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Optimization of ship traffic at berthing areas of maritime container terminals via Simulation Experiment

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ABSTRACT

Maritime transportation plays a leading role in the movement and minimization of transportation costs of goods between regions. One of the major challenges faced by port managers/operators is the growing number of containers or ship traffic which can affect the port container terminal productivity. Mathematical and simulation based models for berth assignments can help to solve such logistic problems in container terminals. However, existing simulation approaches are computationally intensive for optimizing the relevant factors that may affect the berth operation or port productivity. In this study, we propose a computationally efficient approach of combining simulation with Design of Experiments (DOE) to optimize the container port productivity. Further, based on a case study of container port terminal in Malaysia, we systematically examine the effect of tug pilots, berths numbers, cranes numbers and type of queue on port container terminal productivity. We found that only berth numbers, crane numbers and type of queue had significant effect on port productivity. It is recommended to adopt low container value, first serve queuing approach for serving the ships. We could achieve a maximum productivity of around 86% through our optimization model. Further, an increase of about 22% in port productivity as compared to the existing port productivity of the terminal was observed through our method.

KEYWORDS: Maritime Transportation · Container port Terminal · Productivity · Computer simulation · Design of experiments (DOE)

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1 INTRODUCTION

Maritime transportation plays a leading role in the movement and minimization of transportation costs of goods between regions. In addition, containerization has a considerable effect on transportation improvement at ports. Container ports serve as an interface between the sea, rail and roadway and therefore have a critical effect on the transport chain. Most transport customers use containers to move their goods as container sea-freight transportation has reduced transit time, increased reliability and reduced shipping cost [1]. In the recent years, ships size have increased dramatically. Today's ships are able to carry more than 7000 TEU (Twenty feet equivalent unit container). Therefore, minimization of ship operation time at port would enable to enhance the productivity of handling ship traffic at port. In order to reduce ship docking time, ships have to be loaded or unloaded within a short time period which demands the use of expensive equipment [2].

Currently in the competitive world of shipping, it is important for container management to construct efficient port facilities. Moreover, existing container ports should have enough capacity and this capacity must extend for considerable periods of time. Hence, container port terminal management face many problems which have an effect on port productivity [3].

There have been many studies in the past to improve the productivity of the port container terminal system. It has been found that high rates of shipping demand have negative effects on port terminal productivity because of delays and high turnaround time [4]. As the demand increases, this bottleneck problem becomes worse [5]. New strategies and methods were developed by port terminal managers to design cargo systems to satisfy customer demand [4]. For example, cranes are used to tranship containers from vessels to the quay. However, a significant problem in port terminals is related to quay crane allocation and scheduling to load and unload the vessels [6].

Legato and Mazza [7] tested different scenarios using SLAM language at the Gioia Tauro container terminal in Italy in order to enhance productivity by decreasing turnaround time. They considered the port terminal queuing network based on arrival and berthing times. Zhang et al [8] investigated container port terminal problems in China via simulation analysis, and prepared a model for port scheduling time. They provided valuable information to the port management to enhance the scheduling of port terminals at yard processes. Narasimhan et al [9] minimized ship loading time to enhance port terminal service rates. The problem was formulated with integer programming and was solved with heuristic algorithms. Goodchild et al [10] investigated ship loading and unloading operations at container port terminals. They tried to solve the problem of double cycling to reduce the number of operations. This problem was formulated as scheduling problem and solved using greedy algorithm. This research illustrated that the crane double cycling operation has a significant effect on the productivity rate at container port terminals.

In another study, quay crane scheduling problem was considered by enhancing the ship loading and unloading operations with a fixed number of cranes in the berth area of container port terminals [11]. Likewise, a dynamic programming and Tabu search algorithm was proposed by researchers to find an appropriate plan for crane scheduling in Singapore [12]. In the berthing process, ships arriving at the terminal must wait at the roadstead until a proper slot area is free at the berth. It can result in a huge queue that will decrease the container port terminal efficiency. Rashidi et al. [13] surveyed existing literature on the problems that ports encounter at container terminals. They described all operations at port terminals and classified all problems into the five categories relative to scheduling decision. In addition, an overview for each problem was presented and to better understand these problems, they illustrated the impact of these problems on the port operation. Rashidi et al. [13] tried to optimize the problem by formulating these problems based on constraint satisfaction to enhance the efficiency of container port terminals.

Zhuo et al. [14] presented Micro Port as a general simulation platform in order to evaluate the efficiency of a container port terminal system. Researchers also used Hybrid Genetic Algorithm (GA) and Artificial Neural Network (ANN) to optimize ship waiting time through enhancement of ship berthing operation [15]. In another study, the ships' waiting time were reduced by enhancing tug pilot operation [16]. Hsu [17] used Fuzzy Analytic Hierarchy Process (AHP) to enhance ship berthing safety by evaluating the port safety factor in the port of Taiwan.

Grubišić et al. [18] developed a mathematical model and tested it in the environment both with and without sea-depth limitation alongside a quay to find optimum. They tried to optimize berth allocation problem with focus on sea depth restrictions encountered by ships alongside of quay at port container terminal [18]. Liu et al. [19] proposed a bi-objective integer program which can comprehensively address the import, export and transshipment routine tasks in port. They studied the joint optimization of the tactical berth allocation and the tactical yard allocation in container terminals, which typically consists of berth side and yard side operations. In another investigation, Dry Bulk Cargo Terminal at multipurpose seaport was considered as a main factor to improve the port productivity and create a model for optimizing berth productivity [20].

Chu et al. [21] used double cycling as an efficient tool to increase the efficiency of quay crane at port container terminal. Optimization model was developed for double cycling at berthing area and design algorithms to solve this model. Brouer et al. [22] worked on the ship speed optimization as one of the planning problems in port container terminal. Liner shipping network was designed based on the data which were collected from several organizational entities. Moreover, the problem was formulated mathematically as an extension of the multi-commodity flow problem, and therefore the authors minimized the sum of the fuel cost and penalties for moving port call times. Longaray et al. [23] optimized ships operation time by enhancing anchorage area of the Brazilian port terminal with application of integer programming algorithm. Zhou et al. [24] developed a discrete event simulation model based on the understanding of the operations of a port terminal in Singapore and controlled the arrival method, to determine the coordinated arrival schedules of trucks thereby reducing congestions in the lighterage terminal. Another study considered the optimal planning problem for container pre-staging and dynamic discharging/loading at seaport rail terminals subject to uncertainties [25]. The researchers formulated the problem as a stochastic dynamic programming model to minimise the total logistics cost [25].

In summary, port managers or operators try to increase port productivity and decrease the ship traffic at the berth area of container port terminals by improving the ship berthing capacity. There are some operational resources and economic factors which influence various aspects of productivity and ship traffic at port container terminals. Specifically, there is a knowledge gap on robust methods to evaluate and analyze the effect of different resources such as number of cranes, tug pilots, number of berths and type of queue on port container terminal's productivity and ship traffic. It is to be noted that the effect of different operational and economic factors on productivity is not only limited to port management, but is also applicable to other industrial applications. For example, to address those issues, researchers have applied computer simulation and Design of Experiments (DOE) in the fields of manufacturing systems [26,27] construction management [28] and energy management at buidling [29,30]. DOE is known as an experiment or series of experiments that are done through changing the input process variables, which may have an effect on the output responses [31]. On the other hand, simulation can generate and evaluate the performance of a system but it is a time consuming task. Therefore, by combining DOE and computer simulation, companies can deal with the challenging problem of reducing simulation times for simulation models [32]. By leveraging the strengths of the DOE along with the computer simulation, it will assist the modelers to improve the performance of the simulation process by decreasing the time spent on the trial and error method to seek solutions [31]. However, to our knoweledge, we are not aware of any work that have utilized the simulation-DOE approach for evaluating port terminal productivity.

Further, a simulation-DOE model for evaluating port terminal productivity rate can be useful due to following reasons:

(1) Different scenarios can be generated and examined through the model that will assist in making key decisions to the port managers/operators, as decision making is a significant issue in maritime industry.
(2) Robust analysis on productivity of maritime container terminal can be conducted by taking into account the limitations in labor, time and cost.
(3) Insights and assements on factors or measures that can affect the operations of the system can be conducted before implementation of any measures to improve the productivity of port terminals.

Therefore, the aim of this study is to develop a simulation-DOE model to evaluate the productivity of port container terminal. The model will improve the overall productivity of maritime transporation system in a timely and cost-effective manner by evaluating the effect of different resources (e.g. number of cranes, berths, tug pilots) and type of queue (e.g. first in first out, first out) on port terminal productivity and ship traffic. The maximum productivity of the port terminal will be also determined by the optimum setting of operational factors relevant to port container terminal management. The paper is structured as follows. The next section explains a case study of a port container terminal in Malaysia. The data from this case study is used to develop the simulation-DOE model which is presented in the methodology section. We then present the results and discussions based on the simulation outputs from the model. Finally, we present the conclusions.

2 CASE STUDY

A Port Container Terminal (PCT) located at southern Malaysia was chosen as the case study in this paper. PCT consists of 12 berthing areas divided into 3 types of the berths for different ships with different characteristics (16 meters for small ships, 17 meters for medium ships, 18 meters for large ships). In addition, berthing area of PCT involves 44 cranes and 4 tug pilots. There are also some maintenance plans for PCT that should be applied each year. On average, 4 cranes are not working as they are in scheduled maintenance. Moreover, with one berth occupied with maintenance, the PCT operates with 11 berths.

Fig. 1 shows the ship berthing operation process in PCT. Queuing is one of the critical problems that PCT management team are trying to deal with. Ships need a slot in terminal for receiving service when they arrive at the port area. Port management team checks the berth area, and if there is any free place for berthing, gives permission to incoming ships to take berth, otherwise ships should wait at the roadstead queue until a slot is free. On the other hand, if ships get permission to come to the berthing area, they should wait for a tug pilot to tug the ship in to the specific berth. Also, when ships want to leave the berth after finishing their loading/ unloading, they should wait at the tug pilot queue to get a tug pilot for a tug out from the berth. Ships at PCT get service based on first come, first served rule. In other words, ships that came to the PCT line up based on arrival time, and ships that come earlier should be served earlier. The PCT has an agreement with various transit organizations that provide service such as Maersk. PCT management plans berthing for those companies in port terminals and presents this plan to them. However, sometimes companies cannot follow the plan and ships arrive at the port late. This situation leads to a large queue at the roadstead of PCT. Furthermore, such situations cause bottlenecks at berthing areas of PCT.

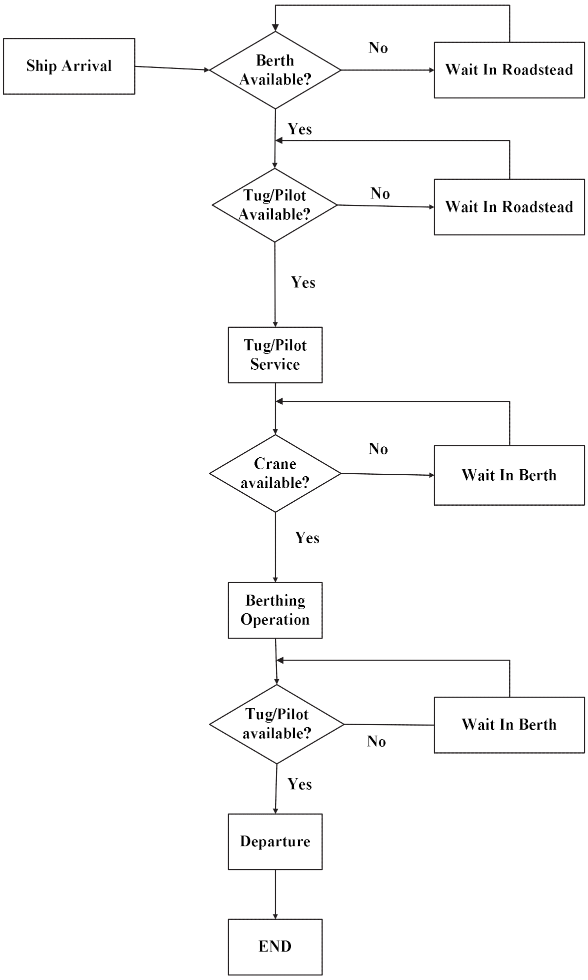

Fig 1: Ship berthing operation

3 MATERIALS AND METHODS

3.1 Simulation model development

Data collection is the first step for developing a simulation model. In this paper, data collection was done at the PCT by observing and analyzing the current layout of the port terminal. Moreover, several meetings were held with port management team to get information about the process flow and all movement at berthing area of port terminal. In particular, a separate detailed interview was conducted with key personnel and an operation manager of PCT. Data gathered during these interviews were used for mapping the existing logistics process at PCT. Then, a probability distribution function was fitted for each activity duration. To develop the model, it is necessary to determine different resources in the port terminal along with their relationship, duty and activity duration. In our paper, the ARENA 13.9 simulation software was used to construct the simulation model. A significant feature of ARENA 13.9 is the ability to categorize the activities into different types such as value added, non value-added, waiting, transfer, and others. This ability is very useful in determining the different time spent on different types of processes. This can help a manager to improve the system by minimizing non value-adding processes, reducing or eliminating bottlenecks, decreasing operating costs and delivery time, and increase profitability through overall improved operations [33].

Fig. 2 shows the logic view of the berth process for small, medium and large ships created for simulation from the Arena software.

As ships should take a free slot at the berthing area of the PCT, the berthing area of PCT were built based on the three types of berth. For example, Fig. 3 illustrates the berth area allocation for medium ships. As can be seen in Fig. 3, there are three process lines as three berths for medium ships. However, all ships get tug service by tug/pilot machines using the same procedures. Furthermore, all ships which come to this model through the entity get service based on the first come first serve rule.

For simplification, ships were distinguished into the two categories based on the number of containers carried by ships: ships with high container value (large number of containers) and ships with low container value (small number of containers). Therefore, as can be seen in the Fig. 2, the inter arrival of ships is divided into 6 groups for model development: 1. Large ships with high container value 2. Large ships with low container value 3. Medium ships with high container value 4. Medium ships with low container value 5. Small ships with high container value and 6. Small ships with low container value. Also, it is assumed that container value is equivalent to number of containers.

3.1.1 Model validation and number of replications

Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended use of the model [32]. In order to do validation, first the number of simulation runs required to produce the desired level of accuracy should be determined. To do so, the number of replications was computed as follows [32]:

$$\text{Number of replication} = (t_{a/2, n-1} * \text{S(m)} / (£* \text{X(m)}) \qquad (1)$$

$t_{a/2, n-1}$: t-value based on the confidence level and the number of runs

X(m): standard deviation of production output from six runs

S(m): mean of production output from six runs

£: allowable error

The confidence level was 95% and allowable error was 0.05.

Therefore, for the calculation number of simulation runs, five replications of simulation are considered (Table 1):

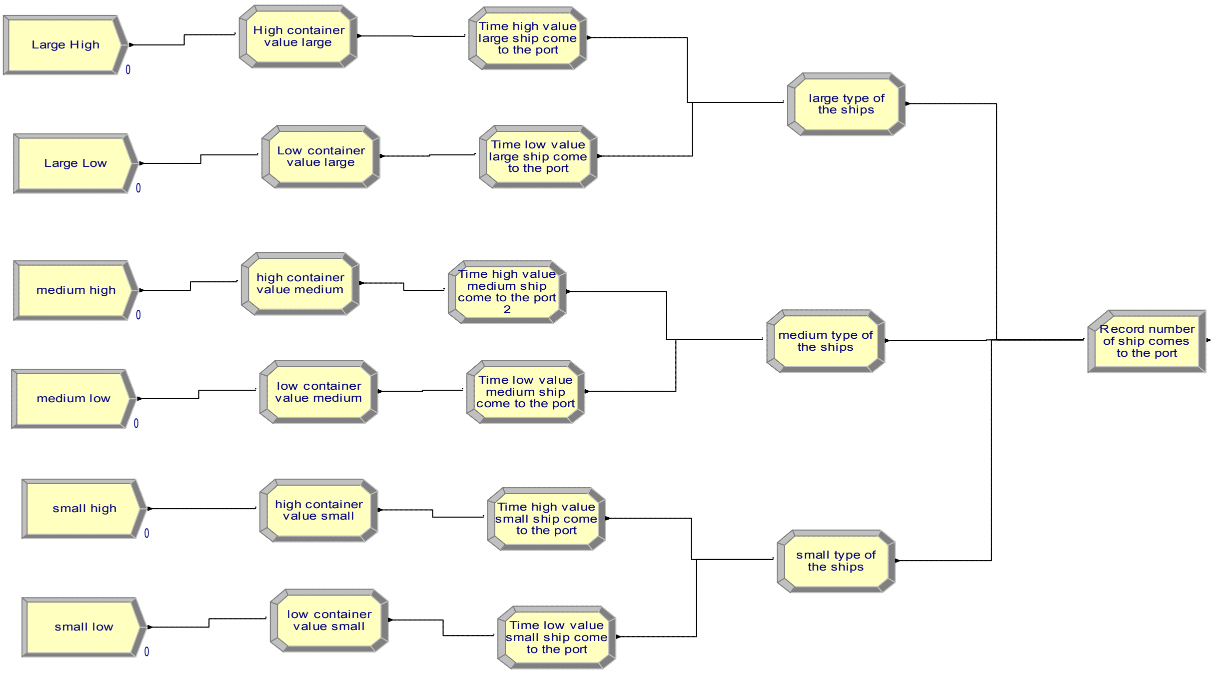

Fig 2:. Logic view of simulation model of berth process

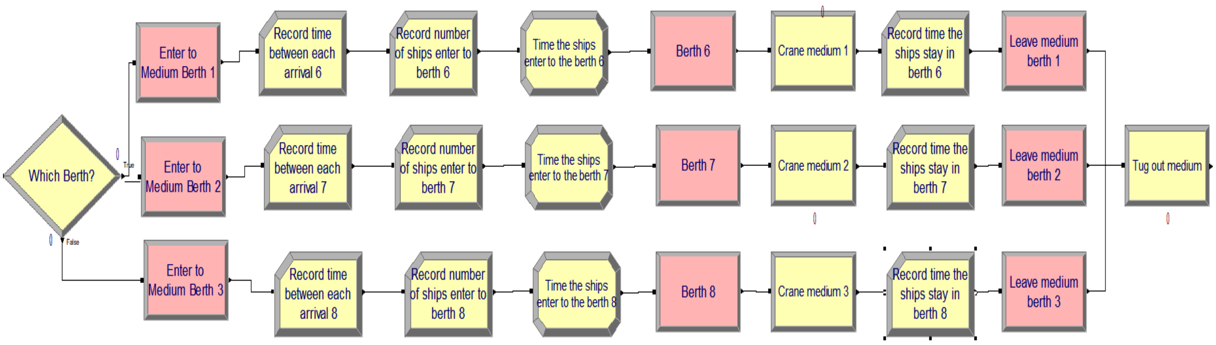

Fig 3: Berthing area for medium ships

Table 1: Results of running model

Number of runs	1	2	3	4	5
Number of output	102	104	100	98	101

So, the number of replications was computed as follows: (2.132*2.23)/(0.05*101) = 0.9414

Since the number of simulation runs to achieve the desired level of accuracy is less than 1, it minimizes the overall time required to obtain the required outputs. After determining the number of simulation runs, validation was done for the simulation model constructed through ARENA. In this study, comparison method is used for model validation of PCT. The comparison is based on productivity and system output. Based on the data given by PCT management team, the annual productivity of PCT is between 65% and 70 %. When the simulation model of PCT was ran for one year, the results revealed that the productivity of the PCT is about 68% (Table 2). Therefore, our model's prediction is valid with less than 5% error.

3.2 Design of Experiments (DOE)

The experimentation is focused on identifying any parameters that have a considerable effect on the

Table 2: Results of Model validation

Items	Actual Productivity	Weekly output
PCT container port terminal	65% - 70%	About 100 ships
PCT simulation model	68%	103 ships
Achievement Ratio	96%	97%

process productivity. Hence, there is a need for a systematic approach to tackle this complex problem. DOE is a statistical technique for analyzing and organizing the experiments. Consequently, in DOE, the factors comprise different parameters which are controlled by the researcher, meanwhile the response represents the dependent variable, which in our case, refers to productivity. The 2k factorial design is one of the very useful types of DOE approaches, and, each of the factors is allowed to take on two values or levels, referred as "High" and "Low". This type of experimental design is believed to be economical and effective in indicating interaction effects [34]. Therefore, this paper used the 2k factorial design to assess the effects of several parameters on productivity..

3.2.1 Choosing the factors, levels and response variable

In order to select the factors, at first, the company's managers and executives discussed to evaluate and analyze different parameters that could potentially help to improve the productivity of production line. The influential factors were selected from previous investigations and production engineer's feedbacks. Then, all selected factors were assessed and reviewed to be finalized. Lastly, the managers agreed to choose four most potential factors which were "number of cranes", "number of berths", "number of tug/pilots" and "type of queue". Table 3 shows the factors and levels that are selected to do the experimental design. Based on the small number of factors the full factorial design (2^n) is used. The experiment is also replicated for two times. The replication is done by using the random numbers stream in ARENA software. As can be seen from Table 3, each factor has two levels: a high (+) and a low (-) level. Therefore, a full factorial experiment includes 32 runs.

To calculate port terminal productivity, some data should be taken into account, like the number of ships that enter the port terminal roadstead queue and number of ships that leave the port terminal each year. Consequently, the response variable investigated was process productivity (equation 2) that can be determined as follow:

$$\text{Port terminal productivity} = \frac{\text{Number of ships that leave berth area per year}}{\text{Number of ships that enter the berth area per year}} \quad (2)$$

4 RESULTS AND DISCUSSION

4.1 Performing simulation experiment

After determining the factor settings and experimental conditions, data collection was conducted by running the simulation experiment. As mentioned earlier, a full factorial design was chosen. This design included 16 experiments with two replicates, which were done to decrease potential errors. Additionally, two replicates for center points were considered to analyze the curvature of the suggested model. In all, 36 experiments

Table 3: Factors and Levels

FACTOR	LEVEL -1	LEVEL 1
Number of Tug pilots	4	10
Number of Cranes	40	50
Number of Berths	12	14
Type of Queue	First Come, First Serve	Low container value, First Serve

Table 4: Result of simulation experiment

Run order	Number of Tug pilots	Number of Cranes	Number of Berths	Type of Queue	Productivity *100	
1	4.00	50.00	14.00	+1	83.3	83
2	4.00	50.00	12.00	+1	65.7	65.7
3	10.00	40.00	12.00	-1	65.3	66
4	4.00	40.00	12.00	-1	64.7	65.8
5	10.00	50.00	14.00	+1	81.4	83
6	10.00	50.00	12.00	+1	66	65.1
7	10.00	50.00	14.00	-1	80.9	82.6
8	4.00	40.00	14.00	+1	73.4	72.2
9	10.00	40.00	12.00	+1	66.1	65.5
10	4.00	40.00	14.00	-1	72.6	72.9
11	10.00	50.00	12.00	-1	76.9	77.1
12	10.00	40.00	14.00	+1	71.5	71.5
13	4.00	50.00	14.00	-1	82	82
14	4.00	50.00	12.00	-1	76.2	71.1
15	10.00	40.00	14.00	-1	72.1	72.1
16	4.00	40.00	12.00	+1	65.5	65.9
17	7.00	45.00	13.00	+1	76.6	75.9
18	7.00	45.00	13.00	-1	76.4	76.4

were conducted by running the simulation model. In summary, the experimental conditions used for this study are as follows:

Number of Factors: 4; Number of Levels: 2; Number of Replicates: 2; Number of Center points: 4; Number of experiments = 16 * 2 (replicates) + 4 (Center Points) = 36. Table 4 shows the results of the simulation experiment.

4.2 Analysis

After running the experiment, statistical software Minitab 16 was used to analyze the data. Table 5 shows the result of ANOVA test for the productivity. The p-value (P) in the table was used to determine which of the effects in the model are statistically significant. If the p-value is less than or equal to 0.05, the effect can be termed significant at 95% confidence level [34]. If the p-value is greater than 0.05, then we conclude that the effect is not significant [34]. Moreover, based on Fig. 4, it can be observed that the significant factors are B (number of cranes), C (number of berths), D (type of queue) and two-way interactions (BC, BD, CD) and three-way interactions (BCD). This result shows that the number of cranes, number of berths and type of queue have significant effect on the productivity rate of container port terminals. Therefore, to enhance container port terminal productivity rates, consideration should be given to increase the number of cranes and berths. In addition, the type of ships lining up for service should be revised.

4.3 Optimization by augmentation

The potential concern in the use of 2 level factorial designs is the assumption of linearity in the factor effects. But, when an interaction term is added to a main-effects model, curvature is introduced into the response surface. Therefore, a 2^n design will support a main effect plus interaction model along with some

Table 5: Analysis of variance (ANOVA) for productivity

Source	Adj SS	DF	Adj MS	F	P
Main Effects	1174.13	4	293.533	427.90	0.000
2-Way Interactions	169.83	6	28.306	41.26	0.000
3-Way Interactions	84.07	4	21.018	30.64	0.000
4-way Interaction	0.04	1	0.045	0.07	0.800
Curvature	64.35	1	64.350	93.81	0.000
Residual Error	14.41	21	0.686		
Lack of Fit	7.84	1	7.842	23.90	0.000
Pure error	6.56	20	0.328		

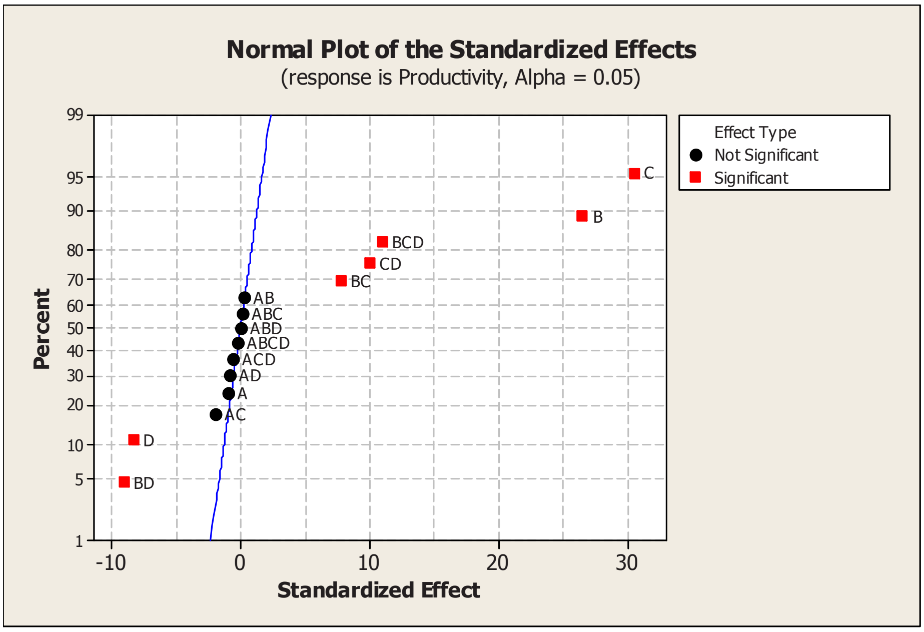

Fig 4: Significant Factors

protection against curvature that is already inherent in the design. In some processes or systems, it will be however necessary to incorporate second order effects to obtain an adequate model. Furthermore, Table 5 presents that the curvature is significant, which shows that there is a nonlinear correlation between the factors and productivity. Therefore, a second order model must be incorporated to have an adequate regression model. Further, the design should be augmented by adding the axial points. Several new runs should be added to obtain the second order model. Table 6 indicates the result of conducting new experiments with the new augmented points. In addition, Table 7 shows the ANOVA test for the new experiments. As can be seen in Table 7, the significant factors are B (number of cranes), C (number of berths), D (type of queue) and two-way interaction of BC and CD.

Table 6: Result of new simulation experiment for augmentation

Run order	Number of Tug pilots	Number of Cranes	Number of Berths	Type of Queue	Productivity *100
1	4.00	45.00	14.00	-1	79.8
2	10.00	40.00	13.00	+1	67.8
3	7.00	40.00	12.00	+1	65.8
4	10.00	45.00	12.00	-1	69.6
5	7.00	50.00	14.00	+1	76.8
6	4.00	50.00	13.00	+1	85.2
7	4.00	45.00	12.00	+1	68.6
8	7.00	50.00	12.00	-1	76.6
9	10.00	50.00	13.00	-1	84.2
10	10.00	45.00	14.00	+1	80.3
11	4.00	40.00	13.00	-1	67.7
12	7.00	40.00	14.00	-1	70.5
13	4.00	40.00	13.00	+1	68.1
14	7.00	50.00	12.00	+1	75.9
15	7.00	40.00	12.00	-1	74.9
16	4.00	45.00	12.00	-1	68.1
17	10.00	45.00	12.00	-1	69.2
18	4.00	50.00	13.00	+1	84.6
19	7.00	45.00	13.00	-1	75.4
20	7.00	45.00	13.00	-1	72.9
21	7.00	45.00	13.00	-1	72.6
22	7.00	45.00	13.00	+1	71.9
23	7.00	45.00	13.00	+1	72.3
24	7.00	45.00	13.00	+1	73

Table 7: Analysis of variance (ANOVA) after augmentation

Source	Sum of Square	DF	Mean Square	F Value	Prob>F
Model	1807.03	14	139	14.66	0.0001
A	4.66	1	4.66	0.49	0.4864
B	836.48	1	836.48	88.25	0.0001
C	733.12	1	733.12	77.34	0.0001
D	48.73	1	48.73	5.14	0.0280
A^2	4.63	1	4.63	0.49	0.4883
B^2	7.97	1	7.97	0.84	0.3639
C^2	30.16	1	30.16	3.18	0.0809
AB	4.20	1	4.20	0.44	0.5091
AC	1.26	1	1.26	0.13	0.7167
AD	7.93	1	7.93	0.84	0.3652
BC	40.03	1	40.03	4.22	0.0455
BD	29.96	1	29.96	3.16	0.0819
CD	59.93	1	59.93	6.32	0.0154

4.4 Second order regression model

As the relationship between the independent factors and response is generally unknown, a low order polynomial model is suggested to explain the response surface. This model is a reasonable approximation in a specific region of the response surface. In this regard, both the first-order and second order models were used based on the approximation of the unknown function. It should be noted that when the curvature is significant, it can be concluded that the first-order model is not sufficient. Therefore, a second-order model is effective and flexible in approximating a part of the correct response surface with parabolic curvature [34]. In this light, Design-Expert software was used to calculate the coefficients of the regression equation. Table 8 shows the regression coefficient of each factor while equation 3, 4 and 5 shows the fitted regression equations. To achieve maximum productivity (85.69%, equation 6), the factors should be placed on the levels which are: B=1, C=1 and D=1. Therefore, the number of cranes and berths should be equal to 50 and 14, respectively. Additionally, implementing the low container value,

Table 8: Estimated regression coefficients for productivity

Factor	Coefficient	DF	Standard Error	95% CI Low	95% CI High
Intercept	75.09	1	0.88	73.33	76.85
B- Number of Cranes	4.40	1	0.47	3.46	5.34
C- Number of Berths	4.17	1	0.47	3.21	5.12
D- Type of Queue	-0.91	1	0.40	-1.71	-0.10
BC	1.03	1	0.50	0.022	2.04
CD	1.19	1	0.47	0.24	2.14

first serve scheduling for loading and unloading the heavy ships which arrive at the container port terminal, as first priority, will maximize port terminal productivity.

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} X_{11}^2 + \beta_{22} X_{22}^2 \quad (3)$$

$$\hat{Y} = 75.09 + (4.40)*B + (4.17)*C + (-0.91)*D + (1.03)*BC + (1.19)*CD \quad (4)$$

$$\hat{Y} = 75.09 + (4.40)*(+1) + (4.17)*(+1) + (-0.91)*(+1) + (1.03)*(+1)(+1) + (1.19)*(+1)(+1) \quad (5)$$

$$\hat{Y} = 85.69 \quad (6)$$

4.4.1 Residual analysis

To evaluate the model validity, the residuals from the least squares play an important role [34]. As can be seen in Fig. 5, the straight line confirms that the model is adequate and correct. Moreover, there is no clear pattern or trend of the residual versus predicted value confirming that the developed model is adequate and has a constant error (Fig. 6).

The 3D response surface and the 2D contour plot (Fig. 7, 8 and 9) are the graphical representation of the regression equation. The main objective of these plots is to determine the optimum values of the factors such that response is maximized. Fig. 7 shows the effect of number of berths (C) and number of cranes

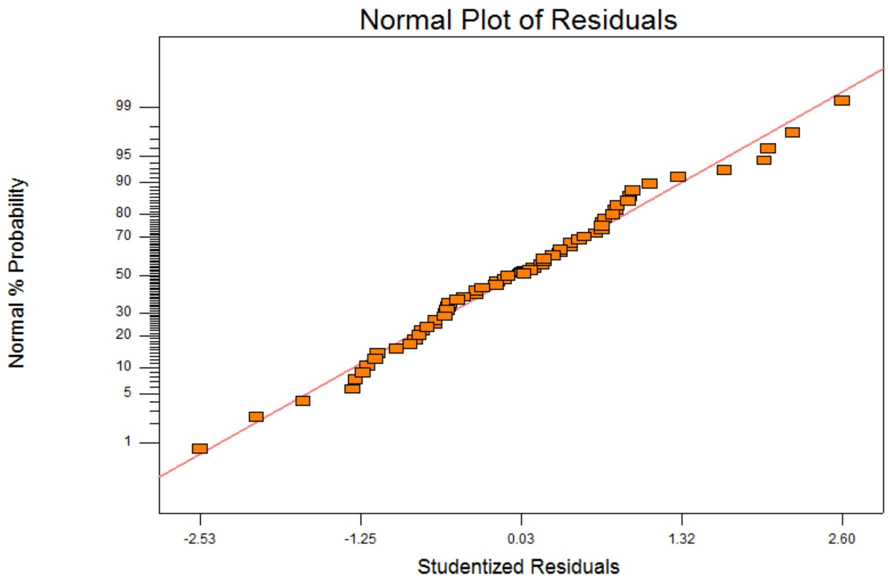

Fig 5: Normal Plot of Residuals

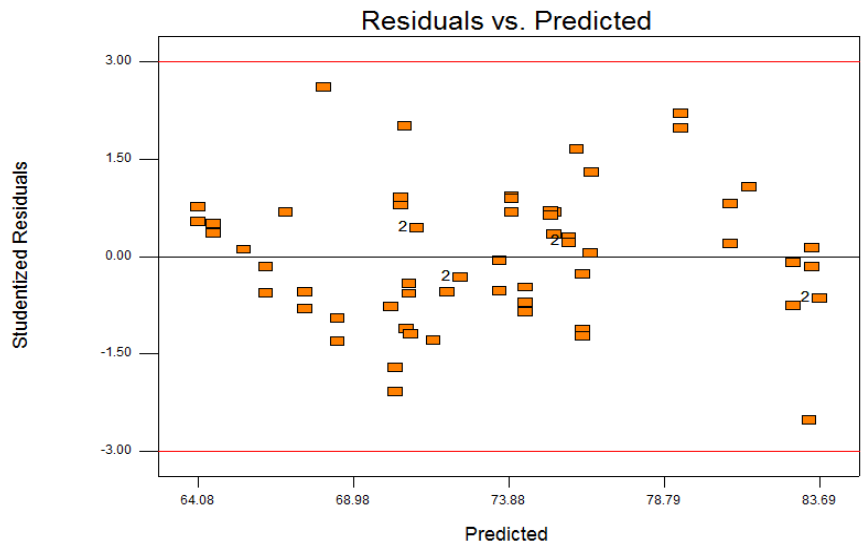

Fig 6: Residuals versus Predicted Plot

(B) on productivity as a response. As can be seen, the maximum response occurs at point 84.26 which is relevant to the number of berths (B) = 14 and number of cranes (C) = 50. In addition, it can be concluded from Fig. 8 that the maximum productivity is obtained when the number of tug pilots (A) = 4. Moreover, Fig. 9 indicates the trend of productivity based on number of cranes and berths. Based on this graph, it can be concluded that the maximum productivity will be obtained when the number of cranes and berths are high.

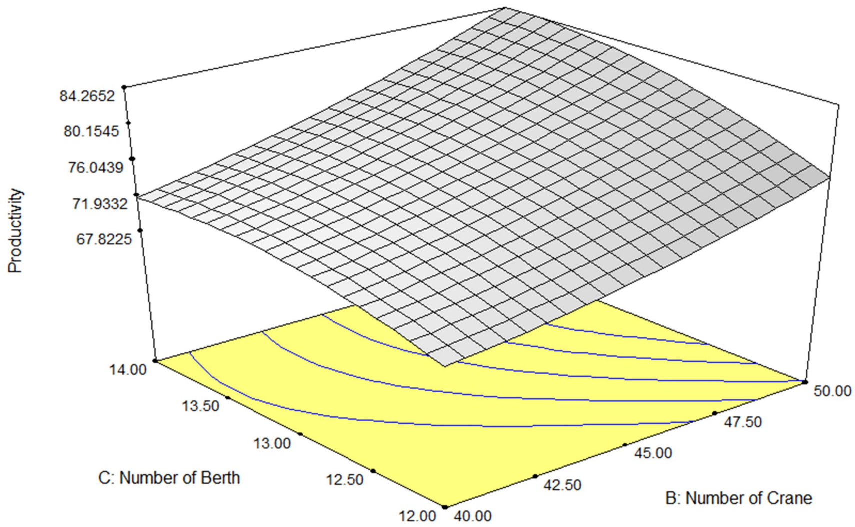

Fig 7: 3D surface (Number of Berths vs. Number of Cranes)

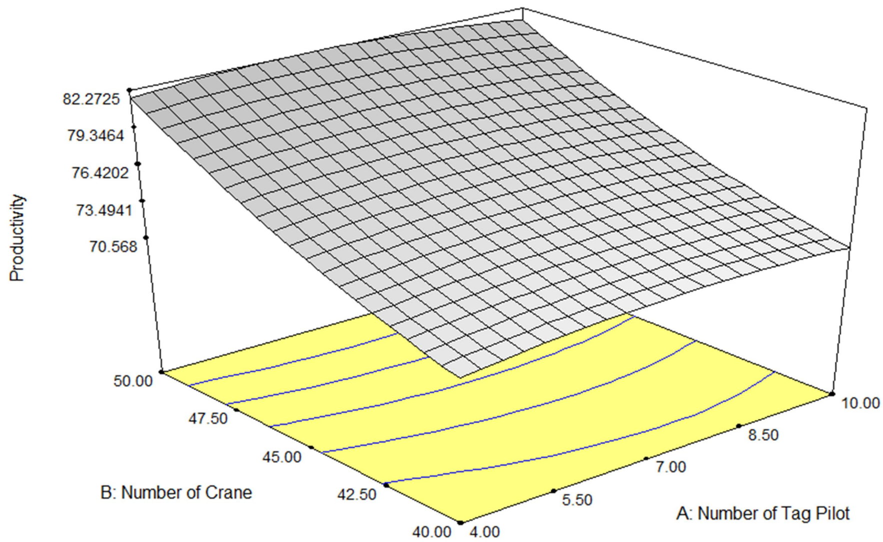

Fig 8: 3D surface (Number of Tug pilots vs. Number of Cranes)

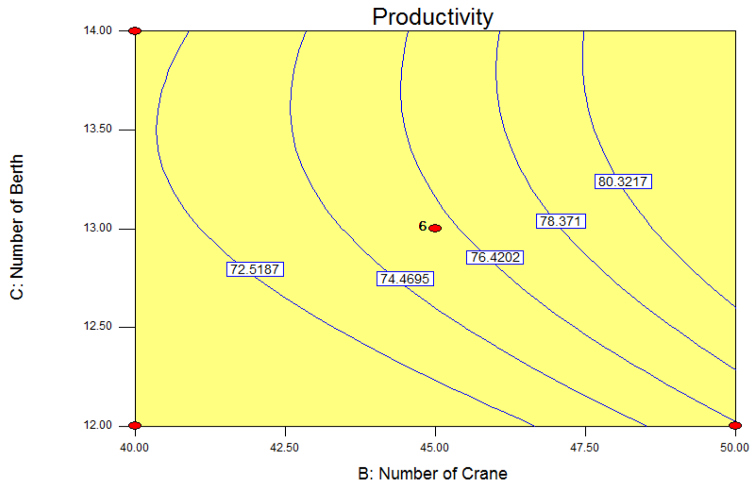

Fig 9: Contour Plot (Number of Berths vs. Number of Cranes)

4.5 Discussion and managerial implication

Our proposed method of combining DOE with simulation modelling is a novel approach for evaluating port terminal productivity. We are not aware of any previous work on port container terminal management that have examined this approach for optimizing the berths operation. The strength of our method lies in being able to have robust insights and assements on factors or measures that can affect the operations and productivity of port terminals before their implementation. Further, our simulation-DOE method needs less computational efforts for optimization of port terminal productivity as compared to traditional simulation only based approach. In addition, there have been no systematic examination of the effect of different resources such as number of cranes, tug pilots, number of berth and type of queue on port container terminals' productivity. By developing and applying simulation DOE model to optimize the productivity of a real port container terminal in Malaysia, we have found that number of berths, cranes and type of queue had a significant effect on port's productivity. For example, to obtain the maximum port productivity (85.69 %), we found that the number of cranes and berths needed to be equal to 50 and 14, respectively. Moreover, based on the type of queue, low container value first serve scheduling for loading and unloading the heavy ships is suggested, as it resulted in maximum port productivity and lowest ships traffic. In other words, when two ships come to the queue for berthing operation at port terminal, the one that is carrying the low number of container with low operation time should be first serve even if it queued later than the other one. It is to be noted that number of tug pilots had no significant effect on total productivity of the port container terminal. This finding contrasts with the previous finding where it has been reported that ships' waiting time were reduced by enhancing tug pilot operation [16].

Therefore, our proposed approach helps the port managers/operators and maritime logistic companies to improve their productivity in a timely and cost-effective manner without stopping or changing the layout of berthing areas of maritime container terminals or resources. This flexibility is important for port managers/operators as it is not possible to end or delay the operating system or replace the layout due to limitations of labor, time, cost and many other parameters.

We compared our model's prediction on productivity with observed real data at the PCT in Malaysia. The results are presented in Table 9. As shown in Table 9, using our optimal values, we could observe a 21.72%

Table 9: Difference between current situation of port terminal and proposed method

actor	Current situation	Proposed method
Number of Cranes	40	50
Number of Berths	12	14
Number of Tug/Pilots	4	4
Type of Queue	First in First Out (FIFO)	Low container value First Out (FO)
Productivity (%)	67%	85.59%
Productivity Improvement = $\frac{85.59-67}{85.59}$ * 100 = 21.72 %		

increase in productivity of the PCT as compared to the existing situation. Hence, practitioners and engineers working in the maritime logistic can deploy our simulation-DOE approach to optimize the ports' productivity for their companies.

5 CONCLUSION

Container terminals face a challenge of coping with the growing number of containers which can affect the port container terminal productivity. Mathematical and simulation based models for berth assignments can help to solve such logistic problems in container terminals, and as such are important decision-making tools. However, existing simulation approaches are computationally intensive for optimizing the relevant factors that may affect the berth operation or port productivity.

In this study, we propose a less computationally intensive approach of combining simulation with DOE to optimize the port productivity. Further, based on a case study of PCT in Malaysia, we examined the effect of number of tug pilots, berths, cranes and type of queue on port productivity. We found that only berths numbers, cranes numbers and type of queue had significant effect on port productivity. It is recommended to adopt low container value, first serve queuing approach for serving the ships. We could achieve a maximum productivity of around 86% through the optimization. Further, an increase of about 22% in port productivity of the PCT as compared to the existing situation was observed through our method.

In future, other statistical methods, such as response surface methodology can be implemented to find the local optimum value of resources. Nevertheless, our approach provides a valuable tool for managers/ operators of port container terminal to optimize the factors that can affect the ports' productivity.

REFERENCES

[1] Celik E, Akyuz E (2018) An interval type-2 fuzzy AHP and TOPSIS methods for decision-making problems in maritime transportation engineering: The case of ship loader. Ocean Engineering 155: 371-381

[2] Vis IF, De Koster R (2003) Transshipment of containers at a container terminal: An overview. European journal of operational research 147(1): 1-16

[3] Lu B, Park NK (2013) Sensitivity analysis for identifying the critical productivity factors of container terminals. Journal of Mechanical Engineering 59(9): 536-546

[4] Cullinane K (2007) Asian container ports: development, competition and co-operation. Palgrave Macmillan, UK

[5] King J (1997) Globalisation of logistics management: present status and prospects. Maritime Policy and Management 24 (4): 381-387

[6] Bierwirth C, Meisel F (2009) A fast heuristic for quay crane scheduling with interference constraints. Journal of Scheduling 12: 345-360

[7] Legato P, Mazza RM (2001) Berth planning and resources optimisation at a container terminal via discrete event simulation. European Journal of Operational Research133(3): 537-547

[8] Zhang JS, Sha M, Easa S (2008) Optimization of Production Scheduling in Container Terminals using Computer Simulation. Transportation and Development Innovative Best Practices (TDIBP). doi:10.1061/40961(319)22

[9] Narasimhan A, Palekar US (2002) Analysis and algorithms for the transtainer routing problem in container port operations. Transportation science 36(1): 63-78

[10] Goodchild AV, Daganzo CF (2006) Double-cycling strategies for container ships and their effect on ship loading and unloading operations. Transportation Science 40(4): 473-483

[11] Vacca I, Bierlaire M, Salani M (2007) Optimization at container terminals: status, trends and perspectives. In Swiss Transport Research Conference (No. TRANSP-OR-CONF-2006-013)

[12] Imai A, Chen HC, Nishimura E (2008) The simultaneous berth and quay crane allocation problem. Transportation Research Part E: Logistics and Transportation Review 44 (5): 900-920

[13] Rashidi H, Tsang EP (2013) Novel constraints satisfaction models for optimization problems in container terminals. Applied Mathematical Modelling 37(6): 3601-3634

[14] Sun Z, Lee LH, Chew EP, Tan KC (2012) MicroPort: A general simulation platform for seaport container terminals. Advanced Engineering Informatics 26(1): 80-89

[15] Shahpanah A, Poursafary S, Shariatmadari S, Gholamkhasi A, Zahraee SM (2014) Optimization waiting time at berthing area of port container terminal with hybrid Genetic Algorithm (GA) and Artificial Neural Network (ANN). Advanced Materials Research 902: 431-436

[16] Shahpanah A, Hashemi A, Nouredin G, Zahraee SM, Helmi SA (2014) Reduction of ship waiting time at port container terminal through enhancement of the tug/pilot machine operation. Jurnal Teknologi 68(3): 63-66

[17] Hsu WKK (2015) Assessing the safety factors of ship berthing operations. The Journal of Navigation 68(3): 576-588

[18] Grubišić N, Vilke S, Barić M (2015) A contribution to berth allocation problem solution with draft restrictions. Pomorski zbornik 49(1): 127-142

[19] Liu M, Lee CY, Zhang Z, Chu C (2016) Bi-objective optimization for the container terminal integrated planning. Transportation Research Part B: Methodological 93: 720-749

[20] Đelović D, Medenica Mitrović D (2017). Some considerations on berth productivity referred on dry bulk cargoes in a multipurpose seaport. Tehnički vjesnik 24(2): 511-519.

[21] Chu Y, Zhang X, Yang Z (2017) Multiple quay cranes scheduling for double cycling in container terminals. PloS one 12(7): e0180370

[22] Brouer BD, Karsten CV, Pisinger D (2017) Optimization in liner shipping. 4OR 15(1): 1-35

[23] Longaray AA, Munhoz PR, Brasil RS (2015) Optimization of vessel operation times using anchorage areas: a case study of a brazilian port terminal. Brazilian Journal of Management and Innovation 3(1): 42-59

[24] Zhou C, Li H, Lee BK, Qiu Z (2018) A simulation-based vessel-truck coordination strategy for lighterage terminals. Transportation Research Part C: Emerging Technologies 95: 149-164

[25] Xie Y, Song DP (2018) Optimal planning for container prestaging, discharging, and loading processes at seaport rail terminals with uncertainty. Transportation Research Part E: Logistics and Transportation Review 119: 88-109

[26] Hatami M, Zahraee SM, Khademi A, Shahpanah A, Rohani JM (2014) Evaluating the effect of main factors in manufacturing production line based on simulation experiment. Applied Mechanics and Materials 606:199–203

[27] Zahraee SM, Shariatmadari S, Ahmadi HB, Hakimi S, Shahpanah A (2014) Application of design of experiment and computer simulation to improve the color industry productivity: case study. Jurnal Teknologi 68(4): 7–11

[28] Zahraee SM, Hatami M, Yusof NM, Rohani M, Ziaei F (2013) Combined use of design of experiment and computer simulation for resources level determination in concrete pouring process. Jurnal Teknologi 64(1): 43-49

[29] Sadeghifam AN, Zahraee SM, Meynagh MM, Kiani I (2015) Combined use of design of experiment and dynamic building simulation in assessment of energy efficiency in tropical residential buildings. Energy and Buildings 86: 525-533

[30] Zahraee SM, Khademi A, Khademi S, Abdullah A, Ganjbakhsh H (2014) Application of design experiments to evaluate the effectiveness of climate factors on energy saving in green residential buildings. Jurnal Teknologi 69(5): 107–111

[31] Farouk H, Zahraee SM, Atabani AE, Mohd Jaafar MN, Alhassan FH (2017) Optimization of the esterification process of crude jatropha oil (CJO) containing high levels of free fatty acids: a Malaysian case study. Biofuels. doi:10.1080/1759 7269.2017.1387749

[32] Zahraee SM, Rohani JM, Wong KY (2018) Application of computer simulation experiment and response surface methodology for productivity improvement in a continuous production line: Case study. Journal of King Saud University-Engineering Sciences 30(3): 207-217

[33] Zahraee SM, Golroudbary SR, Hashemi A, Afshar J, Haghighi M (2014) Simulation of manufacturing production line based on arena. Advanced Materials Research 933: 744-748

[34] Montgomery D (2009) Basic experiment design for process improvement statistical quality contro. John Wiley and Sons, USA