Labour productivity measurement through classification and standardisation of products

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Abstract: In today's competitive world, productivity is a fundamental concept in assessing economic performance of organisations. Due to the fierce competition and customer requirement variation, organisations should produce various types of products. This type of production requires a sophisticated productivity measurement system and organisations still confront with the challenges of lacking an appropriate system. Labour productivity is one of the most important indices among partial productivity indicators and plays a key role in the productions and services as outcome. In this paper, labour productivity issue is examined by nearest neighbour algorithm (NNA) in order to classify products. In the following, considering the required workforce for standard parts in each category and also their production processes, multiple regression method is applied to calculate the value of products and to standardise outputs. A case study is also presented to examine the validity of proposed method. Some advantages of this method include; increasing labour productivity, improving production system, a more precise planning and responding to market fluctuation.

Keywords: product classification; standardisation; labour productivity; nearest neighbour; multiple regression; productivity.

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1 Introduction

In the modern competitive world, productivity is a fundamental concept in assessing economic performance of organisations. Therefore, productivity improvement has become a key objective for industries. Productivity is measured as a ratio of outputs to inputs but it has no meaning by itself. It is meaningful when it is compared to productivity measured in prior periods or is measured from comparable facilities producing similar outputs (Banker et al., 1989). During the last two decades, the role of human capital in economic growth has been extensively discussed (Marelli and Signorelli, 2010). Labour as a production factor affects production costs. So, increasing labour productivity may lead to higher production (Tilton, 2001). Labour productivity is the result of worker ability and promotion. Therefore, it is important to arrange working hours and to determine workforce assignment (Billikopf, 2003).

There are four main methods for measuring productivity. Production function model and stochastic frontier are the parametric methods. But, total factor productivity (TFP) and data envelopment analysis (DEA) are the non-parametric methods (Coelli et al., 2005). According to the theoretical and empirical researches on this issue, there is not a unique method for measuring productivity in organisations (Singh et al., 2000). However, improving performance and increasing productivity requires a well understanding of various indicators in this context (Soekiman et al., 2011). To achieve this understanding, it is important to study those productivity drivers which operate in the micro level productivity (Demeter et al., 2011).

Nowadays, organisations are dealing with a wide range of manufacturing processes, technical specification and physical features of products. These factors which are interrelated with customer requirements influence the production level. These manufacturing systems have multiple outputs and inputs. Standard approaches involving profit or cost function can be calculated, in case of having costs or prices data (Dorfman and Koop, 2005). When these data are not available, some new approaches should be elicited to measure productivity indicator.

There are a number of methodologies which estimate productivity. Van Beveren (2012) provided an overview on the methodologies issues for estimating TFP at the establishment level. The findings confirm that theoretically there are biases in traditional production function estimates.

The main of this paper is to examine the labour productivity. Therefore, nearest neighbour algorithm (NNA) is applied to classify the products and multiple regression method is utilised to compute the value of products and to standardise the outputs. Finally, a case study is presented to examine the applicability of proposed method.

2 Literature review

Productivity and performance measurement has been considered as an essential issue for continuous improvement. Phusavat and Photaranon (2006) addressed two important problems facing the production department at a government pharmaceutical organisation. The two identified issues were lack of productivity and performance measurement and the need to assess the functional readiness. In another study conducted by Markham et al. (2006), the results of using an ordinary least squares approach and combined genetic algorithm with artificial neural network were compared to improve the prediction of employees' productivity. The findings confirm that the results of the two proposed techniques were different. Khazabi (2008) examined the Canadian labour productivity between 1961 and 2003. In this study, time series was utilised to develop an econometric model which considers the relations between labour productivity and R&D activities. The findings reveal that the type of capital involved has a significant influence on the labour productivity and growth improvement.

Islam and Syed Shazali (2011) identified three factors including degree of skills, favourable working environment and R&D which may influence manufacturing productivity of labour-intensive industries. Although all the factors were positively correlated with productivity, the most significant positive correlation referred to R&D expenditure and productivity. Akyüz and Kuruüzüm (2011) proposed a modelling approach in order to measure and improve performance in process industry. In this study, the relations between strategic level decision alternatives and operational level in manufacturing system were examined. Noruzy et al. (2011) investigated the factors influencing the productivity of workers' knowledge through the factor analysis. According to the obtained results, job satisfaction and capability as individual factors and participation, education, motivation and organisational communication as organisational factors were the most important issues which may affect productivity. Razak et al. (2011) proposed a new developed model called 'Workforce competency model' in order to assess maintenance workers' performance in terms of addressed indicators and to improve the effectiveness of the organisation's maintenance system. In another study, Phusavat et al. (2012) addressed some productivity indicators from analysing the business strategies of a company. The key productivity indicators were flexibility, delivery, management and meantime.

Another issue which has been considered by scholars and practitioner is accurate estimation of the equipment utilisation. Jeong and Phillips (2001) presented a new loss classification scheme for calculating the overall equipment effectiveness. The new subjects involved in equipment effectiveness were state analysis, relative loss analysis, lost unit analysis and product unit analysis. Moreover, accessible time is an important factor which can influence productivity. Shepard and Clifton (2000) examined that whether or not the longer hours working time reduce productivity in manufacturing. The empirical findings revealed that use of overtime hours lead to lower average productivity since it operate as an input factor in productivity measure.

3 Productivity

Nowadays, most firms intend to use some appropriate strategic approaches in order to increase their productivity and quality of services.

Productivity has been applied as a measurement instrument for assessing different decisions and preventing resources' wastes (Gunasekaran et al., 1994). Also it can help managers to determine the subsequent investments on a new technology and to divide resources allocation (Chiou et al., 1999). Greasley (2009) stated that "productivity is used at both organizational and national level as a comparative measure of performance". Productivity is a concept in which both effectiveness and efficiency issues are considered (Kurosawa, 1991). In general, productivity can be defined as a ratio of outputs into inputs in a manufacturing or service process. Inputs are the production factors which are used in manufacturing process or delivering services, and outputs are the finished goods or services.

In summary, productivity can be defined according to the following items (Hannula, 2002):

- ratio of outputs to inputs
- the amount of using manufacturing sources appropriately
- organisational efficiency in converting inputs to outputs.

The most familiar definition for productivity is the ratio of outputs to inputs. Productivity is usually measured for the following purposes (Hannula, 2002):

- assessing the technological changes
- verifying efficiency
- verifying saved costs
- benchmarking of manufacturing or services processes
- examining the living standards in the society.

Moreover, it is necessary to analyse the results of productivity measurement in order to improve those purposes. Rao et al. (2005) presented an expert system in which the spreadsheet software is utilised in order to analyse productivity.

4 Productivity measurement

Productivity measurement concept encompasses input measurement, output measurement and the proper method for analysing the results.

4.1 Input measurement

In terms of input perspective, productivity can be classified into two basic parts. Based on the available data and the purpose of productivity measurement, the proper method can be selected.

4.1.1 Single factor productivity/partial productivity

In this method, productivity is measured by a collection of outputs and a single input. One of the most popular types of productivity in this method is the productivity based on the labour or capital input. In this method, output can be assessed according to the gross output or value-added. One of the advantages of single factor productivity method is its simplicity in measuring data and analysing results (Nezu, 2001).

4.1.2 Multiple factor productivity

In this method, productivity is measured by a combination of some inputs and outputs. One of the most common kinds of productivity in this method is the productivity based on labour and capital inputs or based on a combination of capital, labour, energy, material and services (KLEMS). This method is not so different from the previous method in output measurement; and is often used for performance assessment of new technologies in the organisation (Nezu, 2001).

4.2 Output measurement

In order to calculate outputs, the relations between productivity and the variances of standard cost systems should be considered (Banker et al., 1989). Outputs in productivity context can be measured by one of the following methods.

4.2.1 Productivity measurement based on gross output

Gross output can be meant as goods or services produced in a manufacturing department and are used in another place/department. So, gross output indicates sale value or increasing stock value without considering purchased or input raw material values (Nezu, 2001).

4.2.2 Productivity measurement based on value-added

When purchase value of the goods used for manufacturing products or services is deducted from final product value, output can be calculated based on value-added. On the other hand, the value-added is a net measurement method. In this method depreciation may not be deducted from output value. From income point of view, value-added is equal to the income obtained from initial production factors such as labour, capital and tax. Output can be defined according to the output value, actual product number, weight, etc. (Nezu, 2001).

4.2.3 Measurement methods

There are four main methods in measuring productivity. The first two methods are related to time series data, and the two others refer to cross sectional data. In addition, these methods can be divided into parametric and non-parametric methods in this section, the first and fourth methods are in the category of parametric method.

4.2.3.1 Least squares econometrics production models

Production, cost or profit functions are both dependent and independent variables. These concepts while can be presented in different ways, and can be displayed in the form of $Y = f(x_1, x_2, x_3, x_4,\ldots)$, where Y is dependent variable and x_i is explicative variable. Parameters of production function can be estimated through least squared error. These functions make it possible to verify and assess economical specifications of manufacturing technology. In these models, x_i variable is considered as manufacturing input such as labour or capital, and Y is considered as output or final product. After estimating parameters of the model through ordinary least squared (OLS), manufacturing variation are calculated based on the changes of production factors as the first derivation of production function to considered (Coelli et al., 2005).

4.2.3.2 TFP indices

TFP index is defined as a set of outputs to set of inputs. One of the simple method for measuring TFP is the calculation of organisation's profit regarding to various outputs and inputs. Suppose that q_1 and q_2 are output vectors of two companies which are produce with x_1 and x_2 inputs. Sale price vectors are (P_1 and P_2) and input costs are (w_1 and w_2). TFPs of companies 1 and 2 are as follows (Coelli et al., 2005):

$$\pi_1 = \frac{p_1 q_1}{w_1 x_1} = \frac{\sum_{m=1}^{M} p_{m1} q_{m1}}{\sum_{k=1}^{K} w_{k1} x_{k1}}$$

$$\pi_2 = \frac{p_2 q_2}{w_2 x_2} = \frac{\sum_{m=1}^{M} p_{m2} q_{m2}}{\sum_{k=1}^{K} w_{k2} x_{k2}}$$

So, efficiency ratio of the second company to the first company can be defined as below:

$$\frac{\pi_2}{\pi_1} = \frac{\left(p_2 \bullet q_2 / w_2 \bullet x_2\right)}{\left(p_1 \bullet q_1 / w_1 \bullet x_1\right)} = \frac{\left(p_2 \bullet q_2 / p_1 \bullet q_1\right)}{\left(w_2 \bullet x_2 / w_1 \bullet x_1\right)}$$

4.2.3.3 Stochastic frontier

In this method, organisation's efficiency is calculated based on the stochastic frontier of production function. Production function is defined as below:

$$lnq_i = x_i'\beta + v_i - u_i$$

Since the maximum of production function is bounded to $\exp\left(x_i'\beta + v_i\right)$, this function is called stochastic frontier function. Error value in this function can be positive or negative, whereas output value fluctuates around $\exp\left(x_i'\beta\right)$. If q_i is manufactured with x_i input, stochastic frontier value of Cobb-Douglas function is defined as below:

$$lnq_i = \beta_0 + \beta_1 lnx_i + v_i - u_i$$

$$q_i = \exp\left(\beta_0 + \beta_1 lnx_i + v_i - u_i\right)$$

$$q_i = \exp\left(\beta_0 + \beta_1 lnx_i\right) \times \exp\left(v_i\right) \times \exp\left(-u_i\right)$$

In this equation, $TE_i = \exp(-u_i)$ indicates technical efficiency of i^{th} organisation and is used for calculating and predicting efficiency of an industry (Aigner et al., 1976).

Stochastic frontier can be applied to measure the effect of technology changes.

5 Labour productivity

Labour productivity is one of the most common indices among partial productivities. This index describes the role of labour in manufacturing products or services. More labour productivity indicates better efficiency and more useful labour (Nezu, 2001).

$$Labour\ productivity = \frac{Output}{Labour\ input}$$

Nowadays, partial productivities are widely used in industrial organisations. The competitive conditions of marketplaces have forced organisations to improve their productivity. However, partial productivities cannot truly demonstrate performance variations. The problem with applying partial productivities is that calculating output ratio with a specific input does not clearly indicate the trade-off between manufacturing sources. So, increasing in one of the production factors of productivity may lead to productivity reduction in another factor because partial productivities are the ratio of net or gross output to a specific input (Sumanth and Einspruch, 1980).

Census of manufactures (CM) and annual survey of manufactures (ASM) present different information for labour working in industries. There are four methods for calculating the labour input: working time (man hour), paid costs for labours, the number of labours regarding to working time, and the number of direct labours (Ahn and Abt, 2006).

Productivity can be calculated through dividing output into one of the above factors above. Output is the goods or services produced by manufacturing system (Ahn, and Abt, 2006). Hara and Hibiki (2011) considered per hours as an important measure of labour productivity and introduced labour productivity as below:

$$Labour\ productivity = \frac{Real\ value\ added}{Labour\ input} = \frac{Real\ value\ added}{Employment \times hours\ worked}$$

In a study by Masud (1985), time series were applied to predict factory productivity. In this research, labour productivity index was used as a ratio of standard working time to actual working time in order to estimate the number of required labours in the future, in Cessna air industry.

Nowadays, the typical techniques for calculating performance index based on cost accounting, cannot analyse manufacturing problems and complexity. However, developed integrated information system can remove theses constraints. Chen (2008) presented an integrated dynamic performance measurement system (IDPMS) which involve company management, process improvement and manufacturing workshops. In this research, the indices were converted to quantitative indices in JIT system. Therefore, managers can use them to increase manufacturing performance resulted in internal and external customers' satisfaction.

Demeter et al. (2011) focused on the drivers influence labour productivity at the operational level. They categorise the drivers into two sets of level: a. current working practices and b. changing working practices through the programmes proposed by management.

6 Nearest neighbour and multiple regression

6.1 Nearest neighbour algorithm

Humans' minds unconsciously try to categorise and classify different phenomena in order to better understand the real world. Classification is labelling selected objects in the predefined classes. It can be characterised by a well-defined classes, and a training set consist of pre-classified examples (Hair et al., 2009).There are a number of techniques that are useful for classification. Neural networks, logistic regression, decision tree models, as standard binary classification tools, and k-nearest neighbour are some methods that are usually used for classification (Olson and Delen, 2008).

Nearest neighbour is one of the simple intuitive methods in statistic classification field introduced by Fix and Hodges (Silverman et al., 1951). This is a non-parametric method which can be applied to classify a new sample regarding to its differences with learning set. New sample class is determined according to its distance with other samples (Hechenbichler and Schliep, 2004). For this purpose, the distance between the new sample and the learning set is measured in each class. Then, the new sample is assigned to the class which has the least average distance. It is important to note that the new sample can be assigned to more than one class. However, the best allocation refers to the class with the shortest distance (Witten and Frank, 2005).

Where samples are P dimensional, each sample is displayed by (X_{1i}, X_{2i},…, X_{Pi}) assuming that the training set is shown by X_j. Euclidean distance of new sample in training set is calculated as below:

$$d\left(x_i, x_j\right) = \left(\sum_{s=1}^{p}\left(x_{is} - x_{js}\right)^2\right)^{1/2}$$

The distance can be calculated directly, as below:

$$d\left(x_i, x_j\right) = \sum_{s=1}^{p} \left| x_{is} - x_{js} \right|$$

The general method (Minkowski distance) for calculating the distances between samples is as follows:

$$d\left(x_i, x_j\right) = \left(\sum_{s=1}^{p} \left| x_{is} - x_{js} \right|^q \right)^{1/q}$$

In order to determine the best class, average and standard deviation in the class members should be calculated. It is clear that the best class is the class with the least average and deviation (Thomas and Fomby, 2008).

6.2 Multiple regression

Regression modelling is a powerful method for estimating the value of a continuous target variable (Larose, 2006). Multiple regression is a statistical method for studying the relations between a single dependent variable and one or more independent variables.

A simple linear multiple regression is as follow:

$$Y = B_1 X_1 + B_2 X_2 + \ldots + B_i X_i + B,$$

where Y is dependent variable and X_i, i = 1 to n are independent variables.

Ratio scales, interval scales, ordinal scales, nominal scales are different type of variables that can be employed in a multiple regression.

The estimate regression coefficients, OLS value is used (Salvatore and Reagle, 2002).

OLS for computing bivariate regression model; $Y = B_1X_1 + B_2X_2 + B$ are as below: (Cohen et al., 2003).

Step1 Calculating ry_1; correlation between Y and X_1.

Step2 Calculating ry_2; correlation between Y and X_2.

Step3 Calculating r_{12}; correlation between X_1 and X_2.

Step4 Calculating $\beta y_{1.2}$ and $\beta y_{2.1}$; standardised partial regression coefficients.

Step5 Calculating $By_{1.2}$ and $By_{2.1}$ as regression coefficients.

Setp6 Calculating B as regression constant.

After estimating coefficients, OLS assumptions such as multi-collinearity, heteroscedasticity and autocorrelation should be controlled (Renfro, 2009).

These steps will be more complex in multiple regression equations. Therefore some statistical software such as SPSS and Eviews can be used to solve the multiple regression models.

7 Product classification and standardisation

As it is mentioned in this research, a productivity model is presented to assess the labour efficiency in a varied production system. In these systems, demand strategy is usually Make-to-order and products are produced according to customer requirements. Therefore, labour productivity assessment needs an especial model regarding to variety of products, customer requirements and varied manufacturing processes. Different types of products have their own production factors such as labour, material, capital and energy. Considering this assumption, there are two main steps for labour productivity measurement:

- Step 1: products classification regarding to the similarity in manufacturing process. In this step, more frequent products make different predefined classes. According to the manufacturing process and the similarity, the most frequent product in each class is selected as the standard output of that class. Other products' values of each class are calculated as below:

$$W_1 = \left(\frac{\sum_{i=1}^{p} T_i}{\sum_{j=1}^{q} T_j} \right)$$

W_1 is the value of product l in comparison with standard product in its class. T_i is direct man-hour work needed for activity i in manufacturing process of product l. T_j is direct man-hour work needed for activity j of standard product in its class. Therefore, all products in each class can be evaluated as standard products of the class. Finally, these products are used as a training set.

New products that have never been produced should be classified in predefined classes with NNA. This algorithm is useful for numerical samples but not dummy samples. For this purpose, each new product according to its manufacturing processes is assumed as an n dimensional binary variable. Each dimension of new sample indicates a specific operation where 1 means that operation exists in manufacturing process of new product and 0 indicates that it does not exist. In order to determine the best class for new product, it should be compared with training sets according to Table 1.

Table 1 Miss-match quantity

		Sample i	
		1	*0*
New sample	1	P1	*P2*
	0	*P3*	P4

Note: Mis-match quantity = P2 + P3

So, new sample distance from each member of training set is defined as $d = p_2 + p_3$ and the best classis the one with minimum distance average and standard deviation.

- Step 2: estimating W_k; in this step, the value of new product is estimated regarding to product technical specifications and machineries used for manufacturing as a main features of each class. For this purpose, a multiple regression model is developed. This model can be linear or non-linear:

$$W_k = a_1 + a_2X_1 + a_3X_2 + a_4X_3 + \cdots a_mX_m$$

After standardising new products, total output quantity should be calculated as below:

$$Total\ quantity = \sum_{k=1}^{n} W_k Q_k$$

where W_k is value of product k in comparison to standard product and Q_k is the quantity of product k that was produced in this period. In this paper, labour input is the direct labours' working time and labours output is the manufactured parts. Labour productivity is calculated as below:

$$Labour\ productivity = \frac{\sum_{k=1}^{n} W_k Q_k}{Direct\ man-hour}$$

For more accurate estimation of products, first of all weight coefficient of similar products in manufacturing process should be categorised. Then, a multiple regression model can be used to estimate product weight coefficient according to products' technical specification and their technology level.

8 Case study

The empirical study in this paper was performed in Pars Noor Electric Company. Pars Noor Co. produces different types of lighting towers and traffic poles. The manufacturing process consists of 100 to 350 activities depending on product types with make-to-order demand strategy. In this manufacturing system, there are a variety of technical specifications and physical features of products which are formed based on customer requirements or installation regional conditions. These features may lead to intense fluctuations in production level. For instance, in some months, production level fluctuation is recorded up to 50%. In this company, different types of welding processes are used as the main manufacturing activity. Production planning department organises the production line according to the due date and labour productivity. In most cases, the company schedules the activities according to the manufacturing map proposed by customers. In this paper, labour productivity of welding station is measured. The main problems in scheduling activities of work station are pole length, steel thickness, part type and the machine used in welding process.

In order to measure labour productivity, all activities in different manufacturing processes were addressed and each product was considered as a sample with P dimensions. P is the number of detected activities in various processes:

$$X_i = \left(X_{1j}, X_{2j}, \ldots, X_{pj}\right)$$

So, if j^{th} product has i^{th} activity in its manufacturing process, then $X_{ij} = 1$; else $X_{ij} = 0$. For example, if X_{1j} indicates longitudinal welding in j^{th} manufacturing product, then $X_{1j} = 1$, and if it does not exist in product manufacturing process, then $X_{1j} = 0$. As mentioned before, new sample is classified according to NNA using Table 1.

Let us assume a simple case with six categories of products and 12 activities in each manufacturing process (Table 2), if a new product with certain specifications (Table 3) enters the production line, the results would be obtained according to Table 4 in order to determine the best category.

Table 2 Sample of each class

Class	*Activity number*											
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
A	1	1	1	1	1	0	0	1	0	0	0	0
B	1	1	1	1	1	1	1	1	0	0	0	0
C	1	1	0	1	0	0	0	1	0	0	0	0
D	0	0	0	0	1	0	0	0	1	1	0	1
E	1	0	1	0	1	1	1	0	0	0	0	1
F	1	0	0	1	0	0	0	0	1	0	1	1

Table 3 Manufacturing activity for new sample

Sample	*Process number*											
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
N	1	1	1	1	1	0	0	0	0	1	0	1

Table 4 Classification result for new sample

Row	*Class label*	*Distance average*	*Distance St. dev*
1	Class D	3	1.205
2	Class A	4.16	1.329
3	Class C	5	1.423
4	Class B	5	1.820
5	Class F	6	2.190
6	Class E	7	2.070

After determining the best category for each new product, a multiple regression model from effective factors in labour usage index is generated. This model estimates products value in compare to the standard product of the class.

As it is mentioned, in addition to manufacturing process, technical specifications and physical features of product and also machineries are effective on labour usage index of products.

Class D is the best class in this case. It contains four factors which compute product value:

1 length of product (meter) (L)

2 thickness of the sheet used in the product (millimetre) (TH)

3 manufactured part type as dummy variable (1, 2, 3) (D_1, D_2)

4 the type of machine used in production as dummy variable (D_3).

To create a regression model, one dependent variable and five independent variables are needed. D_1 and D_2 are dummy variables related to product type. If $D_1 = 1$, the product is from first type, if $D_2 = 1$, the product is from the second type, and otherwise the product is the third type. D_3 dummy variable indicates the type of machine used in production (1 indicates automatic welding machine and 0 indicates manual welding machine).

The following equation shows the value of a new product:

$$W_{new} = a_1 + a_2 L + a_3 TH + a_4 D_1 + a_5 D_2 + a_6 D_3$$

The analysis of variance (ANOVA) performed by EViews5 software presented in Table 5 shows the results of studying manufacturing drawings and reports of 144 different products.

Table 5 Analysis of variance

	df	*SS*	*MS*	*F*
Regression	5	0.095203	0.019041	171.97
Residual	138	1.250771	0.009064	
Total	143	1.345974	0.009412	

	Coefficients	*Standard error*	*T-stat*	*Prob*
α_1	–0.309357	0.067090	–4.611048	0.0000
α_2	0.165812	0.007186	23.07306	0.0000
α_3	0.131500	0.015867	8.287579	0.0000
α_4	0.143125	0.019433	7.364984	0.0000
α_5	0.049875	0.019433	2.566488	0.0113
α_6	–0.225917	0.015867	–14.23804	0.0000

In this model $R^2 = 0.8617$ states that about 86% of W_{new} behaviours are predictable by explicative variables.

To verify the regression model, OLS assumptions were controlled. Model does not contain multi-collinearity, heteroscedasticity and autocorrelation.

9 Conclusions

In this research, a NNA and a multiple regression model for labour productivity measurement in a varied manufacturing system were presented. Although activities used in nearest neighbour are less than actual number, this algorithm is useful for manufacturing processes with more numerous activities. The proposed regression model is able to estimate weights of coefficients in its category, and there is no need to collect manufacturing data and technical drawings for new product. In order to measure total productivity, it is just enough to extend these coefficients to other manufacturing factors. Also, if labour level and remaining orders are specified, a base for manufacturing lead time estimation and free capacities for future will be obtained. This research can be used to analyse sensitivity of production costs in the same condition.

The proposed multiple regression equation can compute the value of manufactured products regarding to the standard products in each category. Therefore, the output of production line can be easily measured in each period of time. Moreover, it is possible to measure the productivity of labours.

9.1 Research limitations and managerial implications

With increased competitive and challenging environment the role of labours in improving productivity has become more critical. Although labour productivity concept is a general issue, increasing this measure requires a thorough analysis. Specifically in this study, NNA and multiple regression method were undertaken to classify the products and to compute the value of products, respectively. The classification and standardisation of products seems to help managers to improve labour productivity. Besides, it can provide some useful information for managers to prepare a more precise planning and to improve the production system. In addition, the company can better responds to market fluctuations. The proposed methodology can be exploited in a number of manufacturing companies and it is believed that the results may provide great competitive advantages to operational managers.

9.2 Future studies

Regarding to the importance of labour productivity issue and variety of products in manufacturing organisations, the necessity of thorough researches in this context is increasing. Therefore, the following suggestions for further studies in this issue can be proposed:

- In this study, shape of products, type of machines and manufacturing process were considered. Therefore, some other factors such as demand volume, due date, etc can be involved.
- Due to the uncertainty condition in current competitive marketplace, considering fuzzy approach can be applicable.
- Since a number of factors can influence the classification of products and labour productivity, further studies can utilise some meta-heuristics methods such as artificial neural network, genetic algorithm, etc. to overcome the complexity of problems.
- In further research, it would be useful to compute the multiple regression equations for all work stations. Therefore, the findings would be more reliable.

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References

Ahn, S. and Abt, R.C. (2006) 'Productivity measurement with improved index numbers: application to the sawmills and planing mills industry of the U.S.: 1947–2000', *Forest Policy and Economics*, Vol. 8, No. 3, pp.323–335.

Aigner, D.J., Knox Novell, C.A. and Schmidt, P. (1976) 'Formulation and estimation stochastic frontier production function models', *Journal of Econometrics*, Vol. 6, No. 1, pp.21–37.

Akyüz, G. and Kuruüzüm, O. (2011) 'A modelling approach in process industry for improving manufacturing performance', *International journal of Productivity and Quality Management*, Vol. 7, No. 1, pp.74–89.

Banker, R.D., Datar, S.M. and Kaplan, R.S. (1989) 'Productivity measurement and management accounting', *Journal of Accounting, Auditing and Finance*, Vol. 4, No. 4, pp.528–554.

Billikopf, G.E. (2003) *Labor Management in Agriculture*, 2nd ed., ANR Publication 3417, California.

Chen, C.C. (2008) 'An objective-oriented and product-line-based manufacturing performance measurement', *International Journal of Production Economics*, Vol. 112, No. 1, pp.380–390.

Chiou, W.C., Kuo, H.W. and Lu, I.Y. (1999) 'A technology oriented productivity measurement model', *International Journal of Production Economics*, Vol. 60, No. 1,pp.69–77.

Coelli, T.J., Prasada Rao, D.S., O'Donneli, C.J. and Battese, G.E. (2005) *An Introduction to Efficiency and Productivity Analysis*, 2nd ed., Springer, New York.

Cohen, J., Cohen, P., West, S.G. and Aiken, L.S. (2003) *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed, Mahwah, New Jersey.

Demeter, K., Chikan, A. and Matyuse, Z. (2011) 'Labour productivity change: drivers, business impact and macroeconomic moderators', *International Journal of Production Economics*, Vol. 131, No. 1, pp.215–223.

Dorfman, J.H. and Koop, G. (2005) 'Current developments in productivity and efficiency measurement', *Journal of Econometrics*, Vol. 126, No. 2, pp.233–240.

Greasley, A. (2009) *Operation Management*, 2nd ed, Wiley&Sons Ltd., Chichester.

Gunasekaran, A., Korukonda, A.R., Virtanen, I. and Yli-Olli, P. (1994) 'Improving productivity and quality in manufacturing organizations', *International Journal of Production Economics*, Vol. 36, No. 2, pp.169–183.

Hair, J.R.J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2009) *Multivariate Data Analysis*, 7th ed., Prentice Hall, New Jersey.

Hannula, M. (2002) 'Total productivity measurement based on partial productivity ratios', *International Journal of Production Economics*, Vol. 78, No. 1, pp.57–67.

Hara, N. and Hibiki, I. (2011) 'Real-time analysis on Japan's labor productivity', *Journal of Japanese International Economies*, Vol. 25, No. 2, pp.107–130.

Hechenbichler, K. and Schliep, K. (2004) 'Weighted k-nearest-neighbor techniques and ordinal classification', SFB Discussion paper 399.

Islam, Sh. and Syed Shazali, S.T. (2011) 'Determinants of manufacturing productivity: pilot study on labor-intensive industries', *International Journal of Productivity and Performance Management*, Vol. 60, No. 6, pp.567–582.

Jeong, K-Y. and Phillips, D.T. (2001) 'Operational efficiency and effectiveness measurement', *International Journal of Operations and Production Management*, Vol. 21, No. 11, pp.1404–1416.

Khazabi, M. (2008) 'Knowledge-based labor productivity improvements: Canada case study', *Zagreb International Review of Economics & Business*, Vol. 11, No. 1, pp.1–11.

Kurosawa, K. (1991) *Productivity Measurement and Management at the Company Level: The Japanese Experience*, Elsevier, Amsterdam.

Larose, D.T. (2006) *Data Mining Methods and Models*, John Wiley & Sons, New Jersey.

Marelli, E. and Signorelli, M. (2010) 'Employment, productivity and models of growth in the EU', *International Journal of Manpower*, Vol. 31, No. 7, pp.731–754.

Markham, S.E., Makhan, I.S. and Wray, B.A. (2006) 'Improving the prediction of employee productivity: a comparison of ordinary least squares versus genetic algorithms coupled with artificial neural networks', *International Journal of Productivity and Quality Management*, Vol. 1, No. 4 pp.379–396.

Masud, A.M. (1985) 'Forcasting plant labor productivity with a time series model', *Computer and Industrial Engineering*, Vol. 9, No. 1, pp.73–81.

Nezu, R. (2001) *Measuring Productivity OECD Manual*, OECD, Paris.

Noruzy, A., Hayat, A.A., Rezazadeh, A., Najafi, S. and Hatami-Shirkouhi, L. (2011) 'Factors influencing the productivity of knowledge workers: a case study from an Iranian oil company', *International Journal of Productivity and Quality Management*, Vol. 8, No. 4 pp.459–479.

Olson, D.L. and Delen, D. (2008) *Advanced Data Mining Techniques*, Springer, Verlag Berlin Heidelberg.

Phusavat, K. and Photaranon, W. (2006) 'Productivity/performance measurement case application at the government pharmaceutical organization', *Industrial Management and Data Systems*, Vol. 106, No. 9, pp.1272–1287.

Phusavat, K., Nilmaneenava, S., Kanchana, R., Wernz, Ch. and Helo, P. (2012) 'Identifying productivity indicators from business strategies' surveys', *International Journal of Productivity and Quality Management*, Vol. 9, No. 2, pp.158–176.

Rao, M.P., Miller, D.M. and Lin, B. (2005) 'PET: an expert system for productivity analysis', *Expert Systems with Applications*,Vol. 29, No. 2,pp.300–309.

Razak, I.H.A., Kamaruddin, Sh. and Azid, I.A. (2011) 'Implementation of the workforce competency model for assessing maintenance workers' performance', *International Journal of Productivity and Quality Management*, Vol. 7, No. 4, pp.440–462.

Renfro, C.G. (2009) *The Practice of Econometric Theory*,Springer, New York.

Salvatore, D. and Reagle, D. (2002) *Theory and Problems of Statistics and Econometrics*, 2nd ed., New York.

Shepard, E. and Clifton, T. (2000) 'Are longer hours reducing productivity in manufacturing?', *International Journal of Manpower*, Vol. 21, No. 7, pp.540–552.

Silverman, B.W. and Jones, M.C., Fix, E. and Hodges, L.J. (1951) 'An important contribution to nonprametric discriminant analysis and density estimation', *International Statistical Review*, Vol. 57, No. 3, pp.233–247.

Singh, H., Motwani, J. and Kumar, A. (2000) 'A review and analysis of the state-of-the-art research on productivity measurement', *Industrial Management and Data System*, Vol. 100, No. 5, pp.234–241.

Soekiman, A., Pribadi, K.S., Soemardi, B.W. and Wirahadikusumah, R.D. (2011) 'Factors relating to labor productivity affecting the project schedule performance in Indonesia', *Procedia Engineering*, Vol. 14, No. 1, pp.865–873.

Sumanth, D.J. and Einspruch, N.G. (1980) 'Productivity awareness in US companies: a survey', *Industrial Engineering*, Vol. 12, No. 6, pp.84–90.

Thomas, P. and Fomby, B. (2008) 'K-nearest neighbors algorithm: prediction and classification', available at http://faculty.smu.edu/tfomby/eco5385/lecture/K-NN%20method.pdf (accessed on June 2009).

Tilton, J.E. (2001) 'Labor productivity, costs, and mine survival during a recession', *Resources Policy*, Vol. 27, No. 2, pp.107–117.

Van Beveren, I. (2012) 'Total factor productivity estimation: a practical review', *Journal of Economic Surveys*, Vol. 26, No. 1, pp.98–128.

Witten, I.H. and Frank, E. (2005) *Data Mining, Practical Machine Learning Tools and Techniques*, 2nd ed., Elsevier, Typesetter Ltd.