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Stock-Market Related Price Determination in Consideration of Time Dynamic Cost Factors

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Abstract

Providing their customers with the most accurate pricing has become one of the key competitive factors ensuring commercial success for tool and mould manufacturers. However, time dynamic costs influence the pricing calculations significantly, indeed, they are rarely taken into consideration adequately.

This paper presents an approach which allows to improve conventional tool performances by developing a novel forecasting method which combines mechanisms related to the stock market with techniques of stochastic prediction methods.

Keywords: Manufacturing, pricing calculation, forecasting, stock market, time dynamic costs

Introduction

In order to assess the cost effectiveness of the mostly small and medium-sized tool and mould manufacturing enterprises, both the prices which they quote and the actual costs incurred by their individual production should be taken into consideration. Providing their customers with a precise estimate is of a particular importance for such companies, since a prompt and detailed tendering is a prerequisite for a competitive performance on the economic market. In terms of preparing an accurate estimation, the interaction and coordination of the different company departments is of utmost significant. However, in reality, the knowledge of a single employee is often the only basis for the determination of the prices. Moreover, such an employee is confronted by a continuous increase in estimate demands which – combined with the stipulated period for their calculation – results in a greatly reduced processing time for individual requests.

In preliminary work of the Institute of Production Engineering and Machine Tools at the Leibniz Universität of Hannover, an analytical calculation method for quotation costing has been developed and serves as a basis for the software-tool Visual Form Calculator (VFC). The method examines correlations between geometrical characteristics, on the one hand, and manufacturing structure, working operations and production processing times, on the other.

It also factors a number of construction, production planning and production-related interdependencies and uses die casting moulds as an example for their rule-based representation. It aims at a transparent, effortless and exact cost calculation and includes the following essential elements:

- Development of a virtual model of the form: The method takes the customer-specific casting geometry and technological functionalities into consideration and uses them in order to generate a virtual model of the form.
- Rule-based bill of materials (BOM) generation: A BOM providing the technological description and the geometrical details of the product model can be generated by using inference relations in order to select component parts from a component list and by proving a rule-based description of their geometry.
- Calculation of manufacturing times: In order to calculate the manufacturing times, the method differentiates whether the respective process steps pertain to the forming of the contour of the product or not. [1].

Nevertheless, it still remains true that while pricing calculations are usually prepared in the early stages of processing the customers` inquiry, the actual costs incurred become apparent only after the final realization of the order. Furthermore, the order processing procedure itself may take up more than a year. Within that period, the cost of materials, wages, and external services may be subjected to strong fluctuations. The material costs alone, for example, can vary between 16 and 45 percent within a three-month period (e.g. in 2009), thus, affecting the production cost significantly [2]. These time dynamic costs are rarely taken into consideration

systematically. This may lead to greater differences, including price fluctuations of up to 40 percent, between the pre- and post-calculation costs and, thus, to a loss in the company's added value [3]. This paper aims at providing an effortless and cost-optimized quotation preparation model based on pricing-mechanisms comparable to the stock market. By integrating the above-mentioned analytical approach, it allows for a self-regulated cost-prediction. An in-depth analysis of given stock market related mechanisms is a prerequisite for the adaptation of these and for their combination with stochastic prediction methods. Consequently, the prediction accuracy concerning the time dynamic costs is increased and the effort of time for processing is reduced. The result is a method for time-dynamic pricing which is an intelligent combination of an economic cost estimation method with stock-market related as well as stochastic forecasting mechanisms. In the following pages the first steps to develop this dynamic approach will be presented.

Quotation Costing
According to the VDI-Guideline 2234 [4], the quotation costing can be divided into pre-calculation, inter-calculation, and post-calculation. The availability of information increases chronologically: Over time, data availability from manufacturing and job preparation rises, and a detailed description of product and handling becomes available.

The costing methods can be divided into expert, analogous, parametric, and analytical estimations; these are distinguished from each other by their elaborateness and accuracy. The expert estimation represents the simplest method of costing: Planners estimate the costs based on their experiences. The results are rarely reproducible and the accuracy of the estimation is highly dependent on the experience and knowledge of the individual planner [5, 6]. Similarly, the analogous estimation methods utilise past experience to prepare the new quotation; the production-oriented similarity searching is an example for analogous estimation [7]. The parametric estimation methods are based on the assumption that functional relationships exist between the production costs and certain tool characteristics, e.g., between the price and the weight of a tool. The kilo-costs and the material-costs methods are typical representatives of the parametric estimation [8]. Analytical methods estimate the cost of the product to be manufactured with the help of a systematic calculation scheme. For this purpose, material prices, costs for personnel, equipment need to be determined [9]. Due to their transparency and elaborateness, the analytical estimations offer the highest calculation accuracy of all methods which have been introduced so far. In practice, however, the expert estimations remain the most widely used estimation method. A non-representative survey conducted by the IFW among an industrial group of experts, consisting of ten companies from the tool and mould manufacturing industry, shows that ca. 70 % of the manufacturers usually base their quotations on estimations derived from the past experience of highly-qualified, long-time employees. In order to ensure precise and transparent quotation costing, a number of various research approaches to this topic have been investigated.

State of the Art
Askri combines an analytical calculation method, based on a function-oriented tool structure for injection moulds, with the knowledge of the tools already produced by the company [5].

Giannoulis proposes a method for the explicit forecast of installation costs for the single and small batch production. The central element of this approach is a cost model that allows the determination of the assembly costs by taking the assembly operations and the used resources (material, personnel, equipment) into account [10].

Using the casting geometry and the technological requirements of the client, *Schuermeyer* generates a virtual model of the die casting mould. As a result, rule-based bills of material and tasks schedules can be created, and production times calculated [1].

Neff's front load costing method uses product cost and design models as a decision support at an early stage. The main element of the method is the statistical modelling of cost-influencing product information with the aid of a 3-point estimate which is determined by expert interviews [11].

For the calculation of the die casting moulds, *Nagahanumaiah* presents an approach that divides the costs into cost drivers and cost modifiers. Cost drivers encompass those costs which contribute towards the determination of the basic form costs. Cost modifiers include form parameters that ultimately contribute to the total cost of the die casting mould [12].

Petzold's approach aims at improving the quality of pre-calculation for the tool and mould industry by increasing the quality of the data needed for the calculations. The data quality assessment is performed by algorithms that support automatic data analysis [13]. For further information please have a look in [14].

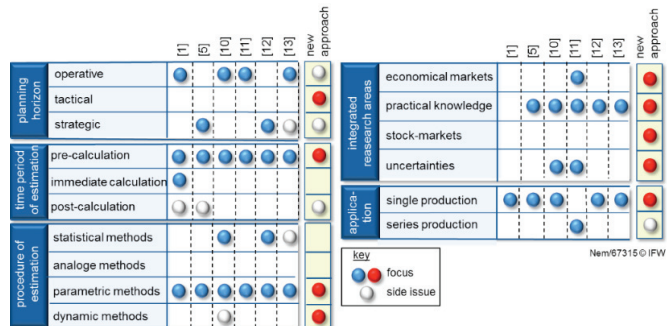Fig. 1 below summarises the research approaches mentioned above.

Fig. 1: Literature summary of current research areas

Call for Action
Fast and precise estimation of the future production costs allows companies to respond promptly to the requests of their customers and to accurately determine the possible future costs, even if there is a longer period between the moment when the costs are initially assessed and the moment when they actually incur. An analytical evaluation of the time dynamic costs, early in the pre-calculation process, is crucial for precise assessment of the production costs; its results are integrated directly into the calculation. Due to the fact that they are both time-dependent and dynamic, such

costs tend to be exceptionally difficult to predict.

Since time dynamic cost factors are an indispensable element if manufacturers are intended to offer precise quotations to their clients, it is necessary to determine how to integrate such time-oriented costs within quotation processing and costing so that the production costs can be estimated as accurately as possible. The methods discussed above illustrate the approaches which aim at transparent quotation costing; however, none of the presented papers offers structured and comprehensive analysis which also includes the time-dependent costs.

Following, a novel method which focuses on the integration of mechanisms related to the stock market within the tool and mould manufacturing industry addresses this lack of sufficient consideration of the time dynamic costs. The approach to this method is based on a detailed analysis of a stochastic and stock market related method.

Analysis of economic and stock market related prediction methods

Time series are defined as a sequence of numerical values in successive order, usually occurring in uniform interval, like months or quarters.

When analyzing a time series, the aim is to predict future developments [15]. In this case, prediction is to be understood as a statement concerning the development of one or more future events; such a statement is based both on observations of the past and on a theory explaining these observations [16]. At this point, the difference from the calculation methods becomes clear: These do not take future costs into consideration but are statistically based on current data concerning the individual costs.

Based on the assumption that trends and patterns, which have emerged from observing past statistical series and interdependencies, also apply to the future, quantitative prediction methods map the observed values and causal correlations of variables. By means of prediction methods, as precise as possible forecast concerning future costs development should be made possible.

The time series analysis is concerned with methods that describe time series processes. It is important to identify and to describe four principal characteristics. A trend is a long-term level change, such as an economic growth. It can be determined by using the moving average method. The seasonal component includes seasonal variations, such as occupations in agriculture. Costing is determined by exponential smoothing of the first and second order [17, 18]. The cyclical component, for example, describes variations in the utilization of production. The random component represents the fourth characteristic of the time series. However, this component cannot be defined precisely, since it either has no known causes or these are the result of non-repetitive events. Further popular quantitative prognostic methods include the simple and multiple regressions, as well as the ARIMA- and the Holt-Winters-models. The individual methods are suitable for different prognostic subjects and time periods [15].

The classification of the methods according to their ability to map the characteristics of the time series is summarised in Fig 2.

	Trend	Seasonality	Noise
Moving Average			✓
Linear Regression	✓		✓
ARIMA	✓	✓	✓
Exponential Smoothing 1. order			✓
Exponential Smoothing 2. order	✓		
Holt-Winter	✓	✓	

Fig. 2: Summarization of the abilities of the economic prediction methods

All economic prognostic methods have in common that they entail fixed assumptions regarding the description of the components, e.g. that the trend function is always linear. As a result, such methods need subjective decisions in order to lead to a definite conclusion. In addition, none of the conventional prognostic methods can provide a costs prediction that is exact to the day. Furthermore, these methods can only predict fixed costs values, without taking into account the uncertainties which might occur within the forecasts over a given time period. However, a forecast within an interval that provides the calculator with leeway, in dependence on the prevailing uncertainties, corresponds much better to reality. Stock market-oriented prediction models are based on the assumption that the price development of financial products is uncertain.

Due to this uncertainty, there is a rising demand for stochastic models which are needed to reflect market trends by means of stochastic interdependencies and, thus, make them predictable. First approaches were made by the Brownian process. Due to its usage by Wiener, it has become popular as the Wiener process [18]. Its basic assumption is that the current price of a share aggregates in itself the entire information concerning the past development. By representing the price of any given derivate as a function of an underlying stochastic variable and time, the Wiener process has been expanded to another stochastic process, the Ito process. Spenkle is the first to model share prices using log-normal distribution, however, without discounting future expectations [18]. Other modifications and enhancements introduced by Black, Scholes and Merton (BSM) have lead to the development of the BSM-model. The BSM-model represents a preference-free valuation model which is used to calculate option prices by means of analytical correlations. This model allows for investors to determine a future option price S_T based on a current share price S_o, regardless of their expectations and willingness to take risks [18].

$$\ln S_T \sim N\left(\ln S_0 + \left(\mu - \frac{\sigma^2}{2}\right)T, \sigma^2 T\right)$$

Formula 1: Calculation of $\ln S_T$ [18]

T is defined as the number of time intervals between the actual value x_t and the future value x_{t+T}. The future time moment T necessary for the determination of the option price can be arbitrary. However, it remains unclear how the

required expectation value μ is determined; qualitative methods have to be used in order to find a solution. Furthermore, a constant volatility – which does not always correspond to reality – is generally assumed.

Definition of the variables of the new prediction method
This chapter introduces and analyses the results which have emerged while developing the innovative forecasting method for the evaluation of the time dynamic costs with the purpose of improving the performance of the product cost estimation techniques.
The formula 1 presented above serves as a basic expression for the evaluation of the future stock prices S_T, which – for their part – are adapted for the prediction of time dynamic costs x. By analysing each possible way allowing the adaptation of that expression for the purpose of the present research, four options related to the forecasting expression, the interval of time τ, the expected rate of return μ and the volatility σ^2 have emerged. Each one of them is presented individually in the next sections.

Forecasting expression
The forecasting expression reported in formula 1 allows the direct determination of the future value $\ln(x_T)$ at generic future time T; consequently, it is referred to as the direct forecasting expression (DE). Introducing τ defined as the interval of time between two sequential values of the time series and i as the number of intervals between time t and T, the formulation of the direct method for the evaluation of $\ln(x_T)$ with $T = i\tau$ is:

$$\ln(x_{t+T}) \sim N\left(\ln(x_t) + \left(\mu - \frac{\sigma^2}{2}\right)T, \sigma^2 T\right)$$

Formula 2: Direct forecasting expression for the evaluation of $\ln(x_{t+T})$

The proposed option is not the only alternative. The formula above can be adapted for a step-by-step prediction in which the value is forecasted one interval of time ahead for every stage. This solution, called step-by-step (SSE) method, determines the future value x_{t+i} by means of i-steps. The formulation of the step-by-step method for the evaluation of $\ln(x_{t+T})$ with $T = i\tau$ is:

$$\ln(x_{t+T}) \sim N\left(\ln(x_{t+T-1}) + \left(\mu - \frac{\sigma^2}{2}\right)\tau, \sigma^2 \tau\right)$$

Formula 3: Step-by-step forecasting expressions for the evaluation of $\ln(x_{t+T})$

Interval of time τ
The BSM expression for the evaluation of stocks depends on the interval of time; consequently, the interval of time τ has been adapted as well. It has to be noticed that the definition of the unit of time is just a convention and set at the beginning, τ is employed as a constant. Technically, the interval of time adapted in the expression of the BSM-method is determined by considering the trading days in which the exchange is opened; as a result, it equals 252 workdays. However, since no precise rules concerning the days in which raw materials, labour and energy are traded exist in the field of time dynamic costs, this assumption is not coherent with the new utilization of the BSM-method. As a consequence, the adapted unit of time has been defined as 1 year, and depending on the frequency of data, the interval

of time τ used for the application of the BSM-method to the time series has been defined as:

$$\tau = \frac{\text{frequency of the time series}}{365 \text{ days}}$$

Formula 4: Calculation of τ

In the BSM-expression for the evaluation of stock prices, the parameter μ is defined as the expected return on a stock per year and is the expected variation of the actual value of a stock price in one year. When applying the BSM-model to time series forecasting, this parameter loses this notation and is generically referred to as the expected value μ. A first option for the determination of μ is based on the characteristic expression of the expected rate of return. Starting from the calculation of the expected value of a stock price S_T and adopting the notations of time dynamic costs, μ has been defined as:

$$\mu_{ln,i} = \frac{1}{\tau}\ln\left(\frac{x_{i+1}}{x_i}\right)$$

Formula 5: First possible definition of μ_i

Due to the way $\mu_{ln,i}$ has been defined, it is possible to evaluate the associated time series $\mu_{ln,1}, ..., \mu_{ln,i}$ starting from a time series $x_1, ..., x_i$. A second possibility is presented in the following formula:

$$\frac{\Delta S}{S} = \mu \, \Delta t + \sigma \, \varepsilon \, \sqrt{\Delta t}$$

Formula 6: Calculation of the return provided by a stock in Δt [15]

In this case, $\mu \, \Delta t$ is the expected value of the return, and $\sigma \, \varepsilon \, \sqrt{\Delta t}$ is the stochastic component of the return [18]. By ignoring the stochastic component of the return and employing the notations introduced so far, formula 7 is subsequently defined as:

$$\mu_{\Delta,i} = \frac{1}{\tau}\frac{x_{i+1} - x_i}{x_i}$$

Formula 7: Second possible definition of μ_i

Both $\mu_{ln,i}$ and $\mu_{\Delta,i}$ represent time series of values employed in the direct and in the step-by-step forecasting expression.
In contrast to the step-by-step method which does not accept alternative definitions of μ_i, the direct method allows for different formulations. The prediction of the generic value x_{t+i} with $i > 1$ can, indeed, be achieved with the direct method presented in formula 2, by employing two different versions of μ. The first one is based on the already presented definition of μ and, given the series $x_t, ..., x_{t+i}$, it consists in using the last value of this parameter corresponding to $\mu_{t+i-1} = f(x_{t+i-1}, x_{t+i})$. The second possibility is to define μ as equal to the sum of all estimable μ_i between x_t (the value at actual time) and x_{t+i} (the future value). Analytically, by accepting $\mu_{t,t+i}^{sum}$ as the new possible formulation of μ, it follows that $\mu_{t,t+i}^{sum} = \frac{1}{i}\sum_{j=0}^{i-1}\mu_{t+j}$ where the sum is multiplied by the factor $\frac{1}{i}$ in order to take into account the number of time intervals i between x_t and x_{t+i}.

The definition of $\mu_{t,t+i}^{sum}$ based on formula 8 is:

$$\mu_{ln,t,t+i}^{sum} = \frac{1}{i}\left(\mu_{ln,t} + \mu_{ln,t+1} + \cdots + \mu_{ln,t+i-1}\right)$$
$$= \frac{1}{i}\left(\frac{1}{\tau}\ln\left(\frac{x_{t+1}}{x_t}\right) + \frac{1}{\tau}\ln\left(\frac{x_{t+2}}{x_{t+1}}\right) +\right.$$
$$\left. + \frac{1}{\tau}\ln\left(\frac{x_{t+i}}{x_{t+i-1}}\right)\right)$$

Formula 8: Calculation of $\mu_{ln,t,t+i}^{sum}$

The definition of $\mu_{t,t+i}^{sum}$ based on formula 7 is instead:

$$\mu_{\Delta,t,t+i}^{sum} = \frac{1}{i}\left(\mu_{\Delta,t} + \mu_{\Delta,t+1} + \cdots + \mu_{\Delta,t+i-1}\right)$$
$$= \frac{1}{i}\left(\frac{1}{\tau}\frac{x_{t+1} - x_t}{x_t}\right.$$
$$+ \frac{1}{\tau}\frac{x_{t+2} - x_{t+1}}{x_{t+1}} + \cdots$$
$$\left. + \frac{1}{\tau}\frac{x_{t+i} - x_{t+i-1}}{x_{t+i-1}}\right)$$

Formula 9: Calculation of $\mu_{\Delta,t,t+i}^{sum}$

Volatility σ^2

The volatility of a stock price can be defined as the standard deviation of the return provided by a stock in 1 year [19]. Starting from this definition, some possible adaptations of volatility to the new application of BSM method to time series forecasting have been proposed. One option has emerged from the analysis of the derivations of the BSM-model.

Referring that the variance of the different μ_i defined as $\mu_{ln,i} = \frac{1}{\tau}\ln\left(\frac{x_{i+1}}{x_i}\right)$ results in an estimation of $\frac{\sigma^2}{\tau}$ [16]. Thus, defined that $var(\mu_i)$ is the variance of μ_i with $i = 1, .., t-1$, it thereby follows that:

$$\sigma_{ln,t-1}^2 = \tau\, var(\mu_{ln,i}) = \tau\, var(\mu_{ln,1}, \mu_{ln,2}, \ldots, \mu_{ln,t-1})$$

Formula 10: Estimation of volatility for $\mu_{ln,i}$

Similarly, when referring to the distribution of $\Delta S/S$, which results from the formula 6 and equals to $\frac{S_T - S_0}{S_0} \sim N(\mu\,T, \sigma^2 T)$, the volatility of $\mu_i = \frac{1}{\tau}\frac{x_{i+1} - x_i}{x_i}$ with $i = 1, \ldots, t-1$ equals:

$$\sigma_{\Delta,t-1}^2 = \tau\, var(\mu_{\Delta,i}) = \tau\, var(\mu_{\Delta,1}, \mu_{\Delta,2}, \ldots, \mu_{\Delta,t-1})$$

Formula 11: Estimation of volatility for μ_i

In order to identify σ^2, the options mention above can be combined with the direct and the step-by-step method for the evaluation of a future value.

It should be noted that for every observed value of the time series x_i, it is possible to determine a value of $\mu = \mu_{i-1}$ and, therefore, a value of $\sigma^2 = \sigma_{i-1}^2$. Consequently, a series of $\mu_1, \ldots, \mu_{t-1}$ and a series of $\sigma_1^2, \ldots, \sigma_{t-1}^2$ which are associated to a time series $x_1, \ldots, x_t$ can always be estimated.

Furthermore, a third way of defining σ^2 in forecasting expressions is also possible; it uses the available data of the time dynamic costs $x_1, \ldots, x_t$ for the determination of σ^2 and then regards it as a constant. With reference to formula 2 and 3, the notation used is $\sigma_{ln,0}^2$ and $\sigma_{\Delta,0}^2$.

Before proceeding with the definition of the ways to combine the BSM-method with the statistical tools, Figure 3 provides a graphical representation of each option which can be used for the adaptation of BSM to time series analysis and which has been proposed in this section.
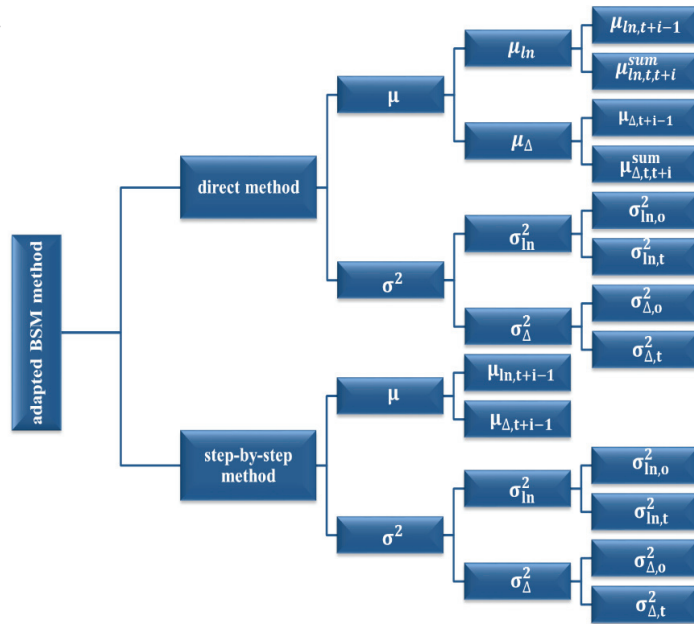

Fig. 3: Possible options for the adaptation of the BSM model

Options for the definition of the combined method

Having presented the possible ways for adapting the BSM-method, the next step of the research focuses on developing a combined method that is able to combine the Black-Scholes-Merton model with statistical tools.

The aim is to link the advantages of the former with the forecasting potentials of the latter in order to investigate whether a new forecasting technique can be defined. The research of the interfaces for the integration has been based on the analysis of the expected value μ and volatility σ^2 of the BSM-model and on the considerations which concerns the possible ways of adapting the BMS-method to the new application and which have been presented in the last sections. The two types of BSM forecasting expressions and the interval of time τ do not provide any opportunity to introduce the statistical tools as a support for predictions. Therefore, the combination with the statistical tools has been based on μ and σ^2. These two parameters have been defined with expressions based on the time series $x_1, \ldots, x_t$. Consequently, in order to develop the combined method, a statistical tool which allows the most suitable prediction of μ and σ^2 should be used and the predicted values should be integrated into the adapted forecasting expressions of the BSM-method. Independently from the specific expressions of μ and σ^2, two basic interfaces for the prediction of these two parameters have emerged:

- First interface: It uses the observed data $x_1, \ldots, x_t$ of time dynamic costs to calculate $\mu_1, \ldots, \mu_{t-1}$ based on the specific expressions presented in the section above. Following, it employs these values with the statistical tools to predict the future $\hat{\mu}_t, \ldots, \hat{\mu}_{t+i}$ and, finally, to calculate $\hat{\sigma}_t^2, \ldots, \hat{\sigma}_{t+i}^2$.

- Second interface: First, it uses the observed data $x_1, \ldots, x_t$ of the time dynamic costs within the statistical tools to forecast the future values $\hat{x}_{t+1}, \ldots, \hat{x}_{t+i}$; then, it uses these data to calculate the future series $\hat{\mu}_t, \ldots, \hat{\mu}_{t+i}$ and $\hat{\sigma}_t^2, \ldots, \hat{\sigma}_{t+i}^2$.

After $\hat{\mu}_t, \ldots, \hat{\mu}_{t+i}$ and $\hat{\sigma}_t^2, \ldots, \hat{\sigma}_{t+i}^2$ have been evaluated, it is possible to use these values for the calculation of all possible formulations of μ ($\mu_{ln,t+i-1}$, $\mu_{\Delta,t+i-1}$, $\mu_{ln,t,t+i}^{sum}$, $\mu_{\Delta,t,t+i}^{sum}$, $\mu_{ln,t,t+i}^{ext}$, $\mu_{\Delta,t,t+i}^{ext}$) and σ^2 ($\sigma_{ln,0}^2$, $\sigma_{\Delta,0}^2$, $\sigma_{ln,t}^2$, $\sigma_{\Delta,t}^2$), which can then serve as a basis for the application of the direct and the step-by-step methods (Fig. 3).

Next steps will be the analysis of the time dynamic cost factors regarding time dynamic characteristics, the assignment of the suitable statistic prediction methods to the dynamic costs and the execution of each of the mentioned options to determine the best fitting possibility of prediction.

Summary

Manufacturing enterprises are confronted with the challenge to integrate future cost developments, like costs for material and labour, into their current process of cost estimation to decrease the deviation between the pre- and post-calculation. This research focuses on a model to increase the reliability of future product cost estimation techniques. For this purpose, the accuracy concerning the estimations of time dynamic costs should be improved. In order to achieve this goal, this paper combines traditional statistical tools with the Black-Scholes-Merton model, a technique employed in finance to forecast stock market prices. Operatively, the development of this innovative approach has required a preliminary definition of any possible options which allow the BSM-model to be adapted to time series analysis as well as its combination with the statistic prediction tools.

Future steps include the definition of procedures which facilitate the selection of those options which offer higher performances. Additionally, time series based on real data are to be employed so that the proposed combined method can be empirically determined and validated.

The knowledge bundled generatively within the VFC provides an optimal basis for the integration of quantitative approach for prediction of future time dynamic cost factors. The integration of the innovative prediction model into the VFC will complete the research area and combine a rule-based cost estimation with a future oriented cost prediction.

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