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Identifying Significant Factors of Brick Laying Process through Design of Experiment and Computer Simulation: A Case Study

M. H. Zarei, A. Nikakhtar, A. H. Roudsari, N. Madadi, and K. Y. Wong

***Abstract*—**Improving performance measures in the construction processes has been a major concern for managers and decision makers in the industry. They seek for ways to recognize the key factors which have the largest effect on the process. Identifying such factors can guide them to focus on the right parts of the process in order to gain the best possible result. In the present study design of experiment (DOE) has been applied to a computer simulation model of brick laying process to determine significant factors while productivity has been chosen as the response of the experiment. To this end, four controllable factors and their interaction have been experimented and the best factor level has been calculated for each one. The results indicate that three factors, namely, labor of brick, labor of mortar and inter arrival time of mortar along with interaction of labor of brick and labor of mortar are significant.

***Keywords*—**Brick laying process, computer simulation, design of experiment, significant factors.

I. Introduction

DETERMINING the key factors that have the major influence on the construction projects has been a challenging task for managers and decision makers. Managers are interested in finding the most significant factors that consume more time and cost. This will enable them to adjust the performance measures such as productivity or cycle time at their best level [1].

Resources are considered as kinds of factors that is engaged in the construction industry. Among the resources involved in the construction projects are manpower, equipment, materials, money, and space [2]. Identifying significant resources and their interaction is a crucial success factor for every construction project.

M. H. Zarei is with Department of Manufacturing and Industrial Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310 Malaysia (phone: +60 197132548; e-mail: m.hosseinzarei@gmail.com).

A. Nikakhtar is with Department of Manufacturing and Industrial Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310 Malaysia (e-mail: aminnikakhtar1987@gmail.com).

A. H. Roudsari is with Department of Manufacturing and Industrial Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310 Malaysia (e-mail: arousha.haghighian@gmail.com)

N. Madadi is with Department of Manufacturing and Industrial Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310 Malaysia (e-mail: najme_m@yahoo.com)

K. Y. Wong is with Department of Manufacturing and Industrial Engineering, Universiti Teknologi Malaysia, Skudai, Johor 81310 Malaysia (e-mail: wongky@fkm.utm.my)

Many researchers and practitioners have tried to provide new ways in order to improve the construction processes. Sensitivity analysis, computer simulation and goal programming are some of the proposed ways in this regard [3]-[5]. Although a great number of studies have been done in the area of quality improvement and optimization of construction processes, fewer studies have focused on the recognition of significant factors in the industry. In this study, we aim at identifying the factors that have the biggest effect on the productivity of a special construction process, brick laying process, by means of design of experiment (DOE).

DOE is a powerful tool that was first introduced in 1920 by R. A. Fischer to be applied in the agriculture field. The application has been spread to a variety of scientific and industrial fields thereafter [6]. 2^k full factorial design is one of the most popular techniques in DOE in which the factors can only have two levels, usually high and low. The power, *k*, indicates the number of factors to be studied. It is an efficient method to achieve an understanding of the process by distinguishing the factors and interactions that have the most significant effect on the desired response [7].

In this study, a 2^k full factorial design has been proposed to be implemented on the brick laying process. It is expected that the results of the experiment will identify the key factors and their interactions in the brick laying process.

Necessary data to run the experiment are collected from a simulation model of the process. We have used the computer simulation model because it is a flexible tool that allows planners to evaluate the response with every possible combination of resources at a much lower cost and time in comparison with real-world practice [8], [9]. In order to assess the process, productivity is chosen as the response of the experiment as it is a strong indicator that shows how well the resources are used to generate outputs. Therefore, it can be considered as a measure to decide on the efficiency of a construction process [3].

II. Simulation of Brick Laying Process

The process map of brick laying is presented in Fig. 1. As can be seen, the result of both flows, mortar flow and brick flow, is the placement of a row of bricks. In order to simulate the process, we have used *ARENA* 13.9 which is generic discrete event simulation software with a powerful 3D animation interface. A pictorial representation for the simulation of the brick laying process in *ARENA* 13.9 is illustrated in Fig. 2.

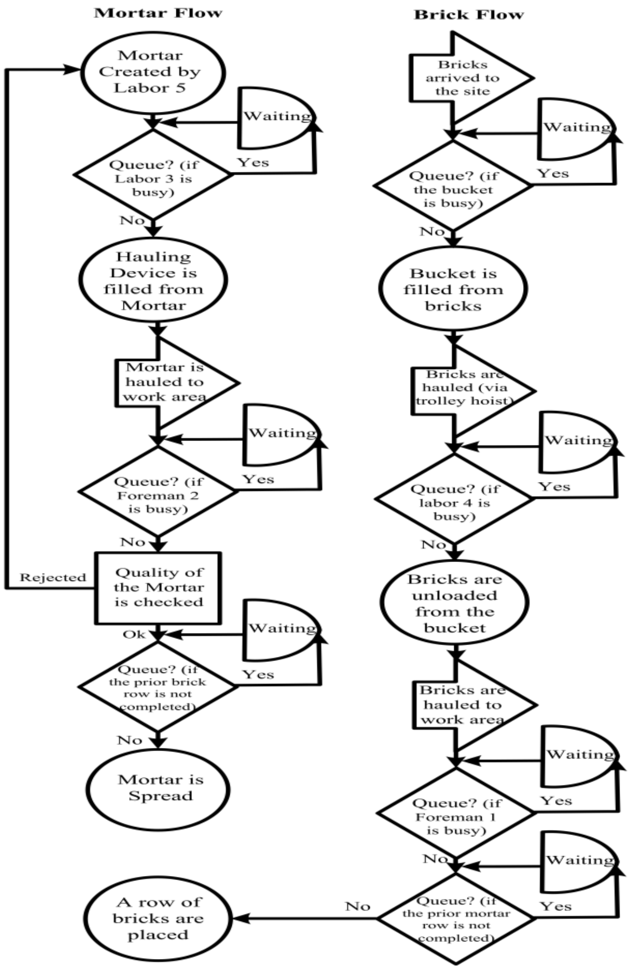


Fig. 1 Process map of brick laying

A. Model Validation

A proper model should be able to provide an accurate presentation of the actual work flow process and interrelationships among different parts. Hence, it is crucial to validate the model before using it. Validation means that the model is almost behaving like the actual system [10]. Here, it ensures that the constructed simulation model is reflecting the real behavior of the brick laying process.

The standard approach to validate a simulation model is making a comparison between the collected actual data and the results achieved from the model. In this study, at first the model is run while the distributions of activities are used as inputs. Then, the cycle times achieved from the model are compared with real data. After each run of validation, the model is modified if it is found to be necessary for the purpose of solving the probable problems. The validation runs continue until the variation is minimized between the model output and actual data.

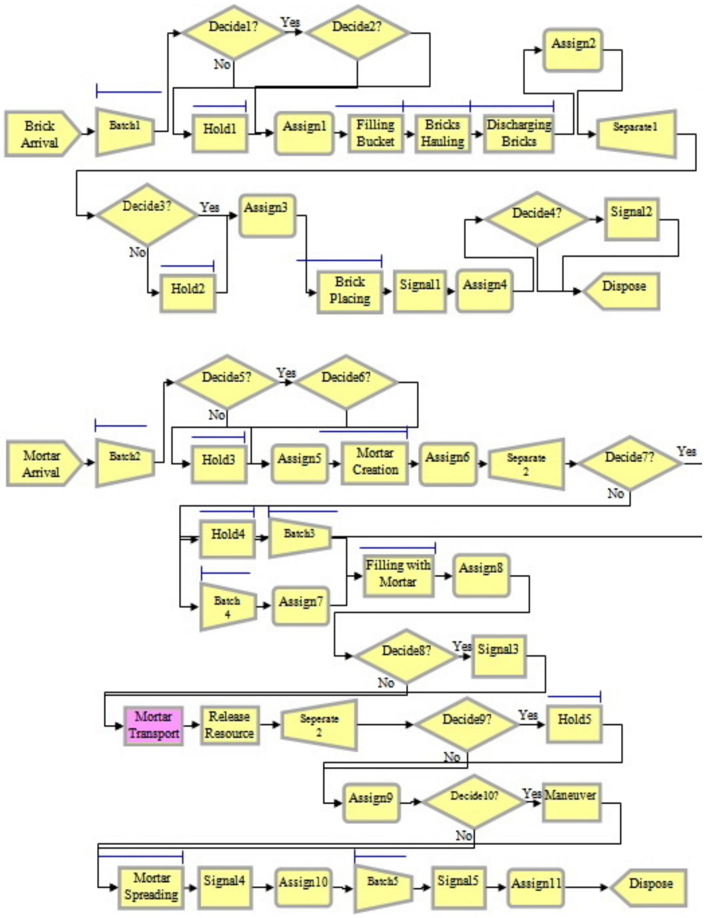
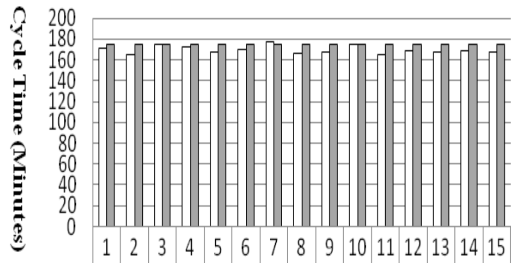


Fig. 2 Simulation of brick laying process in ARENA 13.9



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Simulated Cycle Time (Minutes)	172	165	174	172	168	171	177	166	167	174	165	169	168	169	167
Actual Cycle Time (Minutes)	175	175	175	175	175	175	175	175	175	175	175	175	175	175	175

Fig. 3 Validation of the simulation model

Generally, the favorable level of accuracy is not achieved by a single run of the model [11]. A study on the estimation on the number of necessary simulation runs for a terminating simulation can be found at [12]. According to that, the suitable number for the simulation model in this study is 13 replications or more, while we have used 15 simulation runs to maximize the model reliability. The results for the final validation are illustrated in Fig. 3. The results indicate a

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variation between -6% and +1% (with an average of 3%) which is satisfactory based on [11]. Now the model is ready for application of DOE.

III. Implementation of DOE

A. Choice of Response Variable, Factors and their Levels

As mentioned before, productivity of the process was chosen as the response variable for the process under study. In addition, the experiment consists of four factors that are varied between two levels of low and high. The current situation of the process was considered as the low level and the high level was set based on the experimental and theoretical knowledge of the process. Table I presents the factors and their levels.

TABLE I
FACTORS WITH HIGH AND LOW LEVELS

	Level	
Factors	Low	High
A= Labor of brick (number of workers)	2	4
B= Labor of mortar (number of workers)	1	3
C= IAT of Brick (minutes)	30	36
D= IAT of mortar (minutes)	36	43.2

B. Performing the Experiment

A 2^4 full factorial design was applied with two replications. The responses were achieved from the simulation model and the values are shown in Table II and Table III for the first and second replication respectively.

TABLE II
RESPONSES (PRODUCTIVITY) FROM THE SIMULATION MODEL (THE FIRST REPLICATION)

	A	B	C	D	Response (*10^{-3})
1	-1	-1	-1	-1	58.466
a	1	-1	-1	-1	44.196
b	-1	1	-1	-1	40.867
ab	1	1	-1	-1	35.759
c	-1	-1	1	-1	60.082
ac	1	-1	1	-1	43.653
bc	-1	1	1	-1	40.937
abc	1	1	1	-1	32.102
d	-1	-1	-1	1	56.974
ad	1	-1	-1	1	40.927
bd	-1	1	-1	1	38.156
abd	1	1	-1	1	33.427
cd	-1	-1	1	1	57.969
acd	1	-1	1	1	41.187
bcd	-1	1	1	1	39.089
abcd	1	1	1	1	32.419

TABLE III
RESPONSES (PRODUCTIVITY) FROM THE SIMULATION MODEL (THE SECOND REPLICATION)

	A	B	C	D	Response (*10^{-3})
1	-1	-1	-1	-1	59.576
a	1	-1	-1	-1	43.632
b	-1	1	-1	-1	41.252
ab	1	1	-1	-1	33.927
c	-1	-1	1	-1	59.05
ac	1	-1	1	-1	43.739
bc	-1	1	1	-1	41.205
abc	1	1	1	-1	33.005
d	-1	-1	-1	1	57.112
ad	1	-1	-1	1	40.376
bd	-1	1	-1	1	40.26
abd	1	1	-1	1	34.173
cd	-1	-1	1	1	57.401
acd	1	-1	1	1	39.407
bcd	-1	1	1	1	36.816
abcd	1	1	1	1	31.431

C. Identifying the Significant Factors

In order to identify the significant factors, different methods such as drawing normal probability plot and analysis of variance (ANOVA) have been proposed [13].

In this study, we have used ANOVA for this purpose. The results are illustrated in Table IV. Values of "Prob > F" less than 0.0500 indicate the model terms are significant. In this case A, B, D, and the interaction of A and B, called AB, are significant model terms in the brick laying process. Values greater than 0.1000 indicate the model terms are not significant. Generally if there are many insignificant model terms (not counting those required to support the hierarchy), model reduction may improve the constructed model.

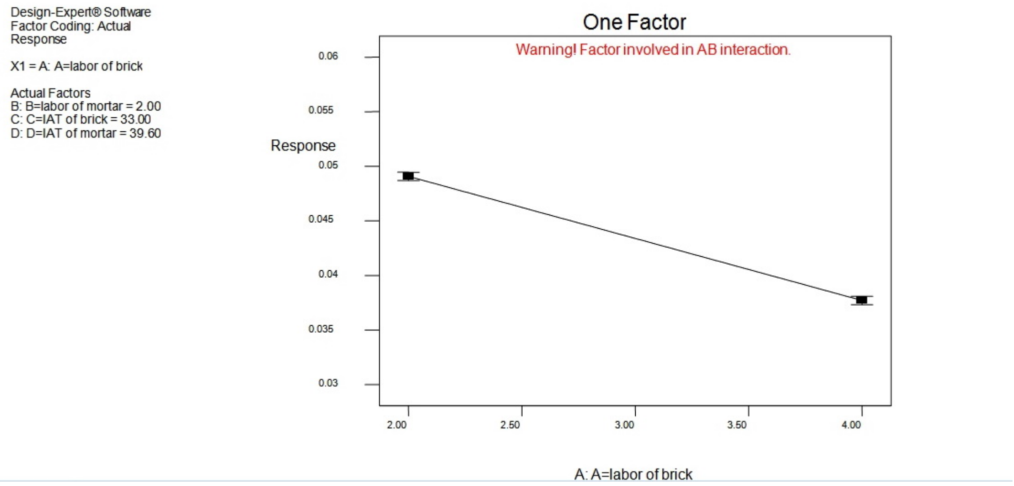
TABLE IV
ANOVA RESULTS FOR SIGNIFICANT FACTORS

	SS	df	MS	F-Value	P-Value	Significat?
Block	4.624E-007	1	4.624E-007			
Model	2.754E-003	4	6.885E-004	632.67	< 0.0001	Yes
A-A	1.033E-003	1	1.033E-003	949.62	< 0.0001	Yes
B-B	1.498E-003	1	1.498E-003	1376.22	< 0.0001	Yes
D-D	3.682E-005	1	3.682E-005	33.83	< 0.0001	Yes
AB	1.861E-004	1	1.861E004	171.02	< 0.0001	Yes
Residual	2.830E-005	26	1.088E-006			
Total	2.783E-003	31				

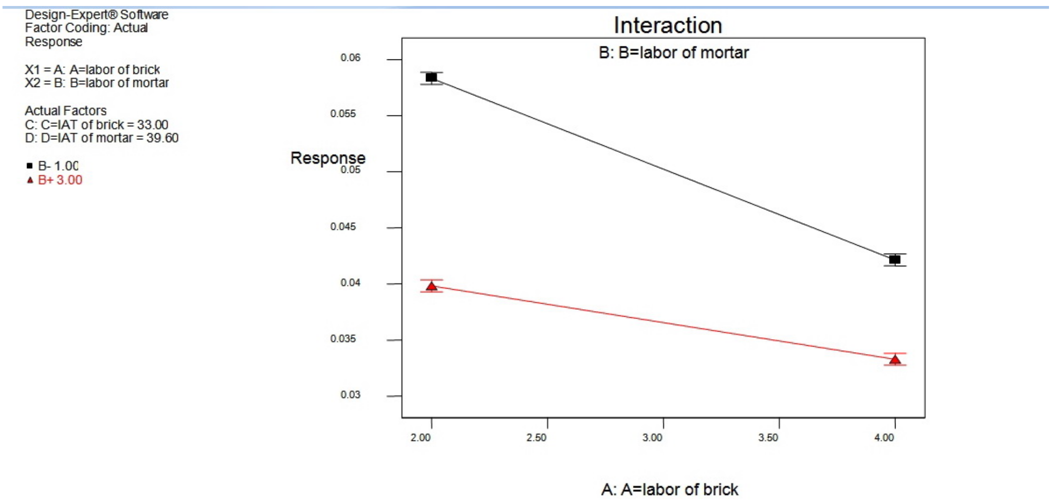
The main effect of a factor can be defined as the change in response which is produced by the change in the level of that factor [13]. We have used *Design Expert* software to visualize the main effect of significant factors. As an example, main effect plots for A and AB are illustrated in Fig. 4.

IV. Testing the Normality Assumption

At the end of each experimental design it is necessary to assess the validity of normality of the model by drawing the normal probability plot of residuals.



(a)



(b)

Fig. 4 Main effect plots for A (a) and AB (b)

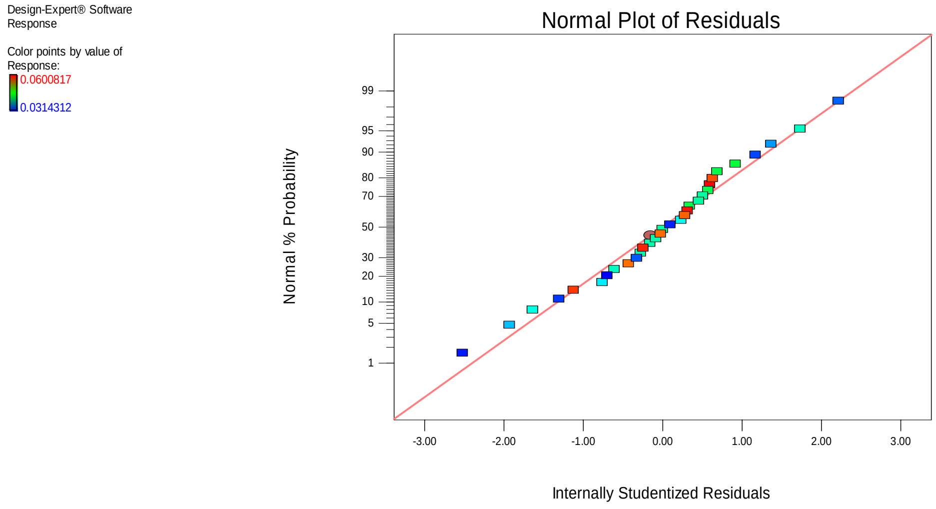


Fig. 5 Normal probability plot of residuals

Normal probability plotting is a graphical tool that helps to determine whether sample data conform to the normal distribution based on a subjective visual examination of data. One of the most important applications of this kind of plot is verification of normality assumption when using statistical inference methods that require the normality assumption [13]. In this paper, normal probability plot is constructed by *Design Expert* software and is presented in Fig. 5. Since the residuals lie approximately along a straight line, we do not suspect any severe non-normality in the data.

V. Concluding Remarks

In this study, a full factorial design of experiment including four factors has been carried out on a computer simulation model of brick laying process in order to identify the significant factors and interactions. The results of the study have revealed that three factors and one interaction are significant which means that they have the greatest impact on the response level.

This study can offer a way to managers and construction planners to recognize the most important factors in the construction site in order to increase the productivity. Application of optimization techniques on the results of this paper is suggested for further studies.

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