ALGORITHM FOR DEVELOPMENT OF EARLY WARNING SYSTEM FOR PRODUCTIVITY PERFORMANCE MEASUREMENT

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ABSTRACT

Most manufacturing industries lack the understanding or knowledge of their productivity levels; this is due to the fact that they do not have necessary tools to assist them in measuring their performance. This paper introduces a performance measuring tool called an early warning system which manufacturing industries can adopt and use for measuring their performances, a detailed process of extracting and populating an Early Warning System (EWS) as well as the benefits are discussed in this paper. Lastly, the algorithm describing the steps involved was as well considered. The system would serve as a tool in detecting the industries' productivity levels in order to identify the factors affecting productivity.

Key words: Algorithm, Early warning system, Manufacturing, Productivity.

INTRODUCTION

Many businesses, industries and firms are going moribund; some have failed due to bankruptcy, mismanagement, poor or lack of market strategy and performance monitoring and unforeseen sudden losses. These failures will eventually affect all the business parties involved like the customers, investors, stockholders, employees, creditors, auditors, financial institutions and the country's economy. Therefore for a virile viable economy to be sustained, there is a need for continuous performance monitoring of these industries. If there are probable warnings or indicators signalling to management the financial doom ahead, steps to avert or arrest such dooms will be taken.

Ozgulbus and Koyuncugil, (2010) defined an Early Warning System (EWS) as a system which is developed for forecasting success levels, possible inconsistencies, probable challenges, suggestive ways in reducing crisis that may occur in transactions, production systems and firms.

Koyuncugil and Ozgulbus, (2012), further revealed that EWS current situations and probable risks can be identified quantitatively as financial EWS monitors, reports and alerts managements the probable problems, risks and opportunities before they affect the financial statements of the firms. EWSs also detect financial performance, financial risk and potential bankruptcies and allow management in taking advantage of opportunities to avoid or mitigate potential problems.

Productivity is a measure of the output produced per unit of input at a given time. While Neely *et al*., (1995) defined performance as “the efficiency and effectiveness of actions within a business context”. He further explained that effectiveness is compliance with customer requirements and efficiency as how the organization’s resources are used in achieving customer’s satisfaction levels.

Performance measurement as compiled by Braz et al., (2011) is the process of quantifying efficiency and effectiveness. The authors affirmed that to achieve this, performance measures should be chosen, implemented, and monitored.

In view of this, the present research work seeks to provide an algorithm indicator that would assist in monitoring productivity performance levels in order to guide industries against sudden failure.

The remaining sections are organized as follows. Section 2 briefly describes the literature review used in this paper. The methodical algorithm framework of this article is illustrated in Section 3. Implementation of the algorithm and discussions resulting therein are presented in Section 4. Finally, conclusions are drawn in Section 5.

LITERATURE REVIEW

Brockett, Golden, Jang, and Yang (2006) discussed the effects of statistical model and neural network methods in detecting financially troubled life insurers by considering two neural networks (back-propagation (BP), and learning vector quantization (LVQ)) and two statistical methods (multiple discriminant analysis, and logistic regression analysis). The findings showed that BP and LQV outperform the traditional statistical approaches.

Abumustafa (2006) detected early warning signs for predicting currency crises in Egypt, Jordan and Turkey. The study proposed real exchange rate, exports, imports, trade balance/gross domestic product (GDP), foreign liabilities/foreign assets, domestic real interest rate, world oil prices, and government consumption/GDP as indicators to predict currency risk. The results showed that all crises were predictable, and EWSs should use for detecting crises.

Kyong *et al.,* (2006) developed a construction process that tagged Daily Financial Condition Indicator (DFCI), which can be used as an early warning signal using neural networks and nonlinear programming. The technique employs the use of three sub-DCIs which are based on the financial variables of DFCI and the integration of the same into the final DFCI. The resulting process was implemented on the financial crisis of a Korean company, and the outcome could predict the alarm zone for financial crisis forecasting.

Katz (2006) proposed the use EWS and early warning signs through the listing of the common warning signs and the best suitable approaches in solving the problems. The items listed as warning signs and best approaches are: sales tax, payroll taxes, and other fiduciary obligations; communications with executive management and company leaders; accounts receivable; customers and product profitability; accounts payable; inventory, management; for capital-intensive or manufacturing operations; and checks as an indicator of problems.

Kashiha *et al.,* (2013) developed an early warning system for a broiler house using computer vision. The authors introduced an automated method to detect problems in a broiler house using cameras and image analysis software. Thus, integrated system that could report malfunctioning in a broiler house of the farmer in real-time was developed based on a linear real-time model, which was tested to model the animal distribution index in response to light input. Using this model, the animal distribution index could be predicted online. To validate the developed system, experiment was conducted with Ross 308 broilers in a commercial broiler house with 28,000 animals, analysis software then translated these images into an animal distribution index. Result obtained reported 95.24% of events (20 out of 21) in real-time, demonstrating a high potential of using automatic monitor tools for broiler production over a complete growing period.

Boken, (2009) worked on the improvement of a drought early warning model for an arid region using a soil-moisture index. His model employed two variables derived from the daily rainfall data and estimated pearl millet yield in order to issue a drought early warning. The soil-moisture index and other variables derived from the rainfall data model forms a potential tool for developing drought early warning models for other arid regions.

For the reviewing and improving the performance measurement systems, an action research was carried out by (Braz et al., 2011). The review carried out was on an energy company's maritime transportation. Their findings showed that the difficulty and complexity of reviewing are as a result of PMS users' involvement, assessment of performance measures, establishment of targets, and availability of data.

Chenhall, (2005), Driva *et al.,* (2005), Morgan, (2002), Tuomela, (2005) and Ren *et al*., (2013) worked respectively on: integrative strategic performance measurement systems, strategic alignment of manufacturing, learning and strategic outcomes: an exploratory study; measuring product development performance in manufacturing organisations; marketing productivity, marketing audits, and systems for marketing performance assessment integrating multiple perspectives; the interplay of different levers of control: a case study of introducing a new performance measurement system; and development of collaborative design performance measurement matrix for the measurement of collaborative design performance in construction.

However, considering the existing design performance measurement frameworks and the works of the aforementioned authors, their respective works could not address the integration of early warning system as tools for performance monitoring. Authors like: El-shazly, (2003); Jacobs and Kuper, (2004); Berg *et al*., (2004); and Davis and Karim (2008)'s discussion only focussed on currency and could not make the approach to be flexible and dynamic.

Therefore, the purposes of this article are to fill up the gaps and present a general dynamic framework algorithm for productivity performance measurement using early warning system.

METHODOLOGY

On a general note retrieved from Productivity SA, (2010), for the EWS to be developed, the followings are steps to be taken.

Step 1: Identify indicators that drive the business/ organisation. What are those things/ items that when measuring on monthly basis will be able to give an indication of performance? Once the indicators are identified, populate them on the first column (as KPAs). This is

Step 2: Provide information on how the indicators will be measured.

Step 3: Set targets for the identified indicators. On the indicators identified, what will be the Worst, Critical, Acceptable, Good, and best values (1, 2, 3, 4, 5). It is advisable to start with the target, number 5.

Step 4: Collect data on a daily basis and weekly basis to compile monthly statistics. Once the monthly figure is available, populate it under the Current Value (CV) column.

Step 5: Compare the Current Value and the targets set (1, 2, 3, 4, 5), and score accordingly.

Algorithm

In order to give a methodical approach to the algorithm formulation for the EWS, some of the identified basic indicators will be explained.

The EWS contains ten key indicators namely: production index (PI), total factor productivity (TFP), labour productivity (LP), machine productivity (MP), material productivity (MTP), utilization (U), efficiency (E), absenteeism (A), waste (Ws) and quality (Q).

The mathematical model expression for all these indicators are as stated in equations 1-9.

$$TFP = {}^{Monthlystatementsales}\!\big/_{all\cos ts} \tag{1}$$

$$LP = {}^{Output}\!\big/_{Labourhour} \tag{2}$$

$$MP = {}^{Output}\!\big/_{Machinehour} \tag{3}$$

$$MTP = {}^{Output}\!\big/_{Kg} \tag{4}$$

$$U = \left({}^{actualtime}\!\big/_{availablet\,ime}\right) \times 100\% \tag{5}$$

$$E = \left({}^{allowedtim\,e}\!\big/_{actualtime}\right) \times 100\% \tag{6}$$

$$A = \left({}^{losthours}\!\big/_{possiblehours}\right) \times 100\% \tag{7}$$

$$Ws = \left({}^{lostunits}\!\big/_{availableu\,nits}\right) \times 100\% \tag{8}$$

$$Q = monthly\ number\ of\ customer\ complaints \tag{9}$$

The production price index is always available online from the Statistics of the country at which the EWS is to be used.

The algorithmic steps defined for the development of the EWS based on the above general procedure is as stated below.

Step 1: Establish the current values, CV. (These are values arrived at from the previous month preceding the present month)

Step 2: Determine the acceptable value using the industry norms or credible source (to be guided by the initial records or values, A for PI, *Step 3: Determine the worst value, W for each indicator index, (This is value that is chosen on assumption that the industry is not functioning at its peak.*

Step 4: Determine the best value for each indicator index, B

Step 5: Calculate the critical bench mark, C, which is $C = \frac{A+W}{2}$

Step 6: Add worst value, W to acceptable value A, that is (W+A)

Step 7: Divide result from step 6 by 2, that is $\frac{W+A}{2}$ *to give "first critical Benchmark value,* CB_1*"*

Step 8: Determine 2nd critical Benchmark value, CB_2*, by adding* CB_1 *to B and divide by 2. That is* $CB_2 = \frac{CB_1 + B}{2}$

Step 9: Compare CB_2 *values with B modulus values using comparable percentage computation on the basis of* $\left|\frac{B - CB_2}{B}\right| \times 100\%$

Step 10: Assign score to CB_2 *between 1 to 5 as "1" to be the worst, "2" to be critical, "3" to be acceptable, "4" to be good and "5" to be best using outcome from step 9*

Step 11: Subroutine for assigning scores based on the outcome of step 9 and step 10.

Subroutine Scoring Algorithm for assigning scores

Assign "5" if compared percentage computation is less than 10%

Assign "4" if compared percentage computation is between (10 to 20%)

Assign "3" if compared percentage computation is between (20 and 30%)

Assign "4" if compared percentage computation is between (30 and 40%)

Assign "5" if compared percentage computation is greater than 40%

Step 12: Carry out steps 1-11 to calculate for indicator TFP, LP, MP, MTP, U, E, A, Ws, and Q.

The above algorithm was tested to see if there are abnormalities. After which it was transformed to mini program using Microsoft Excel 2010.

RESULTS AND DISCUSSION

The package was used on one company, XXX Bakery, to see the effect of the developed algorithm. XXX Bakery is a small medium enterprise (SME) Gauteng Province industry. This is a small medium enterprise (SME) to see the effect of the developed algorithm. The resulting outcome is discussed in the subsequent section. The anonymity on the bakery name is the result of ethical, and security issues as well as agreement between the SME industry used.

The months of September and October were used for the implementation of the algorithm as the EWS is based on monthly population of the daily and weekly data recorded in the month under review.

The data collected were input into the Microsoft Excel packaged design to assist SMEs in calculating values for the various indicator indices. The results from the two months are as shown in Table 1 and Table 2.

Table 1: September 2014 EWS for XXX Bakery

EARLY WARNING SYSTEM

Company: xxx Bakery

…………………….……………..

Indicator Title	How obtained	Current Value	Worst (W)	Critical (CB1)	Acceptable (A)	Good (CB2)	Best (B)	J	F	M	A	M	J	J	A	S	O	N	D	Remark
								score	score	score	score	score	score	score	score	score	score	score	score	
Production Price Index: food	Statistical South Africa. Based on September 2014	121.8	126	120,5	115	113,5	112									1				
Total factor productivity	Monthly statements Sales/all costs	1.5	1,38	1,357	1,334	1,417	1,5									5				
Labour productivity	Output/labour hours	130	110	119	128	130,5	133									3				
Machine productivity	Output/machine hours	410	330	360	390	394	398									5				
Material productivity	Output/Rand of material	1.9	1,8	1,91	2,02	2,01	2									1				
Utilisation	Actual time/available time x 100%	70	68	71,6	75,2	77,1	79									1				
Efficiency	Allowed time/actual time x 100%	80.2	82	84,4	86,8	88,4	90									1				
Absenteeism	Lost hours/possible hours x 100%	11	15	12,22	9,44	8,52	7,6									2				
Waste	Lost units/available units x 100%	17	22	17	12	10	8									2				
Quality	Monthly number of customer complaints	5	7	6,5	6	5	4									4				

Table 2: October 2014 EWS for XXX Bakery

EARLY WARNING SYSTEM

Company: xxx Bakery

…………………….……………..

Indicator Title	How obtained	Current Value (CV)	Worst (W)	Critical (CB1)	Acceptable (A)	Good (CB2)	Best (B)	J	F	M	A	M	J	J	A	S	O	N	D	Remark
								score	score	score	score	score	score	score	score	score	score	score	score	
Production Price Index: food	Statistical South Africa. Based on September 2014	122.2	126	120,5	115	113,5	112										1			
Total factor productivity	Monthly statements Sales/all costs	1.147	1,38	1,357	1,334	1,417	1,5										4			
Labour productivity	Output/labour hours	133	110	119	128	130,5	133										5			
Machine productivity	Output/machine hours	394	330	360	390	394	398										4			
Material productivity	Output/Rand of material	2.01	1,8	1,91	2,02	2,01	2										4			
Utilisation	Actual time/available time x 100%	77.1	68	71,6	75,2	77,1	79										4			
Efficiency	Allowed time/actual time x 100%	88.4	82	84,4	86,8	88,4	90										4			
Absenteeism	Lost hours/possible hours x 100%	8.52	15	12,22	9,44	8,52	7,6										4			
Waste	Lost units/available units x 100%	10	22	17	12	10	8										3			
Quality	Monthly number of customer complaints	5	7	6,5	6	5	4										3			

rom Table 1 and Table 2, for clarity in discussion and comparison, Table 3 is created by extracting the CB_2 and the score values for the two months.

Table 3: Early Warning System Summary scores of XXX Bakery for September and October, 2014

EARLY WARNING SYSTEM				
Company: xxx Bakery …………………….……………..		S	O	
Indicator Title	**How obtained**	**score**	**score**	**Remark**
Production Price Index: food	Statistical South Africa. Based on September 2014	**1**	**1**	**Same**
Total factor productivity	Monthly statements Sales/all costs	**5**	**4**	**Down**
Labour productivity	Output/labour hours	**3**	**5**	**Up**
Machine productivity	Output/machine hours	**5**	**4**	**Down**
Material productivity	Output/Rand of material	**1**	**4**	**Up**
Utilisation	Actual time/available time x 100%	**1**	**4**	**Up**
Efficiency	Allowed time/actual time x 100%	**1**	**4**	Up
Absenteeism	Lost hours/possible hours x 100%	**2**	**4**	**Up**
Waste	Lost units/available units x 100%	**2**	**3**	Up
Quality	Monthly number of customer complaints	**4**	**3**	Down

Reading through Table 3, there is need to give reason or determine why TFP score reduced to 4. Through the analysis of the two months under review, there is a need to proffer reasons for the differences observed in Table 3. Some indicator like; Labour productivity, Material Productivity, Utilisation, Efficiency, Absenteeism, and Waste have increased in October as compared to September. While indicators like; Total Factor Productivity, Machine Productivity, and Quality have decreased, Production price index is the only indicator that remains unchanged.

The indicator titles that are same at the best scoring level is an indication that they are all interconnected as machine productivity is high, labour productivity will be high as well as utilization index, this then results in improved efficiency.

Since absenteeism scoring shoot up in October (in other words, it means that number of staff indulging in absenteeism has reduced), then the effect is felt on the quality of products being produced as there is no pressure on one staff than the other, the production process received the best attention from the workers.

With the reduction in TFP, there is need to extend the scope of productivity measures as some measures are not quantifiable or estimable. This factor is not like any other factors such as human factor which is caused by the negative influence. These human factors include supervision, conditions of employment, leadership, motivation, communication and leadership.

CONCLUSION AND FURTHER WORK

The algorithm discussed has been fully justified and has been satisfactory helpful in monitoring the production activities of SME industries in order to provide ways or decisions on how to manage or make them viable under the various indicators. The worth of the EWS will be incomparable if other human factors such as fair and firm discipline, grievances between others, objectivity in pay and performance are fully catered for.

The authors planned progressing on the EWS by translating the algorithm into programming codes using C# which are users' coming up with branded software that will be affordable by the SMEs and friends.

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