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A Quantitative Approach for Measuring Technological Forecasting Capability

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ABSTRACT: Successful technological forecasting is important to invest scarce funds to emerging technologies. A generic model to measure the success of forecasting overall technological changes is introduced in this paper, called degree of Technological Forecasting Capability. It measures the success rate of forecasts in manufacturing processes based on four important aspects of a manufacturing system; Flow Time, Quantity/Day, Scrap Ratio, and New Investment Revenue. The proposed approach has been verified with a case study in manufacturing industry, where each of 4 facets have been calculated based on the data provided and aggregated into the degree of forecasting capability.

KEYWORDS: Technological Forecasting, Metric, Degree, Capability, Manufacturing.

1 INTRODUCTION

Technological forecasting is the process of predicting the future characteristics and timing of technology. If it is possible, the prediction will be quantified, made through a specific logic, and will estimate the timing and degree of change in technological parameters, attributes, and capabilities [1]. The importance of Technological Forecasting appears to be a principal impetus in economic development. Based on this importance, technological forecasting has often been used to support policy making processes in technical issues [2]. Companies and even the countries perform technology foresight programs, which are mostly assessed with Delphi method by the expert estimates [3]. Companies capable of undertaking technology forecasting can benefit in numerous ways including maximizing financial gains and minimizing the losses [4]. For example regarding a study performed by Linstone [5], which sets three eras of technology foresight and for the future era imposing the importance of nano and bio technologies, can provide benefits for the companies dealing in this sector. Since technological forecasting is an important concept, various studies attempt to find a proper way to perform, can be classified into 2 types of studies; Numerical Techniques, and Judgmental Techniques, and summarized below (See for examples, [1], [4], [6], [7], [8], [9], [10].

1.1 NUMERICAL TECHNIQUES

These are the ones, which generally base on numerical computations and less subjective compared to the Judgmental Techniques. *Trend Extrapolation*, which assumes a stream of technological change to continue from past to future, includes Statistical Curve Fitting, Limit Analysis, Trend Correlation, and Multivariate Trend Correlation techniques (See for more detail [9]. *Growth Curves* are based on the parameter estimation of a technology's life cycle curve including; introduction, growth, maturity, and decline phases [11]). Combination of trend analysis and growth curves forms the *Envelop Curves*, which is more suitable in case of rapid technological transformations. *Substitution Model* basically demonstrates the advantages of future technologies over past technology in case of a substitution.

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1.2 Judgmental Techniques

Since performing technological forecasting is not only an issue of numbers and calculations, subjective perspectives are also required to anticipate future trends in technology. *Monitoring* allows the forecaster to stay abreast of technologies as they develop through 7 stages namely; Initial Idea, Postulation of Theory, Verification of Theory, Laboratory Demonstration, Field Trial, Commercial Introduction, Widespread Adoption [9]. *Scenarios*, which proposes different conceptions of future technology and each alternative scenarios (for Pessimistic, Base, and Optimistic situations) are based on certain assumptions and conditions [12]. *Relevance Trees* are used to select a specific research project by defining objectives, goals, tasks, and sub-objectives in a hierarchical order to ensure to achieve all possible ways for the main objective. *Delphi Method*, which is the best known judgmental approach, gathers subjective judgments from individuals as written or remote distance to prevent interactions. These judgments are summarized and presented to participants. The past and the future evolution of Delphi method is well summarized in the literature [13].

Moreover, a study is performed to set emerging forms of technological forecasting including; Scenario Management, TRIZ, Multiple Perspectives, Co-evolution of Technology, Scientometrics, Bibliometic Analysis, and Datamining Tools (see for more detail, [14]. Within these, TRIZ needs to be more clarified, which is a Russian acronym for the “Theory of Inventive Problem Solving” developed by G.S. Altshuller and his colleagues in the former U.S.S.R. between 1946 and 1985. It is an international science of creativity that relies on the study of the patterns of problems and solutions, not on the spontaneous and intuitive creativity of individuals or groups (see for more detail, [15]. Although it is widely accepted from different areas of innovation and forecasting studies, the manufacturing perspective is missing in case of technological forecasting. On the other hand technological forecasting is proved to be a method for a decision making tool in respect to the analysis [16].

As seen above there are so many different techniques for technological forecasting. Since the quality of forecasts greatly depends on proper selection and application of appropriate techniques, a method is proposed in selection of complementary and appropriate techniques for a technology [17]. One of the crucial factors about choosing a forecasting strategy is the potential economic value of the forecast compared with the cost of making the forecast. Some methods are much more expensive than others, and some tend to give better results for certain situations. Since data are generally available for short range forecasting problems, extrapolation techniques work best for short term. For long range forecasts, the judgmental methods are more suitable because, as time periods are extended, the dangers of unjustifiable extrapolation grow rapidly.

Hence the discussion of the selection of technology forecasting method is crucial, a recent study adopted the Fuzzy Analytical Hierarchy Process method to obtain professionals’ opinions on this issue [18]. However, its main focus is on the prediction of new materials development, so it is not a generic model for manufacturing systems. Also, in the literature a foresight method is proposed for detecting areas in the Information Technology (IT) industry by applying Delphi and AHP methods [19]. In addition, a data envelopment analysis (DEA) based methodology has been used to predict the future wireless communication technologies in the study which presents a framework to characterize, assess and forecast new technologies [20]. Although they are well organized study, they focus on IT systems not the manufacturing systems. Since the assessment of forecasting is important a study has been performed to analyze forecasting accuracy of wind power technologies across different countries [21]. Although the forecast accuracy is assessed using multiple different measures [22], [23], the aim of forecasting is bounded with technology diffusion models for wind powers only. However technological forecasting for manufacturing systems requires more specific properties to be enlightened.

The emphasis of this study particularly goes towards to set a quantifiable model to measure the capability of performing technological forecasting for manufacturing systems. Since it is more risky to make blind-investments to inconvenience technological improvements especially for the manufacturing processes, it is required to anticipate the outcomes in advance. This can only be held by successful forecasting methods. Although the aforementioned literature delineate some methodologies for technological forecasting, it is hard to observe an evidence of measuring the success rate of performing these forecasts. Selecting the best promising technological developments among various unprofitable and inconvenient ones, the performance to forecast the new technologies needs to be measured especially for the manufacturing systems.

To the best knowledge of the authors, a limited amount of literature is available on measuring the capability of technological forecasting performance especially focusing on the manufacturing processes. Besides, setting a quantifiable metric scale to measure the capability of performing technological forecasting is as well important as performing the forecast. Hence, the main aim is not to measure forecasting but to measure the forecasting capability. Therefore the main motivation of this study is to develop a quantitative approach to measure the success rate of technological forecasting regarding the manufacturing systems. This novel method sets a metric scale relying on 4 important technological aspects of manufacturing systems, which will be elaborated while setting the model to measure the degree of technological forecasting, in the next section.

2 TECHNOLOGICAL FORECASTING CAPABILITY

Most of the studies to forecast the technology are dependent on the specific attribute of the products, for example the flight range or the bomb capacity of the air fighters are examined to be forecasted [24]. However the main aim of this study is to establish a generic methodology to measure the capability of the technological forecasting in different manufacturing areas. Therefore, the focus to measure the technological forecasting capability will be on the general technological aspects of manufacturing systems. These aspects, which should be mutually exclusive and collectively exhaustive to represent the changes in technology, are proposed to be *Flow Time, Quantity/ Day, Scrap Ratio,* and *New Investment Revenue*. In order to measure the capability of technological forecasting, actual values of these aspects should have been recorded. Depending on the existence of a technological development, a forecasting study should have been carried out to find the outcomes of this development. Then by comparing the forecasted and actual outcomes, the degree of forecasting capability is found. Note that, if there is not a technological development then there is nothing to deal with measuring the forecasting capability of the new technology because it does not exist. On the other side, if there is not a forecasting study although a technological development exists, then forecasting capability is assumed to be zero.

In the next sections each of the 4 aspects of manufacturing systems are explained by defining the reason to be selected as the indicators to measure the capability of technological forecasting. In addition the methodology to compute the degree of forecasting capability for each indicator is revealed.

2.1 FLOW TIME (Ƒ)

It is the period required for a material, part, or subassembly to pass through the manufacturing process. It is obvious though, the technological developments, for example a new machine or tool usage, will definitely decrease the flow time of the production. Basically forecasting capability in estimating the flow time is calculated by comparing the actual and forecasted values for each product. However it is cumbersome to cope with and record the actual and forecasted values when there are hundreds of product types. Therefore the average flow time can be found by dividing the available working hour by total production amount, resulting a unit production time on average.

In order to measure the capability in estimating the flow time in this way, the first step is to look for the existence of a technological improvement; note that, when there is no technological improvement whatsoever then there will not be a need to forecast the effects of it. At the second step, actual flow time for the products should be recorded. However, the flow time for each product may vary. Instead of dealing with flow time of each unit, actual average flow time of the products (Ƒ) can be calculated by dividing the available working time (Ʈ), by the actual total production amount (Ɲ) of the system as shown in Eq. 1.

$$\text{Ƒ} = \text{Ʈ}/\text{Ɲ} \tag{1}$$

At the third step, forecasted flow time is required to measure for the sake of comparison of actual and forecasted values. Similarly, average forecasted flow time (Ƒ′) is calculated by dividing the available working time (Ʈ), over the forecasted total production amount (Ɲ′) as shown in Eq. 2.

$$\text{Ƒ}' = \text{Ʈ}/\text{Ɲ}' \tag{2}$$

At the last step, the capability of forecasting is assessed by comparing the forecasted and actual average flow times (Eq.3.). This comparison represents the capability of performing technological forecasting with respect to flow time aspect of the manufacturing system.

$$\mathrm{FC}_{\text{Ƒ}} = 1 - (|\text{Ƒ}' - \text{Ƒ}|/\text{Ƒ}) \tag{3}$$

Where;

$FC_{\text{Ƒ}}$: Forecasting Capability of "Flow Time"
$\text{Ƒ}'$: Forecasted value of "Flow Time"
Ƒ : Actual value of "Flow Time"

2.2 QUANTITY/DAY (Ø)

This is another important aspect of technological change. Although it looks like similar to flow time, it has some differences. The flow time indicates the production *speed*, whereas, the quantity/day represents the production *capacity* of the system. This capacity is not only dependent on the employees working rate, but also high technology machinery usage or highly trained- skilled workers. Hence, forecasting the capacity of the system is an indicator of forecasting the outcomes of the technological machinery used in the system assuming the employees working rate as constant.

Similar to Flow Time, in order to measure the capability of the performance of forecasting the Quantity/Day (Ø), actual monthly production levels (Ƥ) for each year should be recorded at first. Dividing this value by the number of working days (Ɗ) in a month provides the actual daily production level. Note that this should also be divided by the number of workers (Ŵ) to eliminate the effect of worker size (Eq. 4.).

$$\text{Ø} = \text{Ƥ}/(\text{Ɗ} * \hat{\text{W}}) \tag{4}$$

Beyond this, monthly production levels have to be forecasted due to technological changes (if any) for each year. Forecasted production level (Ƥ′), should also be divided by the number of working days (Ɗ) and the number of workers (Ŵ) to achieve forecasted daily production level (Ø'), of the same production line (Eq. 5.).

$$\text{Ø}' = \text{Ƥ}'/(\text{Ɗ} * \hat{\text{W}}) \tag{5}$$

Consequently the comparison between the forecasted and actual daily production levels provides the forecasting capability of "Quantity/Day" ($FC_{\text{Ø}}$) as shown in Eq.6.

$$\text{FC}_{\text{Ø}} = 1 - (|\text{Ø}' - \text{Ø}|/\text{Ø}) \tag{6}$$

2.3 Scrap Ratio (Š)

This is in fact the indicator of quality and an important aspect of the technology in manufacturing systems. If the main aim is to measure the capability of performing technological forecasting successfully, the changes in this respect should be foresighted and the quality of the products should naturally be improved through them. It is clear that, the scrap ratio will most probably diminish in case of implementing new technological machinery or systems even if working with the same workers and environment. Successful capability of forecasting the Scrap Ratio is therefore important as it is definitely affected by the changes in technological investments. By comparing the actual (Š) and forecasted (Š′) scrap ratios, capability of performing technological forecasting regarding "Scrap Ratio" ($FC_{\text{Š}}$) aspect, could be assessed as shown in Eq.7.

$$\text{FC}_{\text{Š}} = 1 - (|\text{Š}' - \text{Š}|/\text{Š}) \tag{7}$$

2.4 New Investment Revenue (Ř)

This is another example of technological aspects of the manufacturing system. To manage the technological changes, new investments on machinery or other systems are inevitable. But, it is desired to know how much revenue, the new investment will gain. In order to achieve this information, a forecasting study should be carried out. The capability of forecasting the "Revenue" ($FC_{\text{Ř}}$) from new technologies is calculated by comparing the actual revenue (Ř) and forecasted revenue (Ř′) values if any new technology is implemented as shown in Eq.8.

$$\text{FC}_{\text{Ř}} = 1 - (|\text{Ř}' - \text{Ř}|/\text{Ř}) \tag{8}$$

2.5 Degree of Forecasting Capability

Four aspects namely; *Flow Time*, *Quantity/Day*, *Scrap Ratio* and *New Investment Revenue* are stated to be important indicators that are highly affected by the changes in technologies. In order to analyze the outputs of technological changes, forecasting studies should be carried out for each of these facets. Degree of Forecasting Capability (δ FC) is calculated as the weighted summation of these 4 indicators as represented in the following equation (Eq. 9).

$$\delta\text{FC} = \sum_{i=1}^{4}(\text{W}_i * \text{FC}_i)/\sum_{i=1}^{4}\text{W}_i \tag{9}$$

Where;

δ FC: Degree of Forecasting Capability
FC_i: Forecasting Capability of Aspect i.
W_i: Weight of Aspect i.
i: Aspects (Flow Time -Ƒ-, Quantity/Day -Ø-, Scrap Ratio -Š-, and New Investment Revenue -Ř-)

Note that the weight values related to respective indicators are required to normalize the effect of each aspect and can be determined by a survey conducted by both the academicians and industrial representatives.

3 CASE STUDY

The proposed model is implemented as a proof of concept with analyzing the capability of technological forecasting in a manufacturing company producing flex pipes, called KAS FLEX Ltd. It is intended to check the capability of forecasting in the manufacturing process after some attempts of technological improvements achieved within the time period from 2006 to 2009.

Within the analysis period, it is realized that there was no technological change implemented on the flex production process in 2006 and 2007. Therefore, there is no need to make a forecast of the outcomes of the technological change for these two years. However, in 2008 welding technology is changed from induction welding to tig welding. Additionally, in 2009 a new welding machine with 4 handles is added to welding center. The actual outcomes of these changes should therefore be compared with the forecasted ones according to pre-defined 4 technological aspects in flex production process namely; *Flow Time, Quantity/Day*, *Scrap Ratio*, and *New Investment Revenue*. Since only in 2008 and in 2009, technological improvement occurs, forecasting capabilities of each aspect, which are found by Eq. 3, 6, 7, and 8, should be averaged for 2 years-period.

3.1 ANALYSIS OF "FLOW TIME"

In order to measure the capability to forecast the flow time, actual and forecasted capacity in each shift -accompanying with the working time- for each year is taken from the company records in KAS FLEX production facility and given in the "Data" part of Table 1.

Depending on this information, actual and forecasted flow time of each unit can be calculated by dividing the working time over the capacity values by Eq. 1 and Eq.2. Forecasting capability for flow time can be measured by comparing the actual and forecasted values by Eq. 3 for each year. The overall forecasting capability is the average of the third and fourth years and found as 85.42% for this respect as shown in "Analysis" part of Table 1.

Table 1. Forecasting Capability for "Flow Time - $\mathbb{F}$-"

	"Flow Time" Forecasting	2006	2007	2008	2009
DATA	Actual Capacity/Shift (unit)	700	700	1250	5000
	Working Time/Shift (min.)	540	540	540	540
	Forecasted Capacity/Shift (unit)	No Forecast	No Forecast	1200	4000
ANALYSIS	Actual Flow Time (min/unit) (Eq. 1)	540/700= 0.771	0.771	0.432	0.108
	Forecasted Flow Time (min/unit) (Eq. 2.)	Not Applicable (NA)	(NA)	0.450	0.135
	Forecasting Capability (%) (Eq. 3.)	Not Measured	Not Measured	95.830	75.000
	Average Forecasting Capability of Flow Time (%)	$\frac{95.83+75.00}{2}=85.42$			

This score represents a high degree for this capability since the forecasted and actual respective values are very close. Hence the company can be stated as successful to measure the capability of performing technological forecasting regarding the "Flow Time" aspect of the manufacturing process.

3.2 ANALYSIS OF "QUANTITY/DAY"

In order to measure the capability of forecasting "Quantity/Day" value, actual and forecasted average monthly production levels -accompanying with the number of workers and working days- for each year is taken from the company records and given in the "Data" part of Table 2.

Depending on this information, actual and forecasted daily production levels can be calculated by dividing the monthly production level over the number of working days and number of workers (Eq. 4 and Eq. 5, respectively). Technological Forecasting capability for each year is calculated by Eq. 6, and the average forecasting capability for Quantity/Day for KAS FLEX are calculated as 72.05% and given in "Analysis" part of Table 2.

Table 2. Forecasting Capability for "Quantity/Day -Ø-"

Quantity/Day" Forecasting		2006	2007	2008	2009
DATA	# of Workers	7	10	22	36
	# of Working Days/Month	22	22	22	22
	Actual Average Monthly Production Level	30000	50000	75000	117000
	Forecasted Monthly Production Level	No Forecast	No Forecast	60000	75000
ANALYSIS	Actual Daily Production/Worker (Eq. 4)	30,000/ (7*22) = 194.805	227.273	154.959	147.727
	Forecasted Daily Production (Eq. 5)	(NA)	(NA)	123.967	94.697
	Forecasting Capability (%) (Eq. 6)	Not measured	Not measured	80.000	64.100
	Average Forecasting Capability for Quantity/Day (%)	$\frac{80.00+64.10}{2}=72.05$			

This result indicates that, company is aware of the yield of technological changes in accordance with this aspect with 72.05%. When the forecasted and actual average monthly production levels are compared, it is seen that the company has underestimated production levels. Although the actual levels are greater than the forecasted values, the differences between these values diminish the forecasting capability of "Quantity/Day" aspect of the manufacturing system.

3.3 Analysis of "Scrap Ratio"

Similarly, to be able to measure the forecasting capability for Scrap Ratio, actual and forecasted scrap ratios for each year is sought from company records as shown in the "Data" part of Table 3.

Table 3. Forecasting Capability for "Scrap Ratio -Š-"

"Scrap Ratio" Forecasting		2006	2007	2008	2009
DATA	Actual Scrap Ratio (%)	15.00	15.00	8.00	3.00
	Forecasted Scrap Ratio (%)	No Forecast	No Forecast	11.00	5.00
ANALYSIS	Forecasting Capability (%) (Eq. 7)	No Need	No Need	62.50	33.33
	Average Forecasting Capability for Scrap Ratio (%)	$\frac{62.50+33.33}{2}=47.92$			

Based on this information the forecasting capabilities for each year are calculated by Eq. 7. The average capability for forecasting the scrap ratio is calculated as 47.92% and shown in "Analysis" part of Table 3. Although it seems good for the actual scrap ratio being less than the forecasted value, forecasting capability is not very high. The company can only estimate the 48% of the decrease in actual scrap ratio.

3.4 Analysis of "New Investment Revenue"

In order to measure the capability to forecast the capability for "New Investment Revenue" of the company, actual and forecasted revenues for each year is used from the company records and shown in "Data" part of Table 4.

Table 4. Forecasting Capability for "New Investment Revenue -Ř-"

"New Investment Revenue" Forecasting		2006	2007	2008	2009
DATA	Actual Revenue (TL)	2,565,461	4,456,065	6,224,000	8,058,268
	Forecasted Revenue (TL)	No Forecast	No Forecast	No Forecast	No Forecast
ANALYSIS	Forecasting Capability (%) (Eq. 8)	Not measured	Not measured	0	0
	Average Forecasting Capability for New Investment Revenue (%)	**0**			

Based on the information obtained, the forecasting capabilities for each year are calculated by Eq. 8. The average capability for forecasting the scrap ratio is calculated as 0% and shown in “Analysis” part of Table 4. Since there is not any forecasting value for the revenue aspect, the overall forecasting capability for the revenue is set to zero. This means that; although two important technological changes occur in the flex production process, there is a lack of information and forecasting study about how the changes will affect the revenue.

3.5 DEGREE OF FORECASTING CAPABILITY OF KAS FLEX

After analyzing the forecasting capability of 4 technological aspects in KAS FLEX, the overall technological forecasting capability is assessed by taking the weighted average of each aspect. These weights have been determined from the expert views retrieved of 386 replies to a questionnaire sent to 784 academic and industrial experts in field. Table 5 summarizes the result of this survey as well as listing the forecasting capability of each aspect and the overall degree of technological forecasting capability, which is found to be 49.62%. That was achieved by Eq. 9;

Table 5. Degree of Technological Forecasting Capability

Technological Aspects	Weight	Forecasting Capability
Flow Time	0.3	85.42
Quantity/Day	0.2	72.05
Scrap Ratio	0.2	47.92
New Investment Revenue	0.3	0.00
Degree of Technological Forecasting Capability (%) (Eq. 9.)		**49.62**

It can be concluded that KAS FLEX is only about 50% capable of performing forecasting 4 important technological change aspects. This score indicates the existence of some forecasting studies, but in average it is not fully successful. Although it is highly and moderate successful of forecasting “Flow Time” and “Quantity/Day” aspects respectively, it is not capable to estimate the “Scrap Ratio” correctly. The remarkable point is about the “New Investment Revenue” aspect. Since there is not any forecasting study for this one, the company can be stated to be unconscious of the return on investment of new technologies. Although there is a high increment in the new investment revenue from new technologies implemented, the company does not make any study to forecast the expected returns from these technologies. In other words, they are successful in implementing the new technologies but not in forecasting the outcomes of these new developments.

4 CONCLUSION

This paper presents a novel performance indicator, called degree of forecasting capability, for monitoring and measuring the capability for technological forecasting in manufacturing processes based on four important aspects of a manufacturing system. We call these facets, which are namely *Flow Time, Quantity/Day, Scrap Ratio, and New Investment Revenue*. The idea behind this approach has flourished after a thorough literature survey, which has been provided in the paper, feeling the requirement of a quantifiable application to make technological forecasts for manufacturing systems. Although there are various techniques for technological forecasting, many of them cannot be applied to manufacturing systems as they require particular attention on unique aspects. Moreover, most of the studies in the literature depends on qualitative metrics, which are hard to define and subjective to set a scale. Hence the main motivation of this study is to fulfill this gap by developing a quantifiable approach to measure the technological forecasting capability focusing on manufacturing systems. The methodology relies on defining 4 important technological aspects of manufacturing processes. It tries to find the capability of technological forecasting based on these 4 aspects, whenever a technological improvement has occurred.

The proposed approach has been verified with a case study in manufacturing industry, where each of 4 aspects have been calculated based on the data provided and aggregated into the degree of forecasting capability. The weights, to normalize the impact of each sub-indicator, have also been compiled of expert views. The results suggest that it is also important to forecast the outcomes of the technological improvements before implementing them. Since even the company in analysis has significantly increased its technological outputs regarding these 4 aspects, it has not successfully forecasted these gains as much. So it is a signal of a threat of investing quite amount of founds in unpromising technologies blindly in the future. This study has also proved that a quantitative indicator can be implemented for measuring the forecasting capability in manufacturing processes based on key technological components of manufacturing processes.

Further aspects of manufacturing processes can be considered to enhance the degree of forecasting capability indicator and the impact of each sub-indicator can be fine-tuned with further verified expert views as well as with the use of analytical hierarchical process (AHP) in the future. Besides, the approach itself can be enhanced with emergent computing technologies such as multi agent systems.

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