction Research Congress 2005, April 5–7, San Diego, CA.
- So, K.C., and Zheng, X.N. (2003). "Impact of supplier's lead time and forecast demand updating on retailer's order quantity variability in a two-level supply chain." International Journal of Production Economics, 86, 169–179.
- Tan, K.C. (2001). "A framework of supply chain management literature." European Journal of Purchasing & Supply Management, 7, 39–48.
- Thomas, R.H., Horman, M.J., Souza, U.E.L., and Zaviski, I. (2002). "Reducing variability to improve performance as a lean construction

principle." Journal of Construction Engineering and Management, **128**(2), 144–154.

- Tommelein, I.D., Riley, D.R., and Howell, G. A. (1999). "Parade game: impact of workflow variability on trade performance." *Journal of Construction Engineering and Management*, ASCE, **125**(3), 304–310.
- Zimmer, K. (2002). "Supply chain coordination with uncertain just-in-time delivery." *International Journal of Production Economics*, 77, 1–15.