Computer-aided cost estimation of manufacturing operations

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Abstract: Current methods for estimating the cost and time are based on decomposing the product into elements, followed by cost estimation of each element and summing of the other costs. As element, we can consider a product component, a manufacturing process component or an activity component. To estimate the cost for each element, its features that are closely related to cost or time are used. With few exceptions, the estimation methods lead to estimation without a mathematic model describing the relation between cost or time and the element’s features. Moreover, these methods have a slight adaptation capacity to different specific situations because the information that is provided in order to make estimations is general and does not adapt to a specific case. Therefore, in this paper, the cost and time will be estimated by a set of appropriate techniques which are based on, neural modeling and k-nearest neighbor regression. Each of these techniques cover a range of specific cases.

Key-Words: manufacturing system, neural network technique, k-nearest neighbor regression, cost estimation

1 Introduction

Garcia-Crespo et al [1] present the principal cost and price estimation methods, implemented in manner of both conventional and knowledge-based. This study is based on another review conducted by Niazi et al. [2], where proposals of other authors were added. The methods are grouped in two categories: intuitive, analogical, parametric, and analytic methods. Shehab and Abdalla [3] notice that little effort was made in cost-modeling at the early stage of the entire product development cycle, and most of the knowledge-based systems for product cost-modeling were mainframe based expensive, and required a long learning curve. Moreover, they lack the material selection capability, and some aspects of the product life cycle such as the assembly stage were not considered. To overcome this, they propose an intelligent knowledge-based system, which additionally provides an environment that assists inexperienced users in estimating the manufacturing cost. Starting from activity-based costing (ABC) approach, H’mida et al.[4] introduce the new concept of cost entity, defined as a cost aggregation associated with resources consumed by an activity. A group of researchers [5] developed a semi-analytical method. According to this method, in a first stage, the analogical approach is used to search for analogies between the shapes to be machined. Nagahanumaiah et al. [6] propose a cost model based on the notion of cost drivers and cost modifiers. According to this approach, the user must identify the different tooling parameters (parting surface complexity, surface finish, etc.) and to assess their impact by considering basic mold cost as a reference. Gara et al. [7] when referring to NC turning of complex profiles give an example of this. To reduce the complexity of analytical models of cost and time, authors propose a simpler method for determining the machined length, the average work piece diameter, and the optimum number of passes. Sanjay Sharma [8] notes that the change in value of production rate causes the change of production cost per unit. Thus, if the manufacturing rate is varied, then the cost will also change, because both the change of manufacturing time, and the cost per unit of time variation. Denkena et al. [9] present a quotation costing model, based on analytic cost functions combined with a rule-based approach. These functions are developed with the help of technical principles instead of using past data, while the experiences of the employees are expressed in rules. Similarly, Masel et al. [10] present a rule-based cost estimation system that can be applied...
during the preliminary design of a part. It provides an accurate estimation of the volume of an axisymmetric forging part based on its geometry. Li et al. [11] propose an analogy-based estimation system, which allows the system, once given a new project, to retrieve similar projects from its historical project database and to derive the cost prediction from the similar projects. The novelty is that an artificial neural network that nonlinearly adjusts the solution is used in order to refine the retrieved solution into the target solution. Mittas et al. [12] propose that the results of cost estimation application by analogy method should be improved by iterative application of bagging method. Caputo and Pelagagge [13] analyze cost estimation performance compared with parametric models and artificial neural networks, both built on the base of historical data. Reference has been made to the production of large-sized pressure vessels for the chemical process industry, aiming to consider a significant application context. Javier de Cos et al. [14] analyzed in a comparative manner the projection pursuit method, the local polynomial approach, and the adaptive neural networks method in terms of performance that can estimate the cost of production of some ring parts. Kutschenreiter-Praszkiewicz [15] presents an application of neural network for time per unit determination. Coelho et al. [16] proposes a method to reduce the difference between estimate and real time. The method considers a variable called machine response time, which characterizes the real CNC machine’s capacity to move in high feed rates. Di Angelo et al. [17] propose neural modeling for building time and its driving factors for estimating time to a group of rapid prototyping technology.

2.1 Cost and time estimation for drilling operation

We have got an experimental database we can build the mathematical models of the manufacturing process by applying the k-NN regression technique consisting in the following steps:

Step 1 - variable clustering;
Step 2 - states clustering;
Step 3 - Building a mathematical model for the domain limited by the states cluster and by the variable cluster.

Variable clustering means to group the dataset variables on the bases of theirs causal relations. From each cluster, one variable is the output and the others are the input. Variables of a cluster are selected from those deriving from dataset, by applying the facility named “the best NN model” offered by available commercial software.

States clustering means to group those previous states that have the lowest Euclidian common distances from the current state.

Building a mathematical model according to identified states and variable clusters means identification of that linear model, which best fits these clusters.

This is a local model because it is valid only near the current state. On the other hand, it is an ephemeral model because after interrogation it will be abandoned. For drilling operation, performed by a specific workstation, all recorded data at this workstation during previous operations make up a good experimental dataset. Each row contains the data corresponding to an operation, meaning the processing of one batch, and represents a particular state of the workstation. An excerpt is presented in Table 1.

The variable clustering is based on facility “best model” provided by the technique of neural networks applied on the experimental data set. Results obtained shown that, for drilling operation, both time and cost (variables v7 and v9) are dependent on the following variables:

\[ v7 = a_0 + a_1v2 + a_2v4 + a_5v5 \]
\[ v9 = b_0 + b_1v2 + b_2v3 + b_4v4 \]  

As consequence, earning power EP is depending on v2, v3, v4, v5. In this case study, the customer

2 Cost and time estimation

We consider the order consisting in manufacturing N samples of the product presented in Fig. 1.

![Fig. 1 Manufacturing part](image)

The order breakdown results are job 1 (rod 1, Fig. 1) and job 2 (plate 2, Fig. 1). Job 1 consists in a turning operation. Job 2 consists in two operations, namely drilling and welding. Turning operation was modeled in [18].

requirements were: $v_1=\text{OL 37}$; $v_2=21$; $v_3=6$; $v_6=82$. For states clustering, the lowest common distances against these requirements are given in Tab. 2. By taking the drilling speed (variable $v_4$ in the dataset) as control parameter, we present in graphical form the earning power (EP), [19] variation depending on the drilling speed, (Fig. 2). One can see that in case of drilling operation, the maximum $EP$ is obtained for the drilling speed of 227 rev/min.

### 2.2 Cost and time estimation for welding operation

In the case of welding operation, the neural network technique was applied. It consists in the following two steps. Variable clustering is the first step giving a cluster for each variable of interest. In our case, the variables of interest are the operation cost and the processing time. It is made just like for k-NN regression technique, by using the facility “Best NN model”. The second step consists in neural network
training for each variable cluster, by using data selected from the recorded dataset. That trained network becomes a model. From database of welding operation (Table 3), we consider the columns containing values of variable v11 - cost of welding operation and v9 - welding time. We searched for the best dependence relationships with the columns v3 – length of welding seam, v4 – number of passes, v6 – rate of welding and v8 – number of pieces. The result will be two clusters of variables, namely (v11, v3, v4, v6, v8) for cost modeling, and (v9, v3, v4, v6) for time modeling. Two neural networks were trained by using the data selected from the operation database. Knowing the cost, time, asset, and price, the earning power for welding operation was calculated. Fig. 3 shows these data in graphical form. One can see that, for a certain welding rate, the earning power is maximum.

Based on EP determined for each order we can accept or reject it. Therefore, there are going to be accepted only those orders that can bring significant profit and can increase the market share. This modeling can provide a better order management and increase the company’s competitiveness.

References

Table 3  Sequence from the table of welding operation variables

<table>
<thead>
<tr>
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<td>3</td>
<td>200</td>
<td>10.2</td>
<td>4.2</td>
<td>63</td>
<td>1375</td>
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<td>128.9</td>
<td>77.913</td>
<td>19.273</td>
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<td>197</td>
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<td>87.875</td>
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</tbody>
</table>

Fig. 3 The variation of the earning power depending on rate of welding

3. CONCLUSION
A customer order can include several jobs. By knowing the price, cost, asset and time values, we can build the order model.


