RELATIONSHIP BETWEEN PRODUCTIVITY AND NON VALUE-ADDING ACTIVITIES

Ying Zhao[1] and David K. H. Chua[2]

ABSTRACT

From lean production perspective, the physics of production flow can be thought of as comprising value adding and non-value adding (or waste) activities. Moreover, one of its core principles for work improvement is the elimination or mitigation of the latter component. This should be translated into increased productivity at the work site. The aims of this paper are to identify the relationship between productivity at the work site and the waste or non-value-adding activities, and to find out the root causes of the wastes. For this purpose, the waste activities are categorized into 20 sources according to their causes. Productivity data of formwork crews on multiple projects are collected together with the associated wastes. A neural network is then developed to model the influence of the wastes on measured productivity. The model is incrementally pruned so that, eventually, only eight significant wastes are identified and remain. The final model shows very good conformance when compared with observed data. After that the eight significant wastes have been correlated to the project level factors to find out their root reasons.

KEYWORDS

productivity, waste, neural networks, artificial intelligence

[1] Research Scholar, Department of Civil Engineering, National University of Singapore, Singapore 117576

[2] Associate Professor, Department of Civil Engineering, National University of Singapore, Singapore 117576, 65/6874-2195, FAX 65/6779-1635, cvedavid@nus.edu.sg

INTRODUCTION

From lean production perspective, the activities in the physics of production flow can be classified as value adding and non-value adding. Value means the fulfillment of customer requirements. Koskela (1994) defined the value adding activity as "activity that converts material and/or information towards that which is required by the customer"; Non value-adding activity (also called Waste) as "activity that takes time, resources or space but does not add value". Non value-adding activity (Waste) is also defined as "any losses produced by activities that generate direct or indirect costs but do not add any value to the product from the point of view of the client". (Formoso et al. 1999)

Non value-adding activities can be further divided into contributory activities and unproductive activities. Contributory activities are work elements that do not directly add to output but are generally required and sometimes essential in carrying out an operation. These include handling material at the work face, receiving instructions, reading drawings, cleaning up the workplace, ancillary work and so on. Unproductive activities, on the other hand, are those that are not necessary such as being idle or doing something that is unrelated to the operation being carried out or that is in no way necessary to complete the operation; and these could be eliminated from the production flow without diminishing the value of the work. These include walking empty handed, work carried out using the wrong tools or the wrong procedures, rectifying mistakes and so on. (Olomolaiye et al. 1998).

Although Christian called these two kinds of activities differently as Essential Contributory and Waiting & Idling respectively, the classifications were in essence the same. With video recording and stopwatch studies, Christian analyzed the working time from seven sites. On average, workers spend only 46% of working time on the value-adding activities, 15% on the essential contributory and the rest 39% on the waiting & idling. (Christian et al. 1995) Some studies report even worse results. Ciampa (1991) claims that usually only 3 to 20% of steps add value, and their share of the total cycle time is negligible, from 0.5 to 5% (Stalk and Hout 1990). These data shows that non value-adding activities dominate most processes. Thus, the reduction of non value-adding activities offers a major development potential in most production processes.

In some articles, researchers have reported that the labor productivity is better as more time is spent in value-adding activities (Thomas et al. 1984; Handa and Abdalla 1989). Therefore being able to reduce the share of non value-adding activities is one of the core strategies for construction process improvement or, similarly construction productivity improvement. To achieve this, one needful task is to identify the most significant waste activities since not all waste activity affect productivity to the same degree so that scarce resources can be adequately directed. It is the aim of this paper then to identify the relationship between productivity at the work site and the waste or non value-adding activities. In particular, a neural network approach is adopted to build the model. Data for the analysis is collected from actual performance on several sites. Then the project level causes for the main wastes will be identified further, this effort enables project manager have a better ability to organize the project to achieve higher productivity.

THE CONCEPTUAL MODEL:

A conceptual representation of the factors affecting the productivity is shown in Figure 1. Construction productivity is a complex problem, for almost all of the factors involved in a project will take effect on the productivity performance. However, through the study these factors could be layered according to the order of direct to indirect influence on productivity. In details, the most direct causes to the loss of the productivity should be those non value-adding activities' occurring on the site. The non value-adding activities (Waiting, Rework and Idling) were product of the work conditions, which could be traced to Project related factors.

This study is built up based on this model to study the determining factors of productivity. By noting what work environment conditions are the critical barriers to productivity at the work face, responses from the upper level, i.e. the level of project related factors, can then be recognized.

DATA COLLECTION

The data collection effort was divided into 2 stages. The first stage comprises interviews and the second is a survey and data gathering of performance at the work interface. The interviews were conducted on a number of project personnel consisting of project managers, site managers and foremen, with the aim of determining the wastes on site and the causes for these wastes. The interviews were carried out either through face to face sessions or through telephone conversations.

The interviewees were asked to identify the kinds of wastes they encounter on site and their causes. They may be categorized into reworks, waiting and idling. The last is distinguished from waiting to emphasize the lack of a process related source. Based on the findings of the interviews and literature review, a list of waste sources was summarized in Table 1 according to the earlier categories. The sources of waste were related to design, material, crew, equipment and site elements.

From the findings of the first stage, a survey form was designed comprising of a section on the project organizational and management characteristics, and a section of log sheets of work performance. The log sheets were to be filled in by foremen on a weekly basis. The reason for making the foremen as the respondents of the log sheets is that they are the ones closes to the work face and the first line of supervision on the project. They would have site knowledge of the root cause of any poor performance on site. The weekly log sheets require the foremen not only to identify the reason for the waste element but also record the duration or extent of the problem, and the number of workers directly affected. The weekly man-hour lost on every waste element is then computed, and these serve as the inputs to the neural network model to be developed.

Altogether eight on-going projects were selected for the study. They were made up of different nature of work – four were commercial buildings, two were residential condominiums and two were civil draining projects. Only repetitive works were studied, and the survey was done after some time into the project. This will ensure that effect of the learning curve is over, and initial problems associated with starting up a work have been removed. The analysis presented in this paper is focused on the carpentry trade comprising both fabricating and installation works. Its productivity was measured in square meters of formwork (m^2) per man-hour. For the purposes of their accounting, the work quantity reported was on a monthly basis. Together with the monthly manpower records, the monthly productivity for every crew was determined. There were several crews in each project. In all, 75 sets of monthly data were collected during a period of about 6 months. The monthly productivities range from 0.43 to 1.09 m^2/man-hour, with an average of 0.78 m^2/man-hour. The weekly man-hours wasted or lost were accumulated monthly and analyzed along with the productivity figures. The neural network will be used to determine the relationships that exist between them. Through the neural network model development, the significant waste sources for the loss of productivity will be identified.

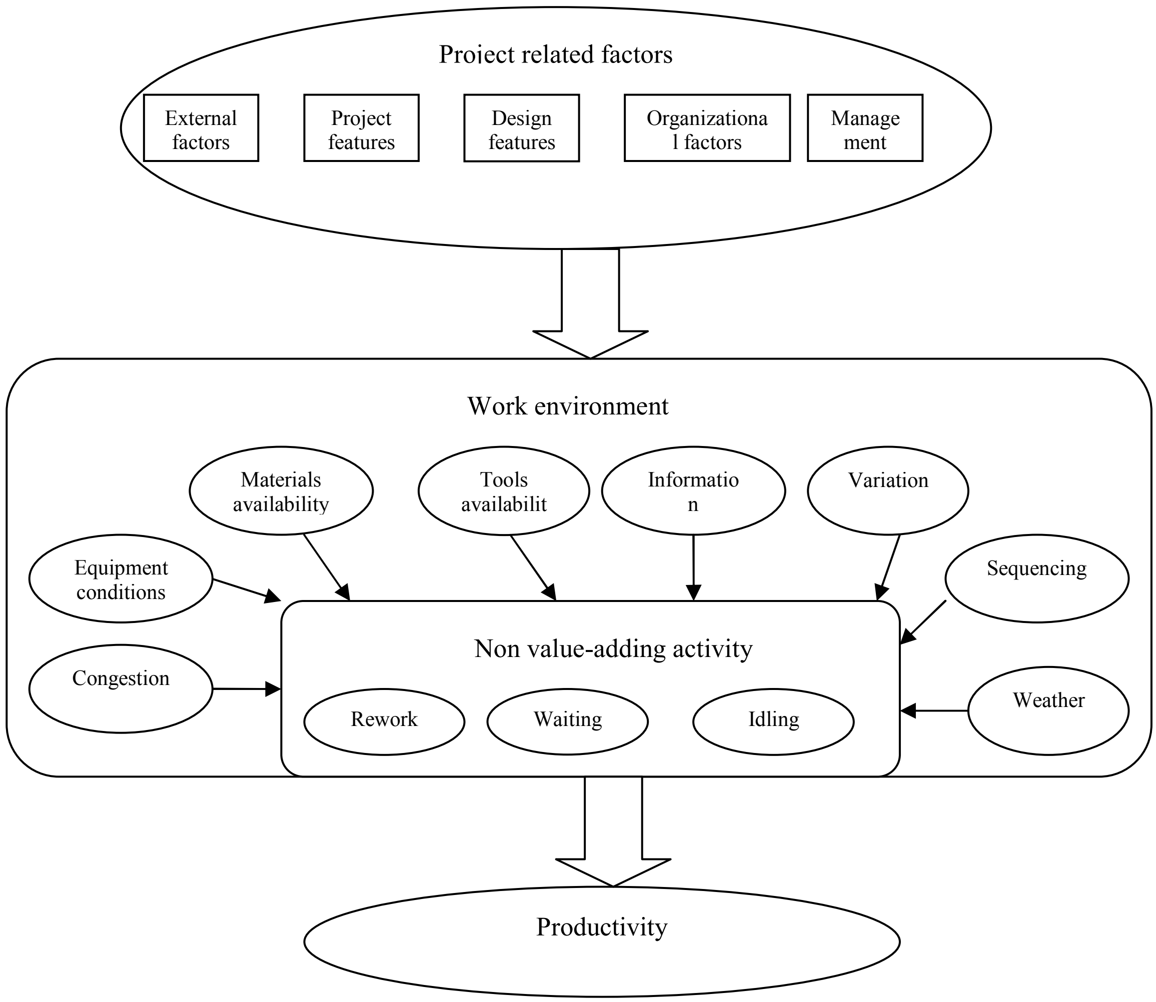


Figure1: Conceptual model for Factors Affecting Productivity

Table 1 Waste sources on site

Category of Waste	Waste Sources	Average monthly man-hours lost (man-hour)
Rework due to	Design error	20.6
	Design change	16.2
	Design omission	6.4
	Field error	15.6
Waiting due to	Wet days	23.9
	Material vendor delay	16.4
	Underestimate to the work	13.6
	Stock problem	5.6
	Equipment used by other crew	52.3
	Equipment was spoiled	21.7
	Equipment’s installation and transportation	20.2
	Tools not suitable	41.4
	Tools was spoiled	22.2
	Instructions	6.5
	Inspection	31.8
	Drawing’s reading	14.0
	Crews interference	14.4
	Congestion of the site	18.3
	Lighting problem	9.7
Idling due to	Worker’s no enthusiasm	8.7

ANALYSIS

Artificial Intelligence (AI) techniques such as Neural Networks (NNs) have received much attention recently. In essence, NN is an information technology that mimics the human brain and nervous system to learn from experiencing past incidents, generalizing knowledge trends and patterns from these previous examples to generate new ones. The Neural Network has been proven to be a powerful approach for solving rather complex nonlinear mappings with higher accuracy. It possesses the ability to learn the relationships based on specific cases of the real work experience, even for data that is highly correlated and nonlinearly-multivariate, and then generalize the solutions to other cases. Therefore, this study will apply the Neural Network approach to model the impact of the wastes on work productivity.

The configuration of the neural network model adopted in this study is four layer back propagation neural network (Fig.2). The input layer has twenty neurons representing the twenty waste sources. There are two hidden layers with ten neurons in each. The output layer has only one neuron representing the productivity. Among the 75 patterns available, 62 data sets were randomly chosen out for training the neural network while the remaining 13 data sets were used for testing.

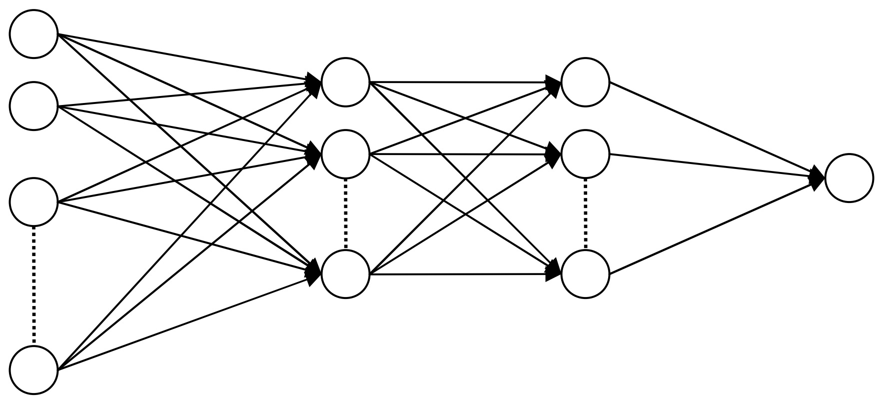


Figure 2: Neural network architecture with 2 hidden layers

For the purpose of assessing the prediction performance obtained by the model, an index is used to measure the prediction accuracy and is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \qquad \textbf{... (1)}$$

Where y_i and $\hat{y}_i$ are respectively measured and predicted data; $\bar{y}_i$ is the mean value of measured data; R^2 is the coefficient of multiple determinations.

A perfect fit would fit in an R^2 value of 1, a good fit near 1, and a very poor fit near 0.

RESULT OF THE MODEL WITH ALL THE VARIABLES

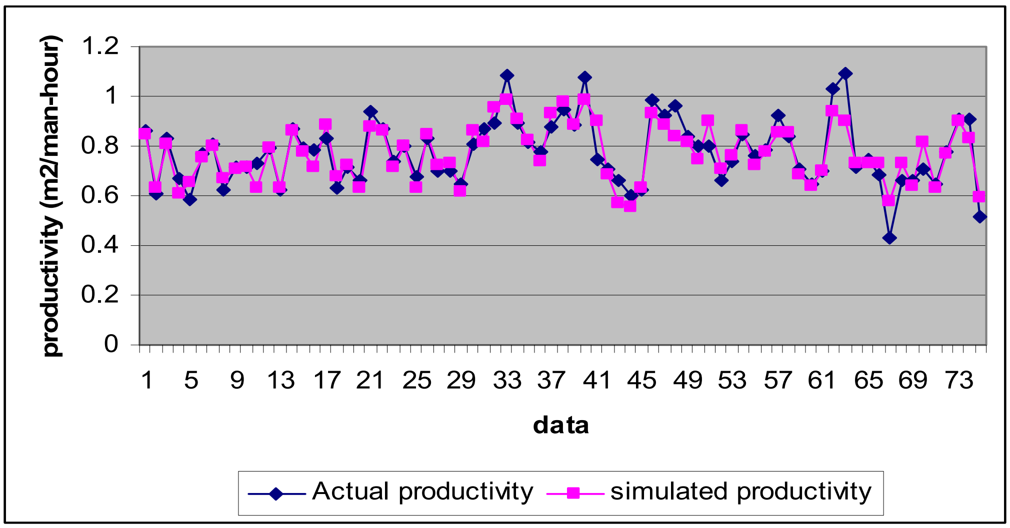
When all the variables (the waste sources) were used as input neurons, the model got a result with R^2 of 0.800. The comparison of measured and predicted productivity for all 75 data sets are shown in Fig. 3a, and the correlation depicted as a scatter plot shown in Fig. 3b. They show a relatively good fit. This could be further improved if the significant waste sources could be identified and the model developed with respect to these.

IDENTIFICATION OF THE CRITICAL VARIABLES:

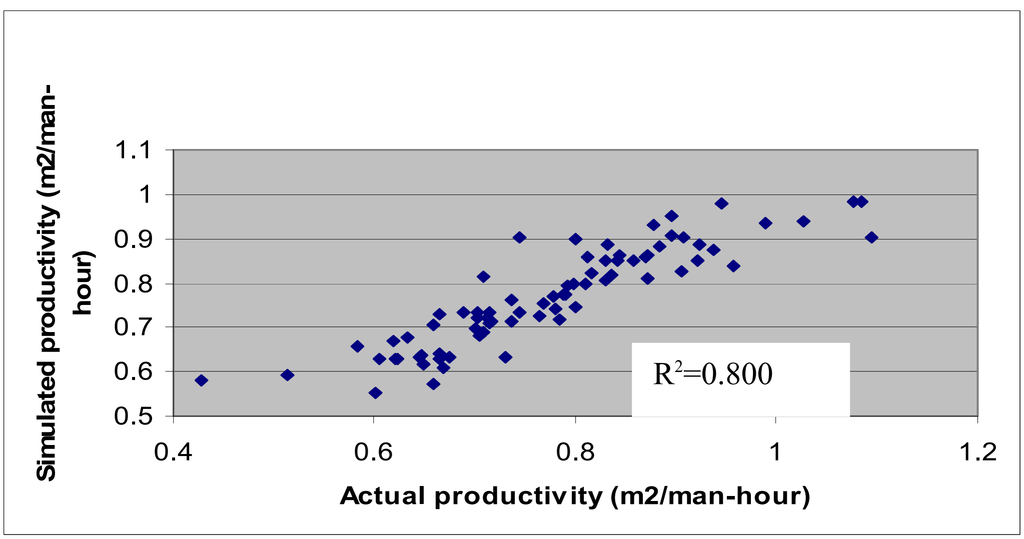
The impact of the waste elements on productivity performance may be determined via an elasticity test **(**Venkataraman, et. al, 1995**)** of the input factors. This was done by perturbing each of the input neurons in the trained network model, one at a time, by 5%. The corresponding percentage change in the output due to the change in the independent variable was taken to reflect the influence of the variable on the output. The elasticity of the productivity with respect to the k-th variable, E_k, is defined as,

$$E_k = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{\Delta P}{\Delta W_k}\right)_j \times 100\% \qquad \textbf{... (2)}$$

where ΔP is the change in the productivity due to a corresponding 5% change in the k-th waste element, ΔW_k, subscript j denoting the ratio obtained for the j-th data set, and N being the number of data sets used in the study.



(a) line plot



(b) scatter plot

Figure 3 - Simulated and Actual productivity for the 20-input neuron model: (a) line plot; (b) scatter plot

The significance of each waste source is ranked according to their elasticities. The NN productivity model is incrementally refined by pruning away the least significant inputs, a few at a time. Each time, the model is retrained and the elasticities computed for the remaining input variables. This is done because of the highly non-linear relationships existing in the model. The performance of the incremental models is monitored so as to obtain the best performance. The final model has eight most significant variables, and its R^2 increased from 0.800 to 0.904. These eight waste elements are shown in Table 2 along with their elasticities. For example, a 5% increase in the waiting due to crew interference results in nearly twice the percentage reduction (8.3%) in the productivity. The remaining waste elements were re-added into the model, in at a time, and found not to be significant.

Table 2: Dominant wastes and elasticities

Waste sources (W_k)	Elasticity (E_k)
Waiting due to crews interference	-8.3 %
Waiting due to inspection	-7.5 %
Equipment used by other crew	-7.2 %
Waiting due to equipment's installation	-6.7 %
Waiting for instruction	-2.1 %
Rework due to design change	-1.7 %
Stock problem	-0.6%
Material vendor delay	-0.5 %

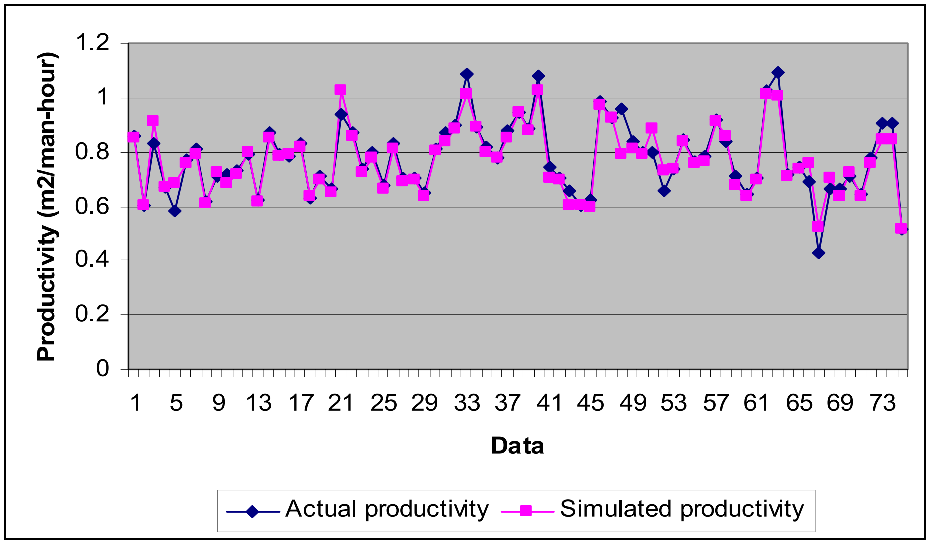
The comparison of measured and predicted productivity for all 75 data sets with the final model are shown in Fig. 4a, and the correlation depicted as a scatter plot shown in Fig. 4b. It is evident that the model shows a better correlation between prediction and measured performance than before. There is considerably less scatter compared with the initial model achieved through eliminating the less significant waste sources in the input.

The critical wastes influencing the site productivity have been identified. They are in order of their impact on productivity: (1) waiting due to crews interference; (2) waiting due to inspection; (3) waiting for equipment used by other crew; (4) waiting due to the installation and transportation of equipment; (5) waiting for instruction; (6) rework due to the design change; (7) waiting due to stock problem; (8) waiting due to material vendor delay. A brief discussion on these follows.

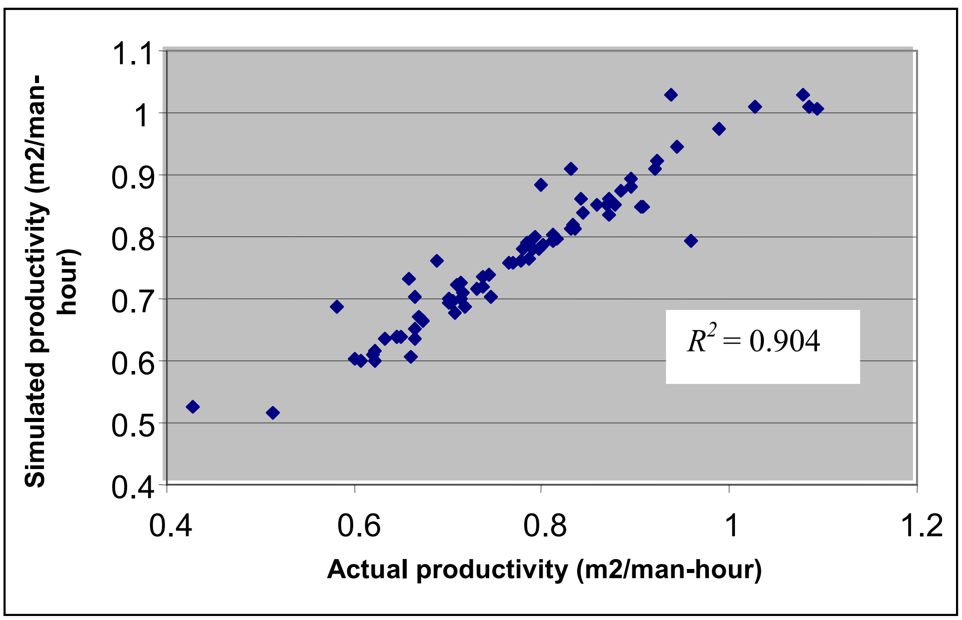
DISCUSSION

In a separate analysis, the correlations between the various project level factors and the significant waste sources were determined. Several high correlations existed between these factors and waste sources, and the relevant ones were noted and included in this discussion.

Over all, waiting due to crews' interference (waste source 1) was found to have the most adverse effect on productivity. One cause for this waste was the congestion of work space for the different crews working at the same time. Poor management of the working sequence was another cause. Furthermore, due to the interdependence of the trades on site, there were considerable delays and disruptions waiting for preceding work to be completed. Project manager's experience and frequent monitoring of the progress were found to have high correlation with this waste source, and thus, would help mitigate such situation.



(a) line plot



(b) scatter plot

Figure 4: Simulated and Actual productivity for the 8-input neuron model: (a) line plot; (b) scatter plot

Waste sources 3 and 4 are related to the lack of equipment. Due to the high cost of some equipment, there is a general inclination for contractors here in Singapore to acquire the minimum number which often led to frequent crew waiting on site. It must be borne in mind that the cost of labor is low and thus there is little incentive for contractors here to invest more in equipment. As evident from Table 1, such waiting is a frequent problem which has contributed to about 72.5 man-hrs lost on average each month, forming the highest proportion of all waste sources. The problem is further compounded by poor management of work sequence and site layout resulting in multiple handling of materials and frequent relocation and set-up of equipment.

Project level factors that were found to have high correlation with waiting for instruction and inspection were supervisory and communication in nature. From cost consideration, contractors are apt to have as few supervisory personnel. It was also found that buildable designs and project simplicity led to less waiting for instruction and inspection.

Rework due to design change is the only waste source that has been linked to design issues in this study. Frequent changes in design are a typical problem even in the construction phase. The level of detail design completed, the accuracy, and the buildability of the design are the main contributory factors. Changes in design lead to numerous change orders involving dimensions and shapes, resulting in components being remeasured and reassembled. When the design changes could not be prevented, improved communication channels and coordination among the different parties would be necessary to effect these changes successfully.

The last two key waste sources are related to materials; one due to stock and the other material vendor. The former may be attributed to inappropriate material planning resulting in unnecessary multiple handling of materials. Poor site layout is another factor causing difficulty in distributing materials to the desired places when they are needed. The possible reasons mentioned above would unnecessarily increase the utilization of the equipment for handling the materials, which may aggravate the effect of shortage of equipment on site. The waste source due to material vendor could be reduced with better supply chain management and coordination between the supplier of material and contractor.

CONCLUSIONS

Low productivity in the construction industry has long been a great concern. This paper attempts to determine the causes for the low productivity from the perspective of flow related issues. In particular, the non value-adding activities or waste elements were identified so that if these could be strategically eliminated, project performance can be significantly improved through better production flow at the work faces.

The study was based on interviews and performance data obtained from weekly log sheets. The neural network approach was adopted. Beginning with twenty waste sources, the final model was obtained by incrementally trimming the inputs so that only the most significant ones were retained. Altogether eight waste sources were deemed to be sufficiently significant. These were: waiting due to crews interference; waiting due to equipment sharing, and setup of equipment; waiting for instruction and inspection; rework due to design change; waiting due to stock problem and material vendor delay. Using this model, the predicted performance on site was found to correlate well with measured data. Then the dominant waste sources identified were traced to the project related factors to find out the possible causes of these non value-adding activities.

The present study has been confined to repetitive type of work related to formwork tasks. The same approach could be extended to other repetitive works to obtain a better picture of the effect of waste sources on productivity. This would help the industry better develop management and control strategies to eliminate these wastes and thus improve project performance.

REFERENCES

Ciampa, D. (1991), *The CEO's role in Time-Based Competition.* In: Blackburn, J.D. (e.d.). Time-based Competition. Business One Irwin, Homewood. IL. Pp. 273-293.

Christian, J and Hachey, D. (1995), "Effects of Delay Times on Production Rates in Construction", *Journal of Construction Engineering and Management,* Vol. 121, No. 1, pp. 20-26.

Chua, D. K. H., Kog, Y.C., Loh, P.K., and Jaselskis, E.J., (1997), "Model for Construction Budget Performance---Neural Network Approach", *Journal of Construction Engineering and Management,* Vol. 123, No. 3, pp.214-222.

Formoso, C.T., Isatto, E.L., and Hirota, E.H. (1999), "Method for waste control in the Building Industry". *IGLC-7 proceedings,* Pp221-232.

Handa, V. K., and Abdalla, O. (1989) "Forecasting productivity by work sampling" *Construction Management and Economics,* Vol. 7, pp. 19-28.

Olomolaiye, P.O., Jayawardane, A.K.W., and Harris, F.C. (1998) *Construction Productivity Management,* Longman.

Stalk, G. J. and Hout, T.M. (1989), *Competing against time*, Free press, NY.

Thomas, H. R., Guevara, J. M., and Gustenhoven, C. T. (1984) "Improving productivity estimates by work sampling." *Journal of Construction Engineering and Management,* Vol.110, No. 2, pp. 178-188.

Venkataraman, S., Fred, M., and Woodrow, B. (1995) "Effect of Roadway Geometrics and Environmental Factors on Rural Freeway Accident Frequencies" *Accident analysis and prevention,* Vol. 27, No. 3, pp371-389.