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OPERATION EARNING POWER MODELLING OF THE MANUFACTURING PROCESS

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ABSTRACT

In order to better represent the specified goal of the manufacturing process we propose (as a novelty) as a criterion the Earning Power (EP). It is both synthetic (because it reflects the essential motivation of the manufacturing process) as compliant with the most important five performance aspects, namely: profitability, conformance to specifications, customer satisfaction, return on investment and materials/overhead cost, selected by researchers in order of importance. We present in this paper three modelling techniques for time and cost: analytic, neural network and k-Nearest Neighbor. Using the achieved models, EP is evaluated at the operation level of the manufacturing process.

KEYWORDS: operation of manufacturing process, control, earning power (EP), operation modelling

1. INTRODUCTION

From the analysis of appropriate literature we can provide the following observations:

- Generally, cost-estimating approaches can be broadly classified as qualitative estimation methods (intuitive or analogical methods) and quantitative estimation methods (parametric or analytical methods).

- Method implementation consists of either the application of an algorithm, or the developing of a knowledge-based estimation system.

- Algorithm or knowledge-based systems are designed so that the field in which they can be used for cost estimation is either a class of processes or a class of geometrical shapes of product, but never a workstation (or a group of workstations). It comes often in the situation to use several different models for calculating cost activity which a workstation makes on a semi-manufactured. Also frequently we can have the case when none of the models takes into consideration the specific behavior of that workstation. On the other hand, this field is extended to the level of processing operations of one part or of any stage of that operation, but never the entire batch processing. Therefore, the total manufacturing cost is estimated by adding the machining cost, material cost, set-up and changeover costs, calculated for one part.

- The data bases on which to build models or knowledge-based systems are collected from machining handbooks, from experts or from records about previously manufactured products. This last source contains only global data because, currently there is no concern to record specific data.

- Finally, after being built, models or knowledge-based systems are not updated, not even periodically. Therefore, evolution of workstations behavior is not considered and recent experience is not used.

2. Model variables

The criterion that we consider to be the most important in analyzing the MTO company ability to make a profit, that is, to be competitive on a market is the earning power, EP criterion. EP modelling is a solid strategy when selecting those orders that bring profit to companies. Thus, the company manager provides a model that can interact with the economic environment to make an offer and a price quotation so that the company is competitive.

We analyze this criterion for processing operation.

In the processing operation, EP control can be obtained by changing the cutting regime parameters, i.e. cutting depth, feed rate and cutting speed. The size of feed rate is used to control roughness. The cutting depth of size cannot be changed only if it makes multiple passes though the judicious addition of processing division. We'll consider that the processing addition must be removed in a single pass. In this situation, one cannot change the cutting depth, because its size is dictated by the size of process addition, which was established according to the method of obtaining the work piece. Following this reason, the only parameter that can control the workstation is the cutting speed v.

Therefore, operation modelling has as input: price, process parameters, part features, tooling, job features, workstation features and as output all service features: operation earning power (*EP*), operation cost (c) and operation processing time (t). The price for processing operation P is the model parameter.

Determining the function between features and operation parameters, job or order, is the operation model for job or order.

3. Modelling techniques

Modelling techniques used to evaluate earning power are: analytical technique, data mining technique and neural network technique.

1) The analytical technique

The analytical method consists in composing elementary models to achieve a complex mathematical model.

Taking the case of a cutting process for an order i with j jobs and k operations, we can define EP_{ijk} as:

$$EP_{ijk} = \frac{P_{ijk} - c_{ijk}(p_{jkn})}{A_{ijk} \cdot t_{ijk}(p_{jkn})} \qquad \left[\frac{Euro}{Euro \cdot \min}\right] \quad (1)$$

where: P_{ijk} is the minimum market price for operation k and for job j in order i [Euro];

The price for operation P_{ijk} can be calculated with the following relation:

$$P_{ijk} = (1+\alpha)\cdot c_{ijk} \quad (2)$$

where:

α – is the share of profit which we seek to obtain and is regulated during negotiations. α is constant for a certain order, for all operations and jobs which form the order;

$c_{ijk}(p_{jkn})$ expenses necessary to achieve job j depending on parameters n for operation i [Euro];

A_{ijk} – is the operation asset k from job j in order i [Euro];

$t_{ijk}(p_{jkn})$ – time for workstation's process when making the operation k from job j [min].

The analytical model of the operation cost can be expressed by (3):

where:

$$c_{ijk} = C_{am\,ijk} + C_{p\,ijk} + c \cdot S_{ijk} \cdot N_{ijk} \text{ [Euro]} \quad (3)$$

$C_{am\,ijk}$ - auxiliary labor costs to process operation k from job j (4):

$$C_{am\,ijk} = \frac{C_{m\,ijk} \cdot N_{ijk}}{4} \text{ [Euro]} \quad (4)$$

$C_{m\,ijk}$ - labor costs to process operation k from job j;

N_{ijk} - the number of pieces processed;

$C_{p\,ijk}$ - preparation costs for operation k from job j [Euro]

$$c = \frac{c_\tau}{10vs} + \frac{\tau_{sr}c_\tau + c_s}{10Tvs} + \frac{t \cdot c_{mat}}{10} + \frac{K_e c_e}{10000vs} + \frac{C_M}{10K_M} v^{\alpha-1}s^{\beta-1}t^{\gamma} \text{ [Euro/cm}^2\text{]}, \quad (5)$$

where:

c_τ - cost per minute when using the workplace;

τ_{sr}- time to change and sharpening tools [min];

c_s- tool cost between two successive re-sharpening processes;

c_{mat} – cost to remove one cm^3 of additional material;

c_e – cost of one KWh (electric power);

K_e- energy coefficient [Wh/min];

K_M – machine tool coefficient;

C_M – cost of machine tool [Euro];

v – cutting speed [m/min];

s – feed rate [mm/rot];

t – cutting depth [mm];

α, β, γ – coefficients;

T – tool durability,

S_{ij} – processed surface [cm^2]

For the same mechanical process, loading time model for a workstation to perform the operation k is:

$$t_{ijk} = t_{p\,ijk} + t_{a\,ijk} \cdot N_{ijk} + \tau \cdot S_{ijk} \cdot N_{ijk} \quad (6)$$

where:

t_{pijk} – time to prepare the operation k;

t_{aijk} –auxiliary time for the operation k, (7);

$$t_{a\,ijk} = 0{,}2 \cdot t_{u\,ijk} \quad (7)$$

t_{uijk} - unitary time to perform the operation k;

τ - specific period to remove one cm^2 of material.

$$\tau = \frac{T + \tau_{sr}}{10 \cdot T \cdot v \cdot s} \text{[min/cm}^2\text{]} \qquad (8)$$

2) Data mining technique

If we cannot determine analytical relations between the parameters of a manufacturing process but we have experimental database, we can use them to determine the mathematical models between parameters of a manufacturing process. One of the most important sources of knowledge acquisition is currently the company’s database. Using acquisition tools and knowledge from database systems became a necessity for all companies using large amounts of data, collected from various sources. These instruments are based on many methods, from methods of statistical interrogation and classical reporting to automatic learning methods.

In the form they are collected, the data have a low relevance. To use the data, they have to be prepared and processed by selection, projection, size reduction, pattern extraction (data mining) and models.

For presentation of this technique we’ll consider the case of a drilling operation performed by a specific workstation. All recorded data at this workstation during previous drilling operations make up a good experimental dataset. This experimental dataset is presented in Table 1.

The algorithm consists of the following steps:

-Step 1: variable clustering based on a causality relations;

- Step 2: status clustering;

- Step 3: building a mathematical model according to status clustering and variable clustering that were set.

Variable clustering

Variable clustering means grouping the dependent variables. This step means identifing groups of variables from which one is an output variable and the others are input variables. Variables of a cluster are selected from variables deriving from the dataset. Thus, the output variable must be associated with the closest variables causally related that form the input set.

Therefore, using the facility “best NN model”, offered by available commercial software, by consecutive selection of one column and determining the best links with 1,2, or i variables, we can determine the cluster of “i” variables in the best relation of dependency.

Status clustering

This clustering consists in identifying the related reports groups which can be starting points for further exploration of relationships. In the process of element grouping, we need to evaluate the minimum distance between these elements by euclidian distance.

Building a mathematical model according to status clustering and variable clustering that were set

We must write the linear mathematic model based on the variables in the table below:

$$vn=a_1\ v2+a_2\ v3+a_3\ v4+a_4\ v5+a_5\ v6+a_6 \qquad (10)$$

The linear model is determined by a local model because it is valid only in the vicinity of the status it is interrogated about and ephemeral because after interrogation it will be abandoned.

Table 1 - Example of experimental data regarding the process variables collected for the drilling process

Item nr.	Type of material	Hole diameter [mm]	Number of holes	Drilling speed [mm/s]	Drilling feed [mm/rot]	Number of pieces	Machining time [s]	Energy consumption [KWh/operation]	Cost of operation[Euro/ Operation]	Waste quantity [Kg]
	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10

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In this paper, we determine the operation cost and processing time mathematical models, which are used to determine the operation’s Earning Power (1).

The proposed method is highly effective because a mathematical model is built for each set of input data. Furthermore, upon examination of the practical solution resulted after negotiation with the customer, it will be added to the initial experimental data table, thus enriching the database with a new experience.

3) Neural network technique

The technique involves the following steps:

- Step 1: variable clustering is made just like for data mining using the facility “Best NN model”. “Best NN model” or the best provided by the neuronal network is the best way to determine the causality relation between variables so that we can determine the variable clustering. By means of neuronal network, the variables are compared one by one, resulting sets/clusters of variables in a causality relation. Procuring clusters is a computer application, training the network with all its database values and determining those variables that have causality relations.

- Step 2: with data from the dataset for cluster variables a neuronal network is trained. That trained network becomes the model we are looking for and when interrogation we can find our values of interest variable. In our case the variables of interest are the cost of operation and the processing time. Once determined, these two variables are introduced in relation to the operation Earning Power.

There are determinations in the literature regarding how to build a time estimator for layer manufactured objects using neural network technique [11].

In [11] most of the significant factors which affect build time are identified and then analyzed. They constitute the input factors of the neural network which is purposely trained beforehand to estimate build time. When using a typical parametric approach, some problems are found both in the identification of the parametric function and in the estimation of the coefficients of the formula. In a neural network-based approach, this task is performed at the training stage of the network, when the weight factors are determined.

4. CONCLUSION

In this paper there were presented different EP modelling methods: analytical, k-Nearest Neighbour regression and Neural Network technique.

We believe that industrial engineers need a fast, easy-to-use, and accurate method for EP assessment in order to have an optimal offer negotiation tool.

In this paper, cost and time have been estimated by techniques that are based on analytical modeling, neuronal modelling, or k-nearest neighbor regression. Each of these techniques covers a range of specific cases, namely: analytical technique covers process cases with all known regularities. The technique based on neuronal modelling covers cases when a large number of similar products are manufactured, in a slightly different. Moreover, k-NN regression technique covers cases when there is little data to produce a model (production is diverse and manufactured series are few).

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