Combined Use of Design of Experiment and Computer Simulation for Resources Level Determination in Concrete Pouring Process

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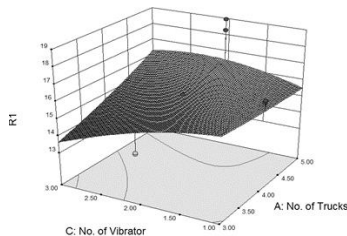
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Graphical abstract

Abstract

Construction managers and planners are always involved in answering questions regarding the effects of changing the level of resources involved in construction activities on project performance. The planners strive to determine the best resource level combination that optimizes the performance measures such as productivity. In this study, a unique approach involving the combined use of a powerful Quality Engineering tool, Design of Experiment (DOE) and Simulation for determining the best combination of resources level for a real-world construction process, viz. concrete pouring process. DOE enabled the experimental plan to be designed in the form of a twice replicated, 24 full factorial designs with 5 center points. This experimental plan involved 37 experiments. Simulation has enabled the construction process investigated to be realistically modelled. Therefore, instead of performing field trials involving 37 experiments, these experiments are simulated in order to obtain the response investigated, which is productivity. A model, for predicting concrete pouring process productivity, was successfully developed and the optimum resources level was also determined.

Keywords: Construction process productivity; concrete pouring process; design of experiment; computer simulation

■1.0 INTRODUCTION

Resource consumption plays a significant role in the construction industry. Indeed, construction planners and decision makers are challenging with this issue. They strive to determine the best combination of resources level involved in the construction processes in such a way that improve some performance measures such as process productivity and total cycle time.[1] Large construction projects involve various types of resources, such as labour, equipment and materials which require planning and design for efficient performance and high benefits. Any combinations of these resources level affect the productivity of construction processes. [2-3] Recently, increased research efforts have been expended for reducing the cost and cycle time of construction projects. Among the factors that affect construction project cost and cycle time are construction resources. Therefore, construction research efforts aim at minimizing project cost and cycle time so that resource limitations and project due date are considered. In order to achieve this, researchers have tried to answer the question about the best resource allocation for each activity in a given construction process. [4-5]

Several attempts have been made to solve the problem of resource management in the construction sector. Zhang and Tam [6] have developed a fuzzy dynamic resource allocation based on a fuzzy decision-making approach. They aimed at improving construction productivity by minimizing the factors such as waiting times or number of resources waiting in queues, etc. The fuzzy decision making model for allocating the resources has been conducted based on the real time data. They have incorporated a discrete-event simulation with an activity based model and activity simulation strategy. Moreover, Huang *et al.* [7] have listed five schemes called SR, MR/CS/FS, MR/CNS/FS, MR/CS/FNS, and MR/CNS/FNS schemes for which sensitivity analysis has been done using computer simulation software Micro CYCLONE. It should be noted that each of the schemes had their own number of resources. The study was aimed at assessing the influence of varying resources on productivity. The results have revealed that different scenarios of resource allocation changed the duration and cost of project considerably. Chen *et al.* [5] have presented an approach called Intelligent Scheduling System (ISS) which applied simulation techniques to allocate different levels of priorities to construction activities. ISS has been applied for using simulation techniques in order to allocate different levels of resources to different activities in every simulation cycle to find near-optimum distributions of resources such as manpower, material, equipment and space according to the project goals and constraints. Nikakhtar *et al.* [1] have also conducted sensitivity analysis for a construction process via computer simulation. They have reported that their work caused the optimum resource combination to be found so that productivity has increased by 7.77%. In order to achieve this, they

have defined different combination of resources involved in a given construction process. After that different scenarios have been simulated based on the defined combinations in order to achieve the best resource combination that maximized the process productivity.

Apart from the aforementioned mentioned efforts reported on managing resources involved in construction processes, limited research efforts have been made on studying the following issues:

1. Determination of the effects of various factors involved in a construction process.
2. Better understanding of the effect of interactions between different resources on construction process performance.

Design of experiment (DOE) is a powerful statistical tool which can address the above mentioned gaps and at the same time the best combination of resources level that maximizes the productivity can be determined. DOE is an experiment or series of tests performed by changing the input process variables that may affect the output responses. DOE techniques also enable planners to determine the variables that have the most significant effect on the response. In fact, experimental design methods are useful tools for improving processes. It also aids the system in reducing the cycle time and overall costs significantly as well as improving process performance. Moreover, DOE provides a full insight of interaction between selected factors that may affect the output results or responses. [8]

Traditionally, the experimental designs have been used in physical experiments such as agriculture experiments and clinical tests. Due to the large number of input variables and high cost of conducting experiments, performance of physical experiment is practically impossible. Therefore, computer simulation is utilized as a powerful and useful tool with which experimental trials could be conducted in a low-cost and reliable environment. [9-11]
In this study, a unique approach involving the combined use of DOE and Simulation for determining the best combination of resources level that maximizes the process productivity for a real-world construction process, viz. concrete pouring process, is investigated.

■2.0 CASE STUDY

The case study is part of a concrete building construction located in the city of Mashhad, Iran. It consists of two floors and each floor, according to design specifications, needs 420 m^3 of concrete to be completed. The concrete operations consist of two main operations. The first one is concrete pouring of slabs and beams and the second one is concrete pouring of walls and columns. In this paper, the authors focus on concrete pouring process of beams and slabs which is divided into 4 parts of about 91 m^3 of concrete. Concrete trucks that contain 7 m^3 of concrete are used for hauling concrete to the construction site. The process starts from the entrance point of the construction site. Following that, seven cubic meters of concrete are hauled by a concrete truck into the construction site. After the entry of a concrete truck into the construction site, it goes for pumping. Once the concrete is prepared and tested, it is time to pour the concrete using a concrete pump. In this step, an operator is responsible for pumping the concrete. After pumping, all the concrete in the concrete truck, the other resource crews do the rest of concrete operations. These operations are spreading, vibrating, and finishing and these are done sequentially. The process map for process is drawn in Figure 1.
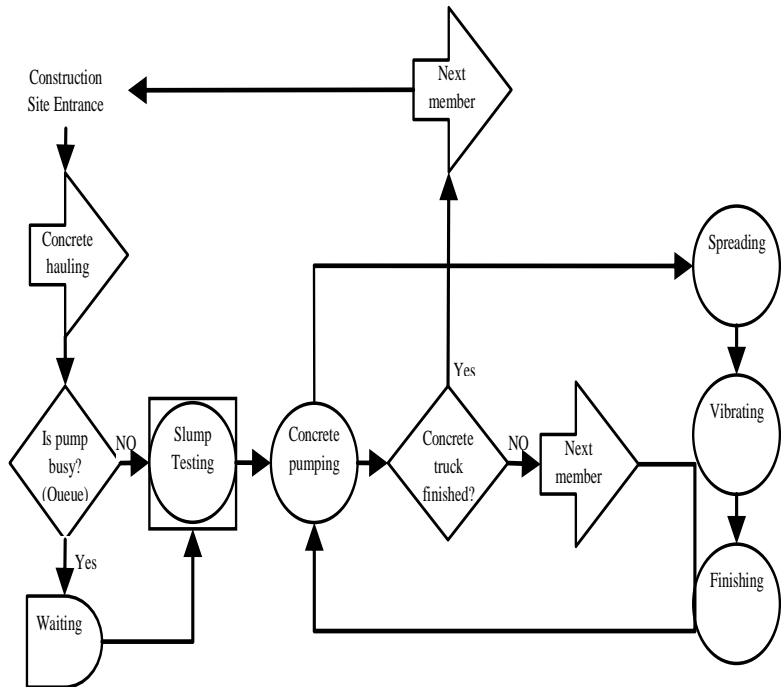

Figure 1 Process map for concrete pouring process

■3.0 SIMULATION MODEL DEVELOPMENT

Having drawn the process map of the concrete pouring process, the necessary data for the simulation model need to be gathered next. A simulation model needs random input data in order to reflect the randomness of the model. In order to do this, different samples of data should be collected first. The necessary input data for the simulation model of the process are the duration for operations such as spreading, finishing, etc. and the time between successive arrivals of concrete tucks. After collecting the required samples of data, a probability distribution function should be fitted to each of them because the inputs of a simulation model are in the form of probability distribution.

After developing the process map for the concrete pouring process and acquiring the input data in the form of probability distribution functions, the simulation model for the process is developed. The model is intended to reflect the current state of the concrete pouring process. There are various computer simulation software available for developing the simulation model of the activity. In this study, Arena 13.9 is chosen as the simulation software for developing the simulation model. Figure 2 shows the current-state model for the concrete pouring process. In order to build the simulation model below assumptions were considered:

1. The working times are 24 hours per day and 5 days in week.
2. The employer fulfils a short-term contract to use the trucks and the trucks did not pay based on the time in the system.
3. Trucks breakdown is not considered in this model.

The Table 1 depicts the distributions of process in simulation model that are fitted to the collected data.

Table 1 Distribution fitted to the collected data

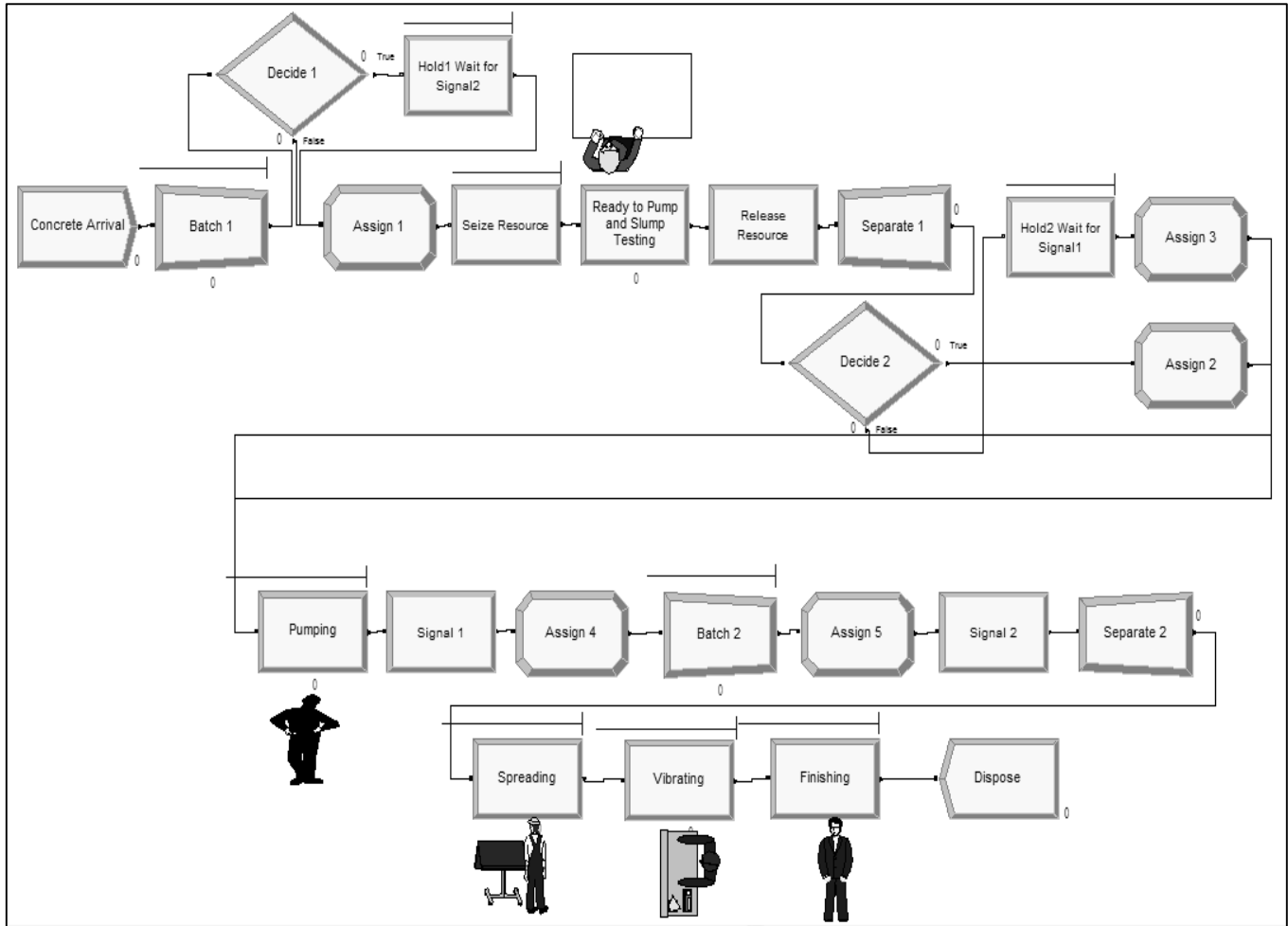| Activity	Distribution	Distribution Parameters
Ready to pump and Slump Testing	Johnson	$\gamma= 0.693\ \varepsilon=3.497\ \delta=2.508\ \lambda=1.6073$
Pumping	Johnson	$\gamma= 0.952\ \varepsilon=0.754\ \delta=1.43\ \lambda=0.87$
Spreading	Johnson	$\gamma= -0.101\ \varepsilon=0.58\ \delta=0.91\ \lambda=0.47$
Vibrating	Johnson	$\gamma= -1.189\ \varepsilon=-0.218\ \delta=1.497\ \lambda=1.506$
Finishing	Johnson	$\gamma= 1.55\ \varepsilon=0.502\ \delta=2.194\ \lambda=1.381$

Figure 2 Simulation model of concrete pouring process developed using Arena 13.9

■ **4.0 SIMULATION MODEL VALIDATION**

After developing the simulation model, the model must be validated to see whether it behaves as the real-world activity. In order to validate the simulation model, a parameter of the process should be selected and a comparison should be drawn between the value of the parameter in real-world process and that of the simulation model. The parameter considered for this purpose is the process cycle time. Data collected from field observations indicate that the average cycle time of the concrete pouring process is 205.8 minutes. Running the simulation model for 4 times, Figure 3 depicts the comparison between simulation and real-world outputs. The average process cycle time of the simulation model is 213.55 minutes. The variation between the simulation model and real-world process is 3.62% which is considered acceptable.

■ **5.0 MODEL ANALYSIS**

Having obtained the simulation model of the real-world process, the performance of the model should be analysed. Analysis of the model is done by defining the process productivity. In this study, productivity is defined as the amount of output divided by the amount of input. The amount of output is considered as the

amount of cubic meters of concrete to be poured in the concrete pouring process. As mentioned before, 91 cubic meters of concrete is poured in the consider process. The process input is defined in terms of cost. It is defined as the total resource cost of the process. Table 2 shows the cost and quantity of critical resources involved in the current-state simulation model. Productivity and resource cost calculation are presented in equations 1 and 2, respectively.
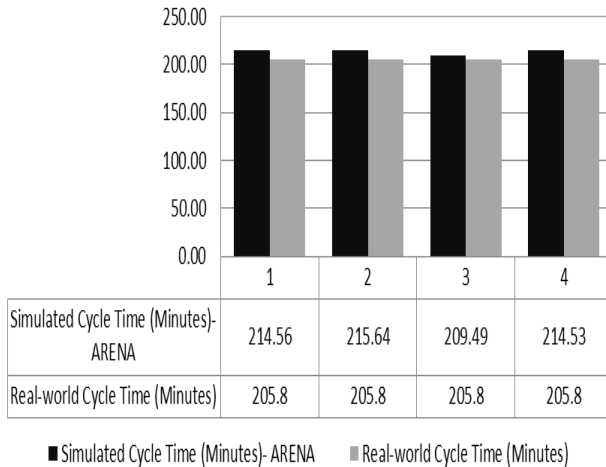

	1	2	3	4
Simulated Cycle Time (Minutes)-ARENA	214.56	215.64	209.49	214.53
Real-world Cycle Time (Minutes)	205.8	205.8	205.8	205.8

■ Simulated Cycle Time (Minutes)- ARENA   ■ Real-world Cycle Time (Minutes)

Figure 3 Comparison of Simulation and real-world outputs

Table 2 Resource cost and quantity

Name	Cost/Hour ($)	Quantity
Truck	25	4
Spreader Crew	10	1
Vibrator Crew	12	1
Finisher Crew	15	1

$$\text{Productivity (m}^3\text{/\$)} = \frac{\text{Area to be Completed}}{\text{Total Resource Cost}} = \frac{91}{\text{Total Resource Cost}} \qquad (1)$$

$$\text{Resource } Cost = Number\ of\ Resources \times Process\ Cycle\ Time \times \\ Resource\ Cost/hour \qquad (2)$$

Having considered the average cycle time of 213.55 minutes (3.56 hours) and the total resource cost of $487.72, the productivity based on the current state simulation model is equal to $(18.66 \times 10^{-2})^{\text{m}^3/\$}$.

■6.0 DESIGN OF EXPERIMENT

DOE technique is used to develop the experimental plan required for determining the significant factors that affect process productivity and the optimum resource level combination that will result in the best process productivity. In order to implement DOE, the following steps are followed. The steps are:

- ✓ Choosing the factors and their levels
- ✓ Choosing a response variable
- ✓ Choice of experimental design
- ✓ Performing experiment
- ✓ Data analysis
- ✓ Conclusions and recommendations

6.1 Choosing Factors and Response Variable

The factors chosen in this study are number of critical resources of the concrete pouring process. The variation range or level of factors is indicated in Table 3. As can be seen, each factor has a high (+) and low (-) level. The specified levels are considered based on discussion with the construction practitioners and the limitations of the process.

Table 3 Factor levels

Factor Name	Low Level (-)	High Level (+)
A= Truck	3	5
B= Spreader Crew	1	3
C= Vibrator Crew	1	3
D= Finisher Crew	1	3

As discussed before, the response variable considered in DOE is process productivity. For the choice of experimental design, due to the small number of factors investigated, the full factorial design is used. In the factorial design all possible combination of factors are in an experiment considered. The experiment is also replicated for two times. As can be seen from Table 3, each factor has two levels. Therefore, a full factorial experiment includes 24 runs. Having considered 2 replications for experiments and five additional centre points, 37 runs are included in the design.

6.2 Performing Simulation Experiments

After obtaining the experimental plan, the experiments are performed. To do this, the simulation model is run for different combination of factors level. Table 4 indicates the results of performing the simulation experiment. It should be noted that the last five rows in Table 4 are dedicated to centre points. The addition of centre points is discussed in the next section.

6.3 Data Analysis

6.3.1 Identifying Significant Factors

In order to analyse the data shown in Table 4, a statistical computer package is required. In this study the Design-Expert software is used. Having entered the data presented in Table 3 in Design-Expert, it analyses them in order to identify the significant factors and recommend the best solution. Table 6 represents the results of analysis of variance (ANOVA) performed by Design-Expert for identifying significant factors. Decision about the significance of a factor or effect is made based on the P-value. If the P-value of a factor or effect is less than 0.05, it is considered as significant factor.

6.3.2 Incorporation Of Centre Points

Since this research conducts a factorial design in which main effect and interactions are considered, studying the curvature in the response surface of the model is of great importance. In order to do this, five additional centre points, as mentioned before, are added to design.

Upon performing the ANOVA for the experimental data, as shown in Table 6, it is revealed that the curvature is significant. Significant curvature implies a second-order-effect has to be incorporated in order to have an adequate regression model. Since the curvature is significant, the design should be augmented by adding axial points. By this it means that several new runs should

be added to enable the second order effect to be determined. Having done the design augmentation, 20 additional runs are added to experimental plan. Table 5 reveals the results of performing the experiment with these new points.

Table 4 Data from simulation experiments

A	B	C	D	Productivity ($*10^{-2}$)	
3	1	1	1	18.26	18.10
5	1	1	1	16.27	15.57
3	3	1	1	15.49	15.48
5	3	1	1	14.28	13.90
3	1	3	1	14.97	15.06
5	1	3	1	13.97	13.93
3	3	3	1	13.06	13.11
5	3	3	1	12.66	12.62
3	1	1	3	14.45	14.32
5	1	1	3	14.20	13.94
3	3	1	3	12.64	12.59
5	3	1	3	12.97	12.76
3	1	3	3	12.66	12.62
5	1	3	3	17.66	17.71
3	3	3	3	11.35	11.31
5	3	3	3	16.25	16.21
4	2	2	2	15.34	
4	2	2	2	15.78	
4	2	2	2	15.74	
4	2	2	2	15.41	
4	2	2	2	15.56	

Table 5 Experiment results of new added points

A	B	C	D	Productivity ($* 10^{-2}$)	
3	2	2	2	13.98	14.04
5	2	2	2	18.94	18.29
4	1	2	2	16.47	16.54
4	3	2	2	14.56	14.63
4	2	1	2	16.22	16.32
4	2	3	2	14.65	14.61
4	2	2	1	16.11	16.05
4	2	2	3	14.22	14.24
4	2	2	2	15.76	15.35

Table 6 ANOVA table for productivity

source	Sum of square	df	Mean square	F value	P-value Prob>F	Remark
model	1.4E-04	14	1.0E-05	378.28	<0.0001	
A	6.0E-06	1	6.0E-06	220.04	<0.0001	
B	3.1E-05	1	3.1E-05	1146.79	<0.0001	
C	6.5E-06	1	6.5E-06	237.43	<0.0001	
D	1.0E-05	1	1.0E-05	373.29	<0.0001	
AB	1.0E-06	1	1.0E-06	37.56	<0.0001	
AC	2.2E-05	1	2.2E-05	793.41	<0.0001	
AD	3.6E-05	1	3.6E-05	1324.48	<0.0001	
BC	4.4E-09	1	4.4E-09	0.16	0.6925	
BD	3.1E-08	1	3.1E-08	1.16	0.2942	
CD	1.7E-05	1	1.7E-05	620.31	<0.0001	
ABC	1.3E-07	1	1.3E-07	4.69	0.0419	
ABD	3.0E-07	1	3.0E-07	10.92	0.0034	
ACD	1.4E-05	1	1.4E-05	522.02	<0.0001	
BCD	9.8E-08	1	9.8E-08	3.61	0.0711	
Curvature	1.1E-07	1	1.1E-05	397.92	<0.0001	significant

Having added the 18 new runs to 37 past runs, ANOVA should be re performed for the combined experiments of 54 runs. It reveals that a quadratic model should be fitted to the data. The significant factors are A, B, C, D, AC, AD, CD, and D^2. The tables 7 and 8 show the ANOVA and estimated effects of significant factors, respectively. An example of 3D surfaces constructed is also shown in Figure 4.
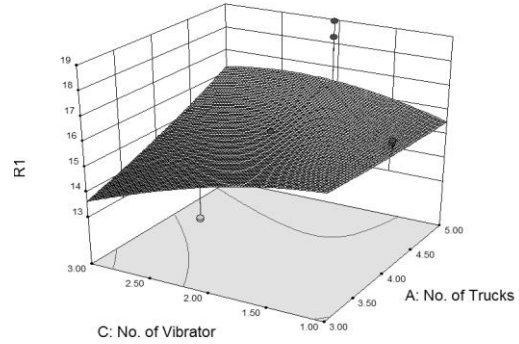

Figure 4 3D surface for productivity (R1)

Table 7 ANOVA table after design augmentation

Source	Sum of square	DF	Mean square	F value	P-value Prob>F
Model	**127.79**	**14**	**9.13**	**14.73**	**<0.0001**
A	10.74	1	10.74	17.32	<0.0001
B	26.40	1	26.40	42.60	0.0002
C	4.95	1	4.95	7.99	0.0074
D	7.83	1	7.83	12.63	0.0010
AB	0.24	1	0.24	0.39	0.5346
AC	16.95	1	16.95	35.42	<0.0001
AD	30.24	1	30.24	48.80	<0.0001
BC	0.28	1	0.28	0.45	0.5059
BD	0.51	1	0.51	0.83	0.3687
CD	20.91	1	20.91	33.75	<0.0001
A²	0.83	1	0.83	1.34	0.2535
B²	0.62	1	0.62	1	0.3244
C²	1.02	1	1.02	1.64	0.2078
D²	2.77	1	2.77	4.48	0.0408
Std. Dev.	0.79	R-Squared	0.840		
Mean	14.89	Adj R-Squared	0.783		
C.V. %	5.29	Pred R-Squared	0.680		
PRESS	48.69	Adeq Precision	16.39		

Table 8 Estimated of coefficient of significant factors

Factor	Coefficient
A	0.55
B	-0.86
C	-0.37
D	-0.47
AC	0.73
AD	0.97
CD	0.81
D²	-0.75

6.4 Regression of Second Order Model

Based on the estimated coefficient of the significant factors, the following second order regression model is fitted to the data. Having considered the report of estimated effects, equation 3

indicates the regression model fitted to the data produced by Design-Expert

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} X_{11}{}^2 + \beta_{22} X_{22}{}^2 \quad (3)$$
$$Y = 14.89 + (0.55)A + (-0.86)B + (-0.37)C + (-0.47)D + (0.73)AC + (0.97)AD + (0.81)CD + (-0.75)D^2$$

6.5 Residual Analysis

Having obtained the regression model, the residual analysis is performed to validate the regression model. The residual, which are the difference between the observed values and predicted values, should be lie on a straight line in the normal probability plot. Figure 5 shows the normal probability of the residuals. As can be seen in the figure, the residuals lie along a straight line. The residuals are considered to be normal and therefore the validity of the model is proven. In addition, Figure 6 reveals the plot of residuals versus the predicted response for productivity. It reveals that there is no obvious pattern and unusual structure. This implies that the proposed model is adequate and the assumption of constant variance is not violated.

6.6 Optimization and Confirmation

After validation of the regression model, it is time to achieve the optimum solution of the achieved model. In order to do optimization Design-Expert is employed. The optimum point calculated by Design-Expert is: A=3, B=1, C=1 and D=1. The productivity at the optimum point is $(20 \times 10^{-2})^{\text{m}^3/\$}$. The point implies that the optimum point is one that in which all factors are at their low level. Having obtained the optimum point, the regression model should be confirmed at the achieved optimum point. By this it means that the simulation model is run at the optimum point predicted by the regression model and the outcome is compared with that of regression model. Table 8 indicates the outcome of 10 runs of the simulation model at the optimum point predicted by the regression model. As can be seen, the variation between the simulation results and that of regression model is 9.25% which is acceptable.
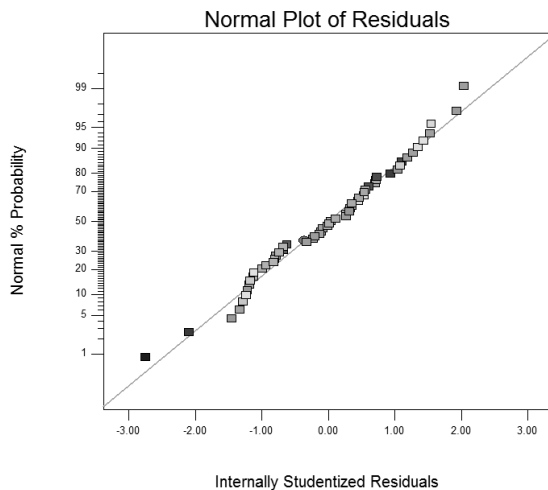

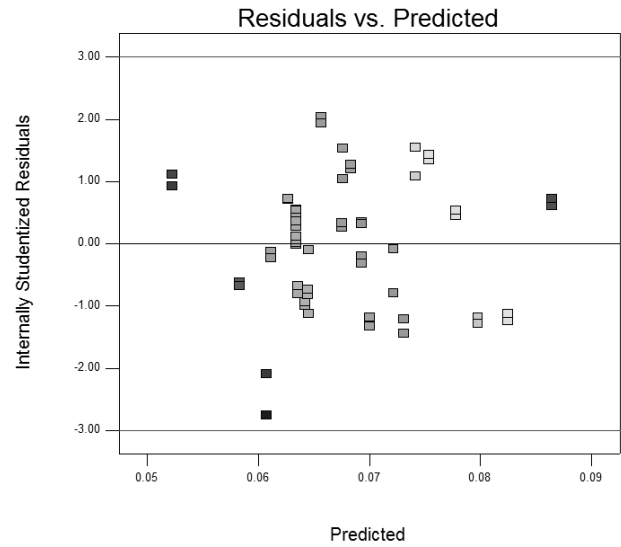**Figure 5** Normal probability plot of residuals

Figure 6 Plot of residuals versus predicted response for productivity

Table 9 Comparison of simulation model and regression model

Replication	Simulation Productivity ($*10^{-2}$)	Regression Model Productivity ($*10^{-2}$)
1	18.26	
2	18.10	
3	18.22	
4	18.06	
5	18.09	20
6	18.24	
7	18.11	
8	18.15	
9	18.14	
10	18.15	
Average	18.15	
Variation (%)	9.25	

■7.0 CONCLUSION

This research strives to conduct design of experiment for determining the best combination of resources level involved in a real-world construction process. The investigation concentrates on finding a resource combination that has high performance measure. Computer simulation is also used as an effective tool for conducting the simulated experiments as called for in the experimental plan designed. Different combinations of resources are modelled to achieve the best performance measure for the process. The result shows that the maximum desirability of productivity will be achieved when the all factors to be at low levels that means A=3(Truck), B=1(Spreader Crew), C=1(Vibrator Crew) and D=1(Finisher Crew).It is hoped that this work has demonstrated the viability of the combined use of simulation and DOE in construction resource management. This leads to the determination of the optimal resource combination in such a way that process productivity is improved. Future study can be done to find the global optimum of resource levels by using other methods such as response surface methodology and meta-heuristic algorithms.

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