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SIMULATION-OPTIMIZATION INTEGRATED APPROACH TO PLANNING READY MIXED CONCRETE PRODUCTION AND DELIVERY: VALIDATION AND APPLICATIONS

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ABSTRACT

Powered by the simulation and optimization engines resulting from recent research, a computer system named *HKCONSIM* is ready to provide concrete plant managers with decision support in making the best operation strategy for delivering concrete to multiple site clients. This paper demonstrates case studies of *HKCONSIM* applications in practical settings with emphasis on addressing two questions: (1) "Can *HKCONSIM* capture the complexities of the real world?" and (2) "How to take advantage of *HKCONSIM* to attain customer satisfaction and cost effectiveness?" A case study describing one-day operations of the batch plant is used to illustrate the decision support functions *HKCONSIM* can provide. The case study consists of four parts: (1) input data preparation, (2) the definitions of relevant measures of the system performance, (3) simulation model validation by comparing the simulation outputs against the actual records, and (4) further optimization analysis under three "what-if" scenarios postulated with practical implications. In conclusion, the batch plant operators can draw on *HKCONSIM* to augment their experiences, corroborate their intuitions, and create new intelligence in coping challenges in day-by-day operations planning.

1 INTRODUCTION

The benefits of ready mixed concrete (RMC) in light of attaining consistent quality standards, being environmentally-friendly, and demanding less site space have accounted for its ubiquitous application in infrastructure and residential building projects. The scheduling of RMC production and delivery is essentially a problem of materials logistics planning, which is "a decision process for strategically managing the procurement, movement and storage of raw materials, finished product inventory and the related information flows throughout the organization and its marketing channels in such a way that the current and future profitability is maximized by cost-effective fulfillment of orders" (Christopher 1992). In Hong Kong, a RMC plant generally requires a three-day advance notice for ordering concrete delivery service, with the order confirmed one day before the actual pour date. Raw material stocks at a plant are replenished on a daily basis in preparation for the next-day's production which is pulled by site orders placed by multiple clients. A RMC plant transforms raw materials into concrete in its production facility and is committed to delivering concrete to different construction sites by truckmixers so as to match the on-site concreting progresses. The elapsed duration from the introduction of water to the final placement of the concrete is of particular importance to the quality control of ready mixed concrete. For example, ASTM C94 (ASTM 2000) allows a maximum of 1.5 hours (90 minutes), or before the drum has made 300 revolutions, whichever comes first. The Hong Kong common practice is to unload concrete into the forms on site within 1 hr 45 min of first mixing as a maximum time limit. Due to the perishable nature of concrete, the batching and delivery operation of the RMC industry is a classic example of Just-In-Time (JIT) construction system (Tommelein and Li 1999).

The dispatching of truckmixers to fulfill site orders is not only constrained by the availability of plant resources (i.e. the batch bay and the truckmixers), but also driven by the demand pattern of concrete by the sites. Thus, the service levels achieved together with the utilization levels achieved for the resources involved are governed by the subtle interactions between the supply and demand factors. The supply is mainly constrained by (1) the resources available at the RMC plant (including mixers and trucks) and (2) the mechanisms for scheduling concrete production and dispatching truckmixers to different sites; while the clients' demand is characterized in terms of (1) the total number and location distribution of sites being served simultaneously, (2) the grade and quantity of concrete for each site, (3) the traveling distance or time from the plant to each site, and (4) the concrete-unloading rate on each pour. Nonetheless, in confronting the complexity, uncertainty and variability within a one-plant-multisite RMC production system of practical size, the current industry practices still largely rely on managerial experiences and heuristic methods, falling short on any effective, straightforward modeling and optimization means to support decision making. Anson and Wang (1994) highlighted the negative effect of the poor coordination between RMC plants and site contractors on the productivity of concreting processes. The relatively poor matching performance between the supply of concrete and the site requirements in Hong Kong building sites was characterized by both truckmixers' queuing on site and site crews staying idle due to late truckmixers' arrivals (Anson and Wang 1998). In addition, the relatively poor matching performance between the concrete supply and the site requirements also caused the serious underutilization of plant resources – an average of 37.6% in terms of truckmixer working percentage was reported as of Hong Kong's experience (Anson et al. 2002). This has undermined not only the efficiency and service of the RMC business, but also the productivity and quality of concrete construction in building sites.

Simulation modeling of complicated, dynamic, and interactive processes in construction is essentially a computer-supported implementation of the systems approach. Riley and Towill (2001) define a system as "an integrated combination of the components and activities, designed to follow a common purpose and exists in order to achieve a better understanding of the problem and hence help create a 'tool' to resolve the problem". Discrete-event simulation keeps track of the changes of the state of a system occurring at discrete points in time (Pidd 1992); and actually builds a logical model of a system for experimenting with it on a computer (Pritsker 1986). As a matter of fact, the methodology of discrete-event simulation is the only general methodology that affords a means of modeling the ready-mixed concrete production and construction systems on a stochastic basis (Zayed and Halpin 2001). Research has proven the power and capability of the simulation technology in tackling the concrete production systems subject to practical constraints. Smith (1998) simulated the stochastic concrete delivery and pumping process with a spreadsheet program, observing the optimal combination of truck interarrival and concrete pump times that would maximize the plant utilization while minimizing the pour duration. Ying et al. (2005) also identified the importance of a site manager specifying realistic time intervals between consecutive truckmixer arrivals by conducting simulation experiments on a VB program developed in house. In addition, Sawhney et al. (1999) described the utilization of Petri nets as a process modeling and analysis tool for deciding the least number of concrete trucks that would lead to the maximum daily production rate in fulfilling the daily site orders at a RMC plant. Chau and Li (2002) developed a resource-interacted simulation modeling approach to analyze general construction operations and particularly employed it to model a concrete delivery operation. Alkoc and Erbatur (1998) and Zayed and Halpin (2001) utilized the simulation system of MicroCYCLONE to generate simulation models for concreting operations and evaluate a set of possible resource combinations. Zayed and Minkarah (2004) also designed a linear programming model to determine the optimal number of transit mixers based upon the required quantity of concrete. Based on a simplified discrete-event simulation approach (*SDESA*) for modeling construction operations (Lu 2003), Lu et al. (2003) developed a special-purpose simulation tool called *HKCONSIM* for rapidly building a simulation model for a typical one-plant-multisite system of concrete production and delivery, thus facilitating the study of the complicated relationships between the pattern of demand for concrete, the resources available to the system, and the service levels achieved together with the utilization levels achieved for the resources involved.

To automatically identify the optimum solution through simulation, evolutionary computing-based optimization algorithms have been integrated with simulation modeling to augment simulation's power in dealing with complex RMC operation planning. By linking up two commercial software systems (the Provess V3 and the Evolver), Hegazy and Kassab (2004) combined the simulation and genetic algorithms (GA) to optimize the resource configuration in placing columns (i.e. the quantities of trucks, crane-buckets, and crews), so as to minimize the unit production cost. Feng et al. (2004) and Feng and Wu (2006) incorporated the standard and enhanced forms of GA (called fast messy GA) with MicroCYCLONE −respectively− to optimize the schedule of dispatching RMC trucks to multiple construction sites, aimed at yielding the minimum truck waiting time on site while also avoiding concrete supply interruptions. One common limitation noted in the above three GA-optimized simulation models is that the input parameters (such as the traveling duration and casting duration) are simply represented with deterministic values instead of statistical distributions. It is noteworthy that GA has also been embedded in *HKCONSIM* featuring stochastic input models to simultaneously optimize (1) the production and delivery scheduling and (2) the truckmixer resource provision (Lu 2002). Lu and Lam (2005) further augmented the *HKCONSIM* modeling platform by incorporating the mortar batching, delivery, and flushing processes for those pumped concrete pours; what is more, two measures of the system performance were compared through GA-enabled optimization, namely, the "site service level" (the summation of crew idle time due to tardy concrete deliveries on all the sites), and the "total operations inefficiency" (the summation of crew idle time plus truckmixer queuing time on all sites). And minimization of the "total operations inefficiency" was found to be the proper objective for optimizing the overall system performance (Lu and Lam 2005). A follow-up attempt was to accelerate the optimization process of *HKCONSIM* by devising a particle swarm optimization (PSO)-based technique for coping with the optimization of stochastic system simulations (Lu et al. 2006). A comparison of

PSO with GA was made in the context of optimizing an 11-site *HKCONSIM* model, showing the PSO-based approach could rapidly (in order of a few minutes) converge at the minimum level for the "total operations inefficiency" while GA failed to converge or required long time (in order of hours) in search of the minimum (Lu et al. 2006).

Hence, the latest *HKCONSIM* system, powered by the *SDESA* simulation engine and the PSO-based optimization engine, is ready to provide concrete plant managers with direct assistance in coping with the challenges of generating the best operation strategy in delivering concrete to multiple site clients. Instead of elaborating on the underlying algorithms and the in-house development of the *HKCONSIM* system, this paper is intended to address such questions as of (1) "Can *HKCONSIM* capture the complexities of the real world?" and (2) "How to take advantage of *HKCONSIM* to attain customer satisfaction and cost effectiveness?" Accordingly, particular emphasis is placed on validation and application of this simulation-optimization integrated solution to planning RMC plant operations in a practical setting. The remainder of this paper presents a case study describing one-day operations of a Hong Kong RMC plant for illustrating what kinds of decision support *HKCONSIM* can provide and how RMC plant operators can take advantage of *HKCONSIM* to augment their experiences, corroborate their intuitions, and create new intelligence in coping with their day-by-day business. The case study spans (1) input data preparation, (2) the definitions of relevant measures of the system performance, (3) simulation model validation by comparing the simulation outputs against the actual records, and (4) further optimization analysis under three "what-if" scenarios postulated with practical implications. Conclusion is drawn at the end.

2 VALIDATION OF SIMULATION: CAN *HKCONSIM* CAPTURE THE COMPLEXITIES OF THE REAL WORLD?

2.1 Input Data

For validating the *HKCONSIM* simulation platform and further demonstrating simulation-based optimization analysis, one day of complete, detailed operations data (including pour orders, truck-dispatching schedules, concrete delivery slips) were obtained from a concrete plant situated near Tin Wan, Hong Kong Island. As illustrated in Figure 1, corresponding one-plant-multi-site simulation models for concrete orders is formed in HKCONSIM. On that particular day, the plant utilized two batching bays (mixers), 29 large mixer trucks (7 m^3 volume capacity each) and 15 small ones (5 m^3 volume capacity each) to deliver a total of 952 m^3 concrete to 13 different building sites. Table 1 gives specifics of the pour orders from 13 sites. Note a pour order provides information on (1) the grade and quantity of concrete ordered, (2) the site location, (3) the particular requirement on the mixer truck type (namely, requesting the delivery service by small truck only, or big truck only, or no requirement), (4) the pour start time (i.e. the arrival time of the first mixer truck), and (5) the estimated supply rate (approximated in terms of the interval time between consecutive truck arrivals, or the quantity of concrete delivered per hour m^3/hr).

Table 1: Details of pour orders processed over one working day

Site ID	Qty. (m^3)	Spec. Truck	First Arrival	Inter-arrival Time (min)	Dist. (km)	Placing Method
1	78	Either	8:30	25	3~4	Pump
2	4	Either	10:45	-	3~4	Direct Tip
3	5	Either	14:30	-	3~4	Direct Tip
4	116	7 m^3	11:00	20	3~4	Two Skips
5	129	7 m^3	9:30	24	3~4	Two Skips
6	54	7 m^3	13:00	25	3~4	Two Skips
7	206	7 m^3	10:30	14	3~4	Pump
8	88	7 m^3	10:45	25	6~10	Two Skips
9	54	Either	12:00	20	6~10	Two Skips
10	88	7 m^3	10:20	30	4~5	Two Skips
11	16	5 m^3	14:00	40	4~5	Direct Tip
12	53	Either	13:15	20	4~5	Two Skips
13	61	Either	9:00	30	4~5	Two Skips

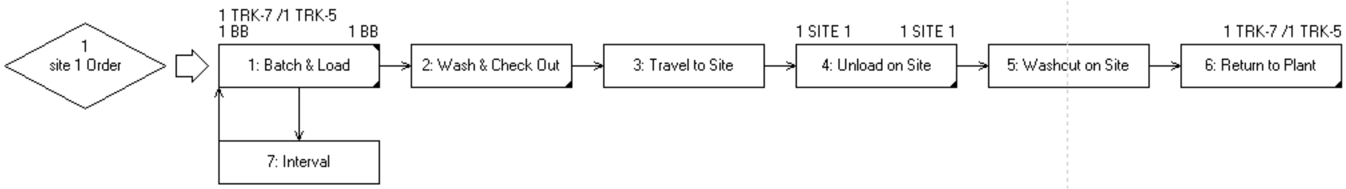

Figure 1: Simulation model of one concrete order in *HKCONSIM*

The plant-to-site travel distance and the placing method employed for each site are linked to the default triangular distributions for travel times and truck-unloading production rates (as shown in Figure 2, input parameters for triangular distributions are in the order of the optimistic, the pessimistic, and the most likely time estimates in min). The default three-point parameters of *HKCONSIM* are estimated based on historical data collected in Hong Kong and can be readily adjusted to stay current. In our case study, most default time parameters closely reflect the actual situations, except that the truck-unloading times for seven large pours (ordering more than 70 m^3) need reassessment and adjustment according to the actual site truck-unloading time records (Table 2).

- **Default time distributions:**
  - General processes

5 cubic meter Truckmixer

Batching Time:	Triangular(1.00, 3.00, 1.70)
Check Out Time:	Triangular(2.00, 11.00, 5.70)
Mortar Unload Time:	Triangular(5.00, 16.00, 8.00)
WashOut Time:	Triangular(0.00, 24.00, 7.90)

7 cubic meter Truckmixer

Batching Time:	Triangular(2.00, 4.00, 2.70)
Check Out Time:	Triangular(3.00, 13.00, 6.20)
Mortar Unload Time:	Triangular(5.00, 16.00, 8.00)
WashOut Time:	Triangular(0.00, 24.00, 7.90)

- **Default time distributions:**
  - Traveling process

Name	Go To Site (min)	Return To Plant (min)
1 KM	Triangular(6.00, 13.00, 8.40)	Triangular(5.00, 10.00, 7.50)
3 KM	Triangular(8.00, 20.00, 10.10)	Triangular(7.00, 16.00, 9.20)
4-5 KM	Triangular(12.00, 28.00, 15.80)	Triangular(9.00, 25.00, 13.00)
6-10 KM	Triangular(16.00, 36.00, 22.60)	Triangular(13.00, 31.00, 18.80)
13-15 KM	Triangular(21.00, 40.00, 28.00)	Triangular(17.00, 37.00, 21.80)
18-26 KM	Triangular(28.00, 51.00, 36.80)	Triangular(21.00, 43.00, 27.30)
30-34 KM	Triangular(37.00, 62.00, 46.90)	Triangular(30.00, 52.00, 35.00)

- **Default time distributions:**
  - Unloading process

Name	Truck 5m Unloading Time (min/truck)	Truck 7m Unloading Time (min/truck)
BACKHOE	Triangular(9.00, 21.00, 14.40)	Triangular(10.00, 31.00, 17.00)
DIRECT TIP	Triangular(5.00, 19.00, 10.70)	Triangular(7.00, 21.00, 12.70)
HOIST & BARROW	Triangular(22.00, 52.00, 36.60)	Triangular(33.00, 62.00, 47.00)
PUMP	Triangular(8.00, 29.00, 14.00)	Triangular(11.00, 38.00, 20.80)
1 SKIP	Triangular(14.00, 48.00, 19.70)	Triangular(17.00, 60.00, 31.40)
2 SKIPS	Triangular(11.00, 43.00, 18.40)	Triangular(14.00, 54.00, 25.30)

Figure 2: Default time distribution settings of *HKCONSIM*

Table 2: Unloading times for several large pour orders

Site ID	Triangular distribution for TM 5m^3 (min/truck)			Triangular distribution for TM 7m^3 (min/truck)		
	Optimistic	Most likely	Pessimistic	Optimistic	Most likely	Pessimistic
1	*9*	*11*	*24*	*11*	*13*	*27*
4	*10*	*15*	*28*	*14*	*20*	*34*
5	*14*	*19*	*23*	*17*	*25*	*35*
7	*9*	*11*	*15*	*11*	*15*	*21*
8	*14*	*17*	*30*	*16*	*28*	*35*
10	*11*	*19*	*33*	*14*	*23*	*42*
11	*24*	*29*	*33*	*29*	*35*	*40*

2.2 Performance Measures

The development of a unified quantitative performance measure is critical to evaluating simulated scenarios, and thereby, optimizing the simulated system of *HKCONSIM* with respect to the truck-dispatching schedule and the truckmixer resource provision (Lu et al. 2003). A confidence level on the performance measure should also be established due to the probabilistic and stochastic nature of simulation modeling (e.g. the uncertainty in activity duration and the variability in resource allocation in *HKCONSIM*). In the current case study, the performance measure of "total operations inefficiency" (TOI) is chosen for evaluating alternatives and determining the optimum state of the system. TOI denotes the total unproductive resource time incurred on all the building sites served by the RMC plant in one-day delivery operations by adding up the total queuing time of mixer trucks on sites and the total idle time of site crews. Hence, the less the TOI value, the less truck queuing and site idleness experienced within the whole system, and the higher the resource utilization rates of mixer trucks and site crews together with the higher the concrete delivery service level achieved by the RMC plant.

Running the *HKCONSIM* simulation −subject to the actual resource configurations (two batching bays, twenty-nine 7-m^3 trucks and fifteen 5-m^3 trucks) and site order requirements− has resulted in an average of 2720 min TOI. Note the TOI value from simulation refers to the average of a distribution, resulting from randomly sampling the simulated system for 500 times (i.e. 500 Monte Carlo duplications) as shown in Figure 3. The TOI distribution's appearance resembles a bell-shaped normal distribution and the 95% confidence interval of the average TOI is determined as [2691, 2750]. It should be noted throughout the case study, the evaluation of a simulation scenario by use of *HKCONSIM* is consistently based on the average of TOI resulting from 500 Monte Carlo duplications.

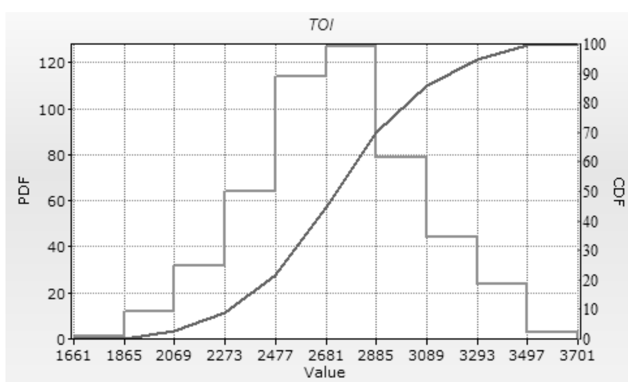

Figure 3: TOI Distribution resulting from case study with *HKCONSIM*

Careful analysis of actual operations data and delivery records has determined the actual TOI value to be 2670 min, which is a close fit to the 2720 min average TOI derived from simulation. The slight difference (50 min) can be attributed to the fact that the actual TOI is not a statistical descriptor of the system performance as the simulated TOI, but a one-time observation from executing the actual system. The high TOI value has also exposed the poor matching performance between supply and demand in the real world (i.e. 2670 min truck queuing plus crew idle time on 13 sites or 205 min per site).

Two site-based performance ratios given by Anson and Wang (1998) imply the average number of trucks seen on a site and the working percentage of the site crew's time respectively, and are instrumental in evaluating system performances and further validating *HKCONSIM* simulation. They are (1) the truck provision ratio (TH/PD%), defined as the truck provision hours on site over the pour duration, and (2) the site idleness ratio (SI/PD%), defined as the site idle time over the pour duration. A diagrammatic performance measure can be devised for the one-plant-multisite concrete delivery system by correlating the two ratios in a scatter plot (Figure 4). The overall trend among all sites can be observed as: with the increase of the truck provision ratio, the site idleness ratio decreases. The ideal performance is to cluster all sites into the "cost-efficient" zone, where the truck provision ratio is within 150% and the site idleness ratio under 20% (Anson and Wang 1998). The site idleness ratio of 20% indicates the concrete supply is interrupted in one fifth of the overall pour duration. The truck provision ratio of 150% can be interpreted as one or two truckmixers residing on site at one time over the pour duration. Note, according to Anson and Wang (1998), the definition of the above ideal performance thresholds along with the "cost-efficient" zone was arbitrary and based on statistical analysis of actual operations data and general perception by site personnel.

Since the definition of TOI also takes into account the truck queuing time on site and the crew idle time, TOI can be closely connected with the above diagrammatic measure based on the two ratios. Note the truck queuing is the unproductive portion of truck provision time on site and should be minimized along with the crew idle time in order to enhance the overall system performance. Therefore, if the TOI of a *HKCONSIM* simulation can be minimized through optimization, it is expected that the diagrammatic measure will automatically reach its ideal state by clustering all the dots within the "cost-efficient" zone. This connection will be clearly illustrated in the ensuing optimization experiments designed of our case study. To further validate the simulation model, similar to the measure of TOI, the diagrammatic measures resulting from actual records and simulation are contrasted in Figures 4 a, b. Figure 4b gives the correlation pattern of the two performance ratios resulting from the averaged results of 500 Monte Carlo simulation runs, which is observed to well match the actual case as given in Figure 4a.

As seen from the above validation case, the HKCONSIN model can serve as a useful parallel to the actual system for gaining more insights of the actual system and enhancing the performance of the actual system. In order to demonstrate how to improve the current practices by taking advantage of the optimization feature within *HKCONSIM*, the following sections postulate three scenarios with practical implications and investigate each by use of *HKCONSIM*.

Figure 4a. Based on Actual Data

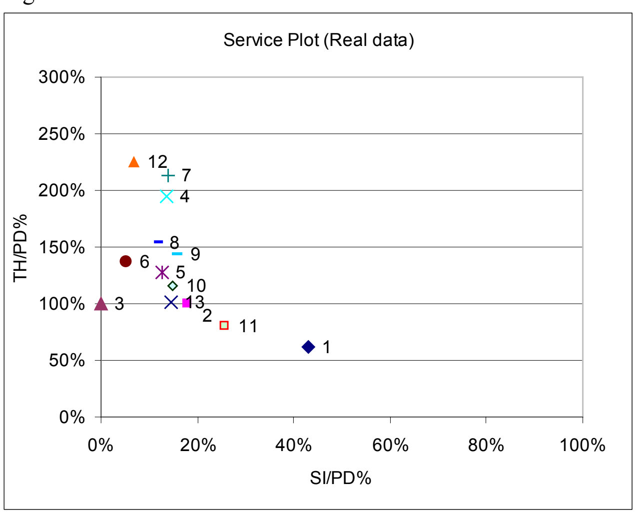

Figure 4b. Based on Simulation Results

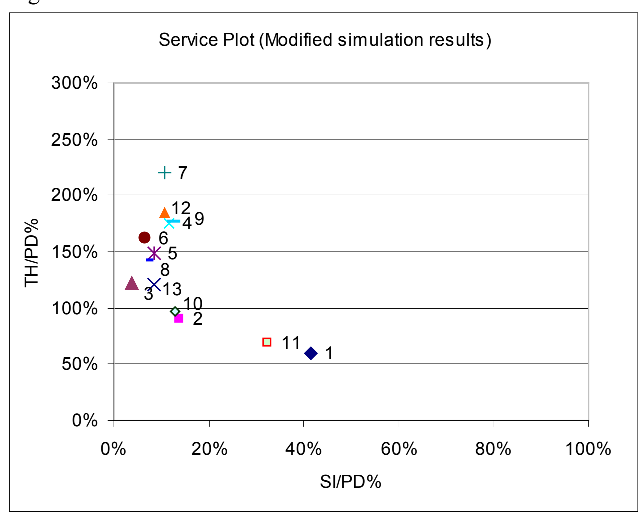

Figure 4: Contrasting the diagrammatic measures resulting from actual records and simulation

3 ROJECT INITIATION

3.1 Scenario 1

With the same mixer truck fleet (29 7-m^3 trucks and 15 5-m^3 ones), can the plant operator improve the delivery service by better marshalling the truck dispatching?

In the actual case, the TOI stood as high as 2670 min– equivalent to the average of nearly 3.5 hours truck queuing plus site idling as per site. Figure 4a also reveals in sites no. 11 and 1 the crews were idle over 20% of the pour time (due mainly to late concrete truck arrivals), while sites no. 12 and 7 experienced considerable truck bunching with over 200% truck provision ratio recorded. So how can the plant operator provide uninterrupted concrete delivery service to all site customers, while reducing truck bunching on site?

Based on a valid *HKCONSIM* simulation, optimization analysis can be performed to fine-tune the inter-arrival time for each site within a certain limit of the original estimates (e.g. ±20 min); as a result, an optimum guide can be derived to assist the plant operator in prioritizing site demands and marshalling the truck fleet in a more masterful way, thereby leading to minimization of truck queuing time and crew idle time on all the sites being served. The overall system performance is expected to be sensitive to adjustments on truck inter-arrival times (Smith 1998, Ying et al. 2005). In our case study, the optimization brought down the simulated TOI from the original 2720 min to 928 min. This is equivalent to a significant decrease on the average of truck queuing plus site idling time per site from nearly 3.5 hours to 1 hr 12 min. Table 3 contrasts the inter-arrival time for each site before and after optimization. Note that for small pours (sites no. 2 and 3) entailing only one truck delivery, optimization of the inter-arrival time is not applicable. On the remaining eight pours the optimization had prolonged the time gap between dispatching consecutive trucks by 1 to 13 min; on three other sites, the time gap had been reduced by 2 to 8 min. Moreover, improvements on system performance are also clearly demonstrated in the scatter plot that correlates the two performance ratios (Figure 5). In Figure 5, all sites have been clustered into the “cost efficient” zone bounded by the 150% truck provision ratio and the 20% site idleness ratio. In short, the site demand in terms of the estimate of the inter-arrival time of truck deliveries is found to exert substantial effects upon the overall delivery service level; and optimization of the inter-arrival times for all sites by *HKCONSIM* helps draw up the best concrete production schedule, thereby significantly enhancing the performance of a concrete plant in utilizing the trucks available to meet demands from multiple site clients.

Table 3: Scenario 1: inter-arrival time for each site before and after optimization

Site ID	Original Inter-arrival time	Optimum Inter-arrival time	Change
1	25	20	-5
2	-	N/A	N/A
3	-	N/A	N/A
4	20	24	+4
5	24	27	+3
6	25	38	+13
7	14	18	+4
8	25	28	+3
9	20	29	+9
10	30	31	+1
11	40	32	-8
12	20	29	+9
13	30	32	-2

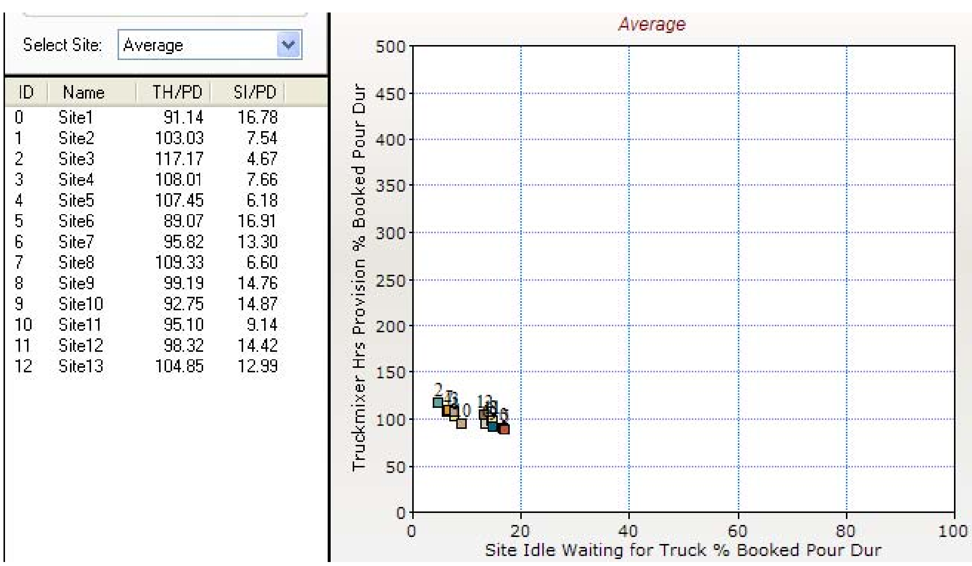

Figure 5: Site-specific performance ratios and scatter plot resulting from *HKCONSIM* optimization in Scenario 1

3.2 Scenario 2

Can the concrete plant utilize fewer trucks to serve the 13 site clients without compromising the concrete-delivery service?

Note in the actual case and Scenario 1, the plant deployed a total of 44 mixer trucks (29 7-m^3 trucks and 15 5-m^3 ones) in handling the 13 concrete pours over one working day. In addition to inter-arrival times, *HKCONSIM* can also help the plant operator optimize the configuration of the truck fleet, aimed to utilize fewer truck resources to achieve the similar service level. With consideration of the cost and availability constraints of truck resources and the actual site demand (a total of 966 m^3 to 13 sites), the quantities of big trucks (7 m^3) and small trucks (5 m^3) were set to be bounded on [15, 25] and [10, 15] respectively before optimization. By adjusting the truck quantities and the inter-arrival times simultaneously, the optimization analysis eventually yielded an optimum solution of 966 min TOI (which is marginally higher than the 928 min TOI of Scenario 1), entailing 20 big trucks and 10 small ones only (i.e. a total of 14 fewer trucks than Scenario 1). The inter-arrival times associated with the optimum solution are given in Table 4 and listed against results from Scenario 1. The changes to inter-arrival times in Scenario 2 are noted to be trivial (within the limit of ±2 min), which indicates that the system optimization is largely enabled by streamlining the truckmixer fleet. Thus, the plant operator is advised to keep her original concrete production schedule but use a much leaner truckmixer fleet in order to achieve cost-efficiency and customer satisfaction.

Table 4: Scenario 2: inter-arrival time for each site before and after optimization

Site ID	**Scenario 1: 44 trucks Inter-arrival time**	**Scenario 2: 30 trucks Inter-arrival time**	**Change**
1	20	20	0
2	N/A	N/A	N/A
3	N/A	N/A	N/A
4	24	26	+2
5	27	29	+2
6	38	38	0
7	18	18	0
8	28	30	+2
9	29	31	+2
10	31	30	-1
11	32	33	+1
12	29	29	0
13	32	31	-1

The site-specific performance ratios are shown in the scatter plot of Figure 6. With the truck fleet being streamlined, the overall concrete-delivery service level and the site productivity level still remain satisfactory, as evidenced by both TOI and the scatter plot. In short, the truck resources are found to be oversupplied in both the actual case and Scenario 1; and reconfiguration of the truck fleet by *HKCONSIM* helps cut the resource cost of the plant by using 14 less trucks while maintaining the similar level of delivery service as achieved in Scenario 1.

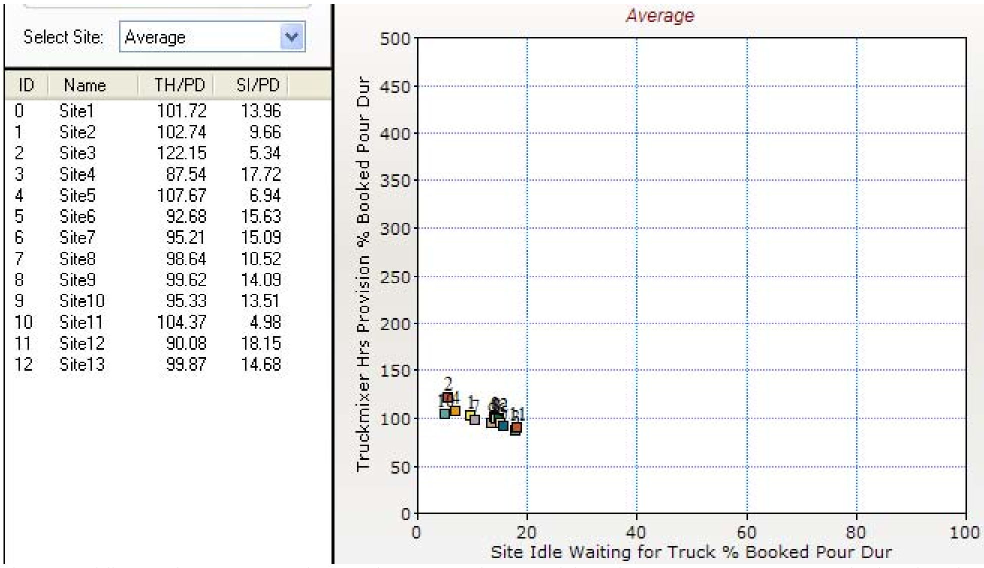

Figure 6: Site-specific performance ratios and scatter plot resulting from *HKCONSIM* optimization in Scenario 2

3.3 Scenario 3

Can the plant operator further improve the concrete-delivery performance by adjusting the pour start time on several large pours?

According to the real-world business practice, site contractors normally give the flexibility to the concrete plant in rearranging the pour start time (earlier or later within certain limits) as long as continuous concrete delivery service can be guaranteed. In the 3rd optimization scenario, the first truck arrival time for thirteen pours in our case study were allowed to be adjusted within the limit of ±30 min, while the quantities of big trucks and small trucks were bounded on the same ranges as in Scenario 2. The optimization results show that 898 min TOI was achieved with the use of a total of 29 trucks (22 big trucks and 7 small trucks). Hence, with reference to Scenario 2 (966 min TOI and 30 trucks in total) it is inferred that the plant operator could possibly obtain further improvement on the overall system performance (i.e. about 30 min less queuing/idle time on all sites) by use of 1 less truck. Comparisons are made in Table 5 on the pour start time and the inter-arrival time on each pour as compiled from the optimum results of Scenarios 2 and 3. Changes on pour start times are notable (-30 to +25 min); in contrast, only minor adjustments (within 5 min) had occurred to inter-arrival times. The resulting site performance ratios for Scenario 3 are shown in the scatter plot of Figure 7. In comparison with the previous Scenarios 1 and 2, the changes of clustering patterns in optimum solutions are not discernible, with all sites falling into the “cost efficient” zone in Figure 7. In short, the resulting changes to the TOI, the inter-arrival times, and the quantity of truck resources by rearranging the pour start times are not significant. And the system can be further fine-tuned by a small margin.

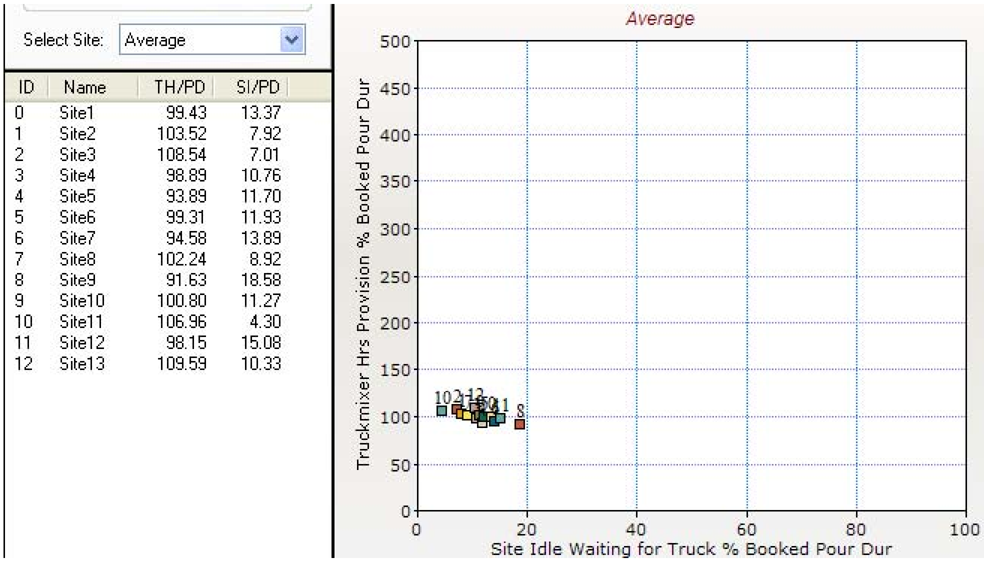

Figure 7: Site-specific performance ratios and scatter plot resulting from *HKCONSIM* optimization in Scenario 3

4 CONCLUSION

Due to the perishable nature of concrete, the batching and delivery operation of a ready mixed concrete (RMC) plant is a classic example of Just-In-Time (JIT) construction system. The service levels achieved together with the utilization levels achieved for the resources involved are governed by the subtle interactions between the supply and demand factors. Nonetheless, the current industry practices for scheduling concrete production still largely rely on managerial experiences and heuristic methods, falling short on any effective, straightforward modeling and optimization means. This has undermined not only the efficiency and service of the RMC business, but also the productivity and quality of concrete construction in building sites.

Research has proven the power and capability of the simulation technology in tackling the concrete production systems subject to practical constraints. To confront the complexity, uncertainty and variability within a one-plant-multisite RMC production system of practical size, we have developed a special-purpose simulation tool called *HKCONSIM* for rapidly building a simulation model for a typical one-plant-multisite system of concrete production and delivery based on a simplified discrete-event simulation approach. To automatically identify the optimum solution through simulation, evolutionary computing-based optimization algorithms have been integrated with *HKCONSIM* to augment simulation's power in dealing with complex RMC operation planning. In this research, particular emphasis has been placed on validation and application of this simulation-optimization integrated solution in a practical setting, as illustrated by a case study describing one-day operations of a Hong Kong RMC plant. The simulation model was validated first by comparing the simulation outputs against the actual records in light of the performance measure of the "Total Operations Inefficiency" and the scatter plot relating two site-specific ratios. Based on valid simulations, optimization analyses were carried out for three "what-if" scenarios postulated with practical implications.

We have gained the following insights from the case study: (1) the *HKCONSIM* model can serve as a useful parallel to the actual system for enhancing its performance; (2) optimization of the inter-arrival times for all sites by *HKCONSIM* helps draw up the best concrete production schedule, thereby significantly enhancing the performance of a concrete plant in utilizing the trucks available to meet demands from multiple site clients; (3) the truck resources are found to be oversupplied in the actual case, and reconfiguration of the truck fleet by *HKCONSIM* helps significantly cut the fleet size while maintaining the similar level of delivery service; (4) and the system can be further fine-tuned by a small margin by rearranging the pour start times on several large pours.

Finally, the latest *HKCONSIM* simulation system, powered by the optimization engine resulting from recent computing research, is ready to provide concrete plant managers with direct assistance in coping with the challenges of generating the best operation strategy in delivering concrete to multiple site clients.

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