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A Capacity Planning through Discrete Event Simulation

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Abstract

The capacity planning serves an important role in strategic decisions involving production facilities. While there are many publications made on capacity planning, most of the models created tend to restrict their applications in real-world due to some initial assumptions being made and/or the run-time execution of the models that may be prohibitive. The objective of this paper is to explore the model construction for in-plant truck movement in a cement company that is based on building a discrete-event simulation one so that the planning may be sufficiently robust while the amount of time for constructing the model and the run-time still serve practical purposes. The model then is used to examine the effects of shifting bottlenecking and thus, allows users to identify critical resources for the production process. The results show that such a model provides the directions and aids for the management to make the strategic decisions.

Keywords: *capacity planning, discrete-event simulation, in-plant truck movement, shifting bottleneck, critical resources.*

INTRODUCTION

Background

In any complex organizations, planning serves to steer different parts of an organization to pursue the organization’s objectives, minimizing unnecessary conflicts among them (March & Simon, 1958). Since manufacturing organizations run to serve the objective of producing goods, production planning activities naturally play important parts in manufacturing organizations and these activities may depend on several factors, in which one of them is the capacity (Tenhiala, 2011).

The capacity, originally defined to supply the means of production for goods or service, can be viewed in two horizons, the long-run and the short or intermediate run. Hence, the implications is capacity planning serves a strategic role in which model for it, then, needs to constructed as it affects resources utilization plan along with investment strategy for the plant (Hammesfahr, et al., 1993).

There are many publications addressing capacity planning. And yet, essentially one may view the planning model in terms of two constructions, stochastic and deterministic, and their combinations (Geng & Jiang, 2009). For example, Ahmed and Sahinidies (2003) employs a hybrid method utilizing a deterministic approach by taking the stochastic inputs. This approach later is expanded in a multi-stage set up (Ahmed, et al., 2003). Cakanyildirim, et al (2004) creates a similar model to improve the planning accuracy. Chou, et al., (2007) constructs a model that allows alternative capacities being considered. However, it is clear that constructing such models in real-world requires tantalizing technical prowess while at the same time, they impose some restrictive assumptions that may not respond well to the nature of the actual setting for the objects being investigated.

Our research is driven by the needs to find models that can provide relatively fast response to the strategic questions being considered by the new management of a cement company in Indonesia.

As part of the new controlling shareholders of the company, the management needed to know whether the cement production plant might meet the intended production target and whether any major investments were needed in doing so. Hence, realistic natures of the decision limited the model types to be constructed.

Problem Description

The cement producer in this study essentially needed to know whether the production facility capacity was possible to be ramped up by 50 percent to reach the theoretical production facility capacity without any additional major investment or not. The question was needed to be addressed in a relatively short period of time of 1 month while it was of a strategic nature since the production plant was part of a newly acquired asset considered for facilitating growth of anticipated demand in Indonesia and neighboring countries.

While the facility is located in the West Java province of Indonesia, due to the nature of the strategic objective of the owner and the cement industry wherein the production process employs continuous process, hence suffering tremendously if there is any downtime, it is clear that the production facility capacity also depends on the efficiency of the closed loop transportation systems in the form of trucks, bringing the products to the market, and moving back to the plant. Ideally, then, this research quandary needs an integrated model to address it, the one that covers the closed loop truck movement inside and outside the production facility and connecting this facility with the markets it serves.

However, the management decided to have two separate investigations, the first one involved the production capacity that was due to internal-plant truck movement and the other one, the production capacity that was due to external-to-plant truck movement. This decision stemmed from the fact that for the latter, the cement producer were considering a plan to acquire a major transportation infrastructure asset that would change the transportation network tremendously. In the meantime, addressing the first issue was extremely urgent for the producer.

Thus, this paper only includes the former one while leaving the latter for future research.

LITERATURE REVIEW

In cement production setting, capacity planning may involve truck scheduling and dispatching to deliver ready-mixed concrete in which an overview of this work shows that this delivery problem is a classic example of a just-in-time production system where the customers' demand dictates batching creation (Tommelein & Li, 1999). The dynamic truck routing in distributing ready-mixed concrete decision support system uses heuristics by splitting the vehicle scheduling for special delivery equipment and concrete-carrying vehicles in Matsatsinis (2004).Naso, Surico, and Turchiano (2007) provides a nonlinear mathematical model to deal with plant capacities and vehicle speeds that takes into account the planning horizon perturbations. A tabu search combined with a time-space network formulation is considered by Hoffman and Durbin (2008). A novel solution that is based on local-search approach and yet only solves very small cases is developed by Asbach, Dorndorf, and Pesch (2009). Schmid et al. (2009) develops a related novel model involving a heterogeneous fleet of vehicles with specialized unloading equipment. In spite of their relevance in determining the cement production plant capacity, our work differs from them by focusing on the truck movement within the plant itself.

In a similar fashion to our works, Brown et al. (2001) focus on developing supply chain planning model for the cement industry, having bulk and bagged cement types. Dikos and Spyropoulou (2013) clip this model by excluding the sales prices of bulk and bagged qualities per market for the Heracles general cement company due to the non-presence of these elements in their study. These authors develop their own SCOP models since taking off-the-shelf solutions may not guarantee smooth integration nor global cost optimization (Chen, et al., 2006). Despite the similarities, the nature of our work differs from these works as we focus on the one-time strategic decision to be made by the cement company.

In the mining industry, several works can be found in capacity planning. Everett, Howard, and Jupp (2010) develop a Microsoft Excel-based model for the design of Cliff Natural Resources in Australia by focusing on optimized blending strategies instead of production volume maximization. In our case, the model is to maximize the production volume. Debottlenecking is also considered by Mutagwaba and Hudson (1003), Pereira et al. (2012), Meng et al. (2013) and Salama et al. (2014). However, their objectives are on equipment selection areas, rather than the production chain. On the other hand, multiple mine-design options are considered by the model combining simulation and optimization techniques developed by Groeneveld and Topal (2011) and yet the model lacks sufficient details for decision making.

A Monte Carlo-based real-options valuation model developed by Sabour et al. (2013) is used to have a quick economy valuation and Bodon et al. (2011), uses a similar model for PT Kaltim Prima Coal operation in Indonesia. However, these works cannot handle infrequent events, unlike ours.

Bouffard et al. (2018) develop a comprehensive model covering ore storage capacities, product sizing infrastructure, critical-equipment redundancies among others. They use a discrete-event simulation approach on this work. Our model differs by focusing on a one-time strategic decision while not extending it into a day-to-day one.

Several other works are found in using discrete-event simulation for capacity planning yet in different industry, namely, the semiconductor one. For example, Fowler, Monch and Ponsignon (2015) provides a tutorial on such an application. Wood (2007) constructs one to support design decisions on tool choice along with its count as well as on operational policy selection. Moreover, Biller et al. (2019) constructs a model to manage risk and value for the GE's silicon carbide manufacturing facility. On the contrary, we work on production plant capacity planning in the cement industry.

RESEARCH METHODOLOGY

Model Development

As mentioned previously, the management of the company was not sure whether this newly acquired production asset would be able to reach the theoretical annual production capacity as advertised by the previous owner. During the due diligence process, they had verified that the production machines and the kilns were in good order and would produce up to the theoretical capacity. Yet, it was clear that for this continuous production system, the transportation resources in terms of the trucks might play a big role for the achievement of the production rate. Moreover, due to patterns of the external to the plant traffic being too unpredictable which in turn forcing the management to consider acquiring another major infrastructure asset so that this traffic would be more in control, the management decided to exclude the external-to-plant truck movement from the study. Instead, the focus was on the in-plant truck movements.

As pointed out in Banks, et al. (2013), the modeling steps consist of: (1) the model construction, (2) verification and validation, and (3) experiment runs. The model construction needs to construe the objective of the study, and conceptualize along with collecting data. After the model being verified and validated, then one can only proceed to the model runs using some prepared scenarios. In our study, each run constitutes one day operation in the plant and being replicated 100 times. Figure 1 below shows the overall modeling steps taken in our study.

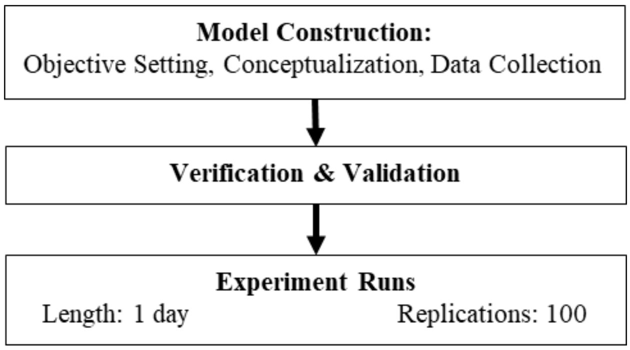

Figure 1. Modeling Steps

Specifically, the objective of the study is to investigate the throughput percentage measured through the truck movements of bag and bulk types, in and out of the facility and to find the effects of changing some operational parameters of supporting production resources, namely, palletizers, silos, and their accessories.

Trucks coming to the production facility in two types: the bag truck, carrying cement products in bags, and the bulk trucks, carrying cement products in bulk form. The bag trucks cater mostly to the retailers and export markets, while the bulk trucks serve major construction projects all around West Java province.

Once these trucks reach the outskirts of the facility, their securities need to be inspected. There may be queue developed before this security gate and such a queue may spill over to the public roads. Upon security clearance, all trucks are to wait for their turns at a common queue yard to go through a weighbridge so that the management can control the tonnage of the product shipments. There are two such weighbridges. These weighbridges only allow trucks to enter if the subsequent stations are clear. Otherwise, the trucks stay in the queue yard.

After the weight has been taken, any bulk truck immediately proceeds to any available hole station. There are four hole-stations in the plant. Here, the driver of the truck opens the container hole of the truck so that the drive can take to the next station which is the silo. In turn, the silo is to churn the cement powders into the container through the opened hole. There are twelve silos at the facility. The driver may go to any available one. The process of filing up the container may take some time before the driver needs to do the next process, i.e., closing the hole and seal it. Upon the completion of these activities, the bulk truck is ready to depart from the facility. And yet, these bulk trucks need to go through to another set of two weighbridge to choose from. Before undergoing this step, the trucks may wait for their turns back at the queue yard. Once weighed, the driver needs to go through a fatigue test to ensure the readiness of the driver in taking the shipping journey ahead. If the driver passes the test, the truck goes through an outbound security check that marks the end of the process taken in the facility for a bulk truck.

For the bag trucks, they take different routes after being weighed in. They are to proceed to the loading preparation station before moving to the palletizer. Here, the trucks are to be loaded by a certain number of bags in a pallet.

After receiving these cement bags, the drivers direct their trucks to the pre-tarping stations before moving to the tarping ones. At these stations, the drivers are to put tarpaulin covers to protect the cement bags from the bad weather.

Once, the tarping process has been done, the bag trucks are considered ready to depart and they proceed through the same departing processes as those of bulk trucks.

Figure 2 shows the flow diagram of both the bulk and the bag trucks.

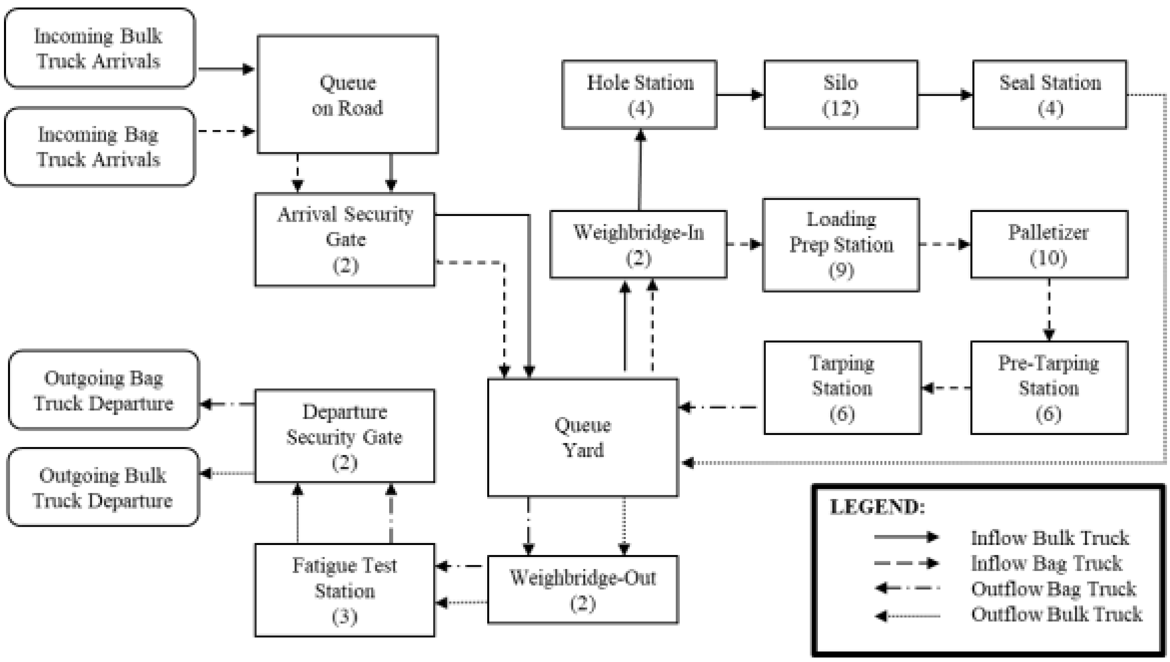

Figure 2. Flow Diagram

The next step is to conceptualize this flow diagram into a discrete-event simulator. For this study, we choose Jaamsim, a Java-based simulator due to its open-source nature and the attractive animation capability. These two features appeal to the management due to the ease of communication that they facilitate.

In our Jaamsim model, we incorporate a third type of truck movement, namely, the truck whose functions are to carry non-cement products. These trucks would neither go the silos nor the palletizers. Thus, our model explicitly considers three types of truck movements, namely those of bulk trucks, bag trucks and non-cement trucks.

Input Parameter

The initial input parameters were taken through observations over two-week period. They were the records of the trucks arriving at from the facility. Based on these data, we did a curve-fitting and determined that the inter-arrival times were to be sampled through exponentially distributed random numbers. The bulk trucks' interarrival time was at a mean of 9.57 minutes, the bag trucks at 4.719 minutes, while the independent one was at mean of 13.0 minutes. The incoming security gate was approximately at around 127 seconds each.

The weighbridge-in clocked in at 62 seconds. Each hole station took 204 seconds to complete. The service time of a silo was 1034 seconds. The seal station's service time was 310 seconds.

On the other hand, the load preparation station for the bag truck consumed 537 seconds while the palletizer's service time was 26.5 minutes. The Pre-tarping station took 853 seconds while the tarping process' service time was 1057 seconds.

On the way out, any truck spent 148 seconds at the Weighbridge-Out. Fatigue inspection test site took 128 seconds. The departing inspection station's service time was 99 seconds.

All these parameters, except for the interarrival times, came from triangular distributions with prescribed means and +/- 10% of the mean served as the minimum and maximum for the distributions.

Table 1 shows the input parameters as described above.

Table 1. Input Parameters

No.	Name	Distribution	Mean	Min, Max.
1	Bag Truck Interarrival time	Exponential	4.719 minutes	N/A
2	Bulk Truck Interarrival time	Exponential	9.57 minutes	N/A
3	Independent Truck Interarrival time	Exponential	13.0 minutes	N/A
4	Security Gate-In service time	Triangular	127 seconds	+/- 10% of mean
5	Weighbridge-In service time	Triangular	62 seconds	+/- 10% of mean
6	Hole Station service time	Triangular	204 seconds	+/- 10% of mean
7	Silo service time	Triangular	1034 seconds	+/- 10% of mean
8	Seal station service time	Triangular	310 seconds	+/- 10% of mean
9	Load prep station service time	Triangular	537 seconds	+/- 10% of mean
10	Palletizer service time	Triangular	26.5 minutes	+/- 10% of mean
11	Pre-tarping station service time	Triangular	853 seconds	+/- 10% of mean
12	Tarping station service time	Triangular	1057 seconds	+/- 10% of mean
13	Weighbridge-Out service time	Triangular	148 seconds	+/- 10% of mean
14	Fatigue Test service time	Triangular	128 seconds	+/- 10% of mean
15	Security Gate-Out service time	Triangular	99 seconds	+/- 10% of mean

Verification and Validation

As discussed by Sargent (2007), verification is to check whether the logical structure and input parameters of the model have been correctly expressed, wherein mostly the process itself relies more on common sense upon debugging the code.

In our research, this step then involved three components, namely, to examine the simulation logic, to test run the model in assessing its logic, and to conduct a simple consistency test while observing the resultsof the queueing behavior through animations.

Following Sargent (2007), the model validation involves an iterative process to compare the model against actual system. Any discrepancies are used to improve the model.

We validated our model by comparing the run results with the actual six month historical data as provided by the company.

RESULTS AND DISCUSSION

Using the default input parameters, we found that the facility incurred less than 100% throughput percentage, indicating the presence of bottlenecks in the system. Figure 3 shows the effect of increasing number of bag truck arrivals per day on the throughput rate holding other types of arrival constant while Figure 4 and Figure 5 show similar effects for the bulk arrivals per day and the independent arrivals per day, respectively. Figure 3 shows the degenerative effects on the throughput rate. Likewise for Figure 4, albeit with lesser effects. Figure 5 shows that at ceteris paribus, the presence of the increasing arrival rate of non-cement trucks means higher throughput rate overall, as the in-plant truck movement starts to be dominated by these trucks whose destinations are to stop at the security gates.

Figure 3. The Effect of Arrival Rate on Throughput Percentage (Bag Trucks only)

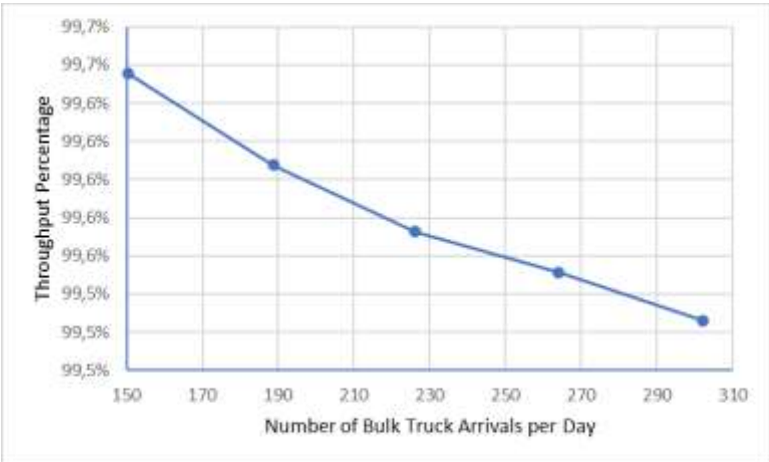

Figure 4. The Effect of Arrival Rate on Throughput Percentage (Bulk Truck only)

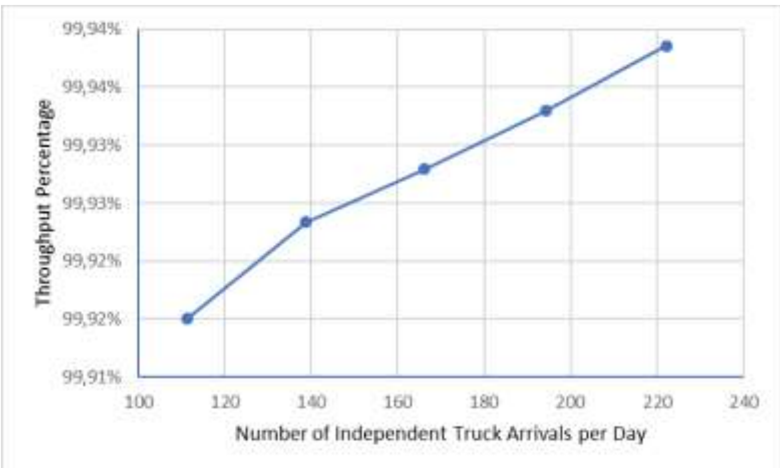

Figure 5. The Effect of Arrival Rate on Throughput Percentage (Independent Truck only)

Figure 3 specifically shows that increasing the bag truck traffics by 50%, from 300 trucks per day to 450 should not pose any major challenges for the existing configuration of the production plant. Thus, it addresses the concerns of the management whether the plant can reach its theoretical capacity without any major investments.

Furthermore, Figure 3 and 4 inform us that we are to focus our attention on the bag trucks, if we are to increase the plant capacity. By ascertaining the configurations of the bag truck processing, judicious approach to optimize the plant capacity is to weigh the option between increasing the number of palletizers, the most potential bottlenecks, and reducing the service times of the palletizers.

Figure 6 shows the effect of palletizer speed improvement on throughput percentage. We can see that a 10 percent reduction on the service time of the palletizer is to bring up the throughput percentage close to 95.5%, near the asymptotic limit of the amount. The rest of the throughput percentage loss may be explained by the presence of bottlenecks on the tarping stations.

Figure 6. The Effect of Palletizer Speed Improvement on Throughput Percentage

Figure 7 below shows the effect of increasing the number of palletizers to the throughput percentage. Just by adding one more palletizer, the production plant capacity starts to approach its asymptotic limit.

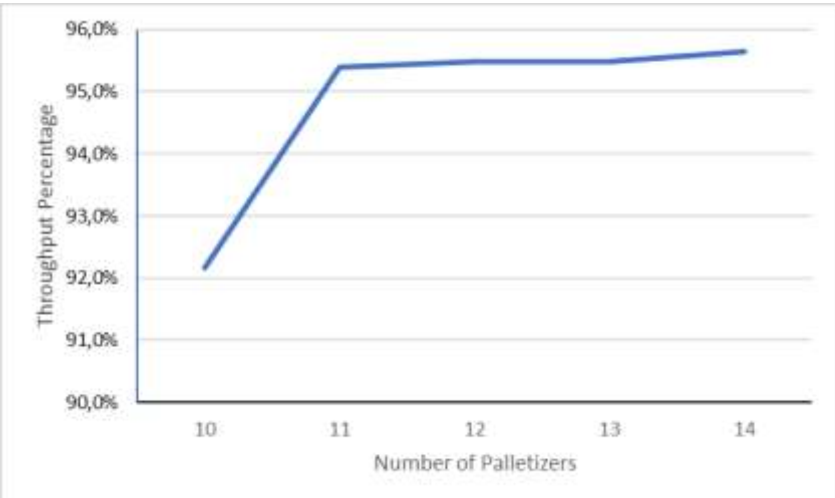

Figure 7. The Effect of Number of Palletizers on Throughput Percentage

Thus, the management only needed to weigh the option of launching an operational improvement project whose target is 10% reduction of the palletizer service time and that of bringing an additional palletizer which would take a capital expenditure. However, before getting into such a decision, an acute analyst might identify another opportunity in the area of tarping processes.

In other words, one may start wondering whether we should experiment with the number of tarping stations along with their associated pre-tarping sections. We believe that such a step is not needed since tarping stations are only areas in which workers cover tarpaulins over the bag truck. Hence, adding them will not incur major investment costs due to the abundant availability of land within the plant area. The management concurred with this suggestion. Thus, the asymptotic throughput percentage obviously may be brought to almost ideal condition in which no bottlenecks exist.

CONCLUSIONS

Our research has addressed the pressing issue of the company on ascertaining the feasibility of the new acquired production plant to reach its theoretical capacity without incurring any additional major investment when one considers only the in-plant truck movements. The study shows that any major investment is not needed for that purpose.

We also have shown that Jaamsim, an open source simulation software is useful in providing us the insights on the issue being investigated while at the same time, during the research process, the animation feature of this software allows the company management team to comprehend and to validate the model without getting into the complex technicality in building the model.

However, as alluded earlier, we believe the management needs to take an integrated model to allow more thorough analyses and deeper insights into the optimum amount of the capacity of this production facility. Hence, the construction of such a model should be considered for future research, wherein the in-plant and external-to-plant truck movements interact with each other.

Lastly, without the constraint of model development time, we believe our model can be enhanced by having more collected data taken over a longer period as the cement industry does have a seasonal pattern over the years. Our observed data points were taken during one of the two peak periods of the year, which means that the conclusion will stay valid over the low seasons.

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