Int J Adv Manuf Technol (2013) 65:1439–1458
DOI 10.1007/s00170-012-4269-y

ORIGINAL ARTICLE

Method for control of the make-to-order manufacturing system on the base of earning power assessment

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Received: 22 November 2011 / Accepted: 28 May 2012 / Published online: 10 June 2012

Abstract A key requirement for the make-to-order (MTO) manufacturing companies to remain competitive is the ability to assess incoming orders in terms of performance and to determine the best orders that they should accept. In this paper, we propose a method to control the entire production process, from customer enquiry up to product delivery, for the MTO manufacturing systems. In practice, decisions on order acceptance and on production planning are often made separately. Sales department is responsible for accepting orders, while the production department is in charge of production planning for implementation of accepted orders. The method proposed in this paper aims to facilitate the connection between the two departments by an integrated control based on the earning power evaluation. The main problems for a MTO manufacturing system manager, i.e. those related to order acceptance and machine control, are solved by the new control method. The solutions are highlighted by presenting the conceptual flowchart of the proposed method, followed by a case study, where three time and cost modeling techniques—namely analytical, neural, and *k*-NN regression techniques—are applied. The models of earning power at operation, job, and order level are further built and analyzed. The results show that the method could lead to a significant increase of the manufacturing system performance.

Keywords Earning power · Manufacturing system control · Order acceptance · MTO manufacturing system · Process monitoring and control

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1 Introduction

Manufacturing companies differ in how they respond to customs demands. Some, called make-to-stock (MTS) companies, anticipate customer needs by producing series of standard products, and deliver the products when customer order occur. At these companies, all given products are usually used for general purpose, and therefore they do not cover the exact customer needs. The estimated delivery periods required by customers can be easily observed. On the other hand, as there is repetitive production, the products can be manufactured on manufacturing systems as single production line. Therefore, manufacturing systems (and even workstations forming these manufacturing systems) are product-dedicated. Changing a product that one MTS manufacturing system performs is time consuming. In addition, inventory costs are high.

Others, called make-to-order (MTO) companies, start the manufacturing process only after the order content was acknowledged and accepted. Compared to MTS companies, these have a better responsiveness, because they can deliver products more varied and even customized. As a result, customer's requirements are fully satisfied and inventory costs are low. However, these advantages can be realized only if the lead times can be reduced enough to respect the delivery period required by the customers. In addition, MTO manufacturing must be job shop and its workstations must be process dedicated.

That is why the problem of developing a system encompassing the advantages of these two kinds of company has occured.

A first approach of this problem is reported by Hemmati and Rabbani [1], who propose a hybrid MTS/MTO production system. In this case, a portion of the production system operates as MTS system and makes certain products, and the other operates as MTO system and makes other products. Moreover, some products will be firstly, partially manufactured in MTS mode, reaching the semi-finished product stage. In this state, the products are kept in stock until the arrival of customer order. Product manufacturing continues then in MTO mode, until its delivery. The point where there is a shift from a mode to another is called order penetration point in the production line. A proper combination of MTO and MTS can exploit the advantages of the lower inventory, short delivery time, and good responsiveness. The authors present a decision-making procedure to determine the appropriate position of the order penetration point for different products in a manufacturing system. In this way, we can use with a greater extension the advantages of both types of manufacturing systems. However, the disadvantages remain unchanged.

The second approach consists in solving the problem by improving one of the two kinds of company. Since the high inventory and low responsiveness of the MTS manufacturing system are hard to improve, most researchers propose improvement of MTO manufacturing system, by considering that it is easier to reduce its disadvantages.In this paper, the second approach will be considered.

Regardless of how researchers have approached this problem, they decomposed the production process in the following generic activities: (a) cost and time estimation, (b) price and due date quotation, (c) order acceptance and scheduling, (d) manufacturing process planning (where manufacturing operations are established, including workstation which will perform each of them), (e) production activities scheduling, and (f) performance measurement. Moreover, they have grouped these activities into two stages, namely order entry stage, which is followed or not by an order acceptance, and order fulfillment stage, ending with product delivery.

By analyzing the results reported in the literature, we obtained the following picture. Then, upon studying each activity, we proposed solutions for the improvement of MTO manufacturing system control, in order to increase its performance.

(a) Cost and time estimation

Garcia-Crespo et al. [2] 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. [3], where proposals of other authors were added. The methods are grouped in two categories: intuitive, analogical, parametric, and analytic methods.

Shehab and Abdalla [4] 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 additionaly provides an environment that assists inexperienced users in estimating the manufacturing cost. Starting from activity-based costing approach, H'mida et al.[5] introduce the new concept of cost entity, defined as a cost aggregation associated with resources consumed by an activity. A group of researchers [6–8] developed a semi-analytical method. According to this method, in the first stage, the analogical approach is used to search for analogies between the shapes to be machined. Nagahanumaiah et al. [9] 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. [10] 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 [11] 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. [12] 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. [13] 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. [14] 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. [15] propose that the results of cost estimation application by analogy method should be improved by iterative application of bagging method. Caputo and Pelagagge [16] 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. [17] 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 [18] presents an application of neural network for time per unit determination. Coelho et al. [19] 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. [20] propose neural modeling for building time and its driving factors for estimating time to a group of rapid prototyping technology.

(b) Price and due date quotation

Due date quotation is most often capacity driven and orientated towards the integration of the due date setting with the capacity planning. On the other hand, the analysis of the system workload is carried out at aggregate level from temporal viewpoint. An example is given by Corti et al. [21] who proposed a model aiming to support the decision makers when they have to verify the feasibility of the due date (DD) required by a potential customer.

Zorzini et al. [22] present an empirical analysis regarding the managerial practices regarding supporting capacity and delivery time management in the capital goods sector. The analysis is based on a sample of 15 Italian manufacturers. Its results show that some approaches on capacity and delivery time management seem to be more suitable to specific industrial contexts.

Charnsirisakskul et al. [23] present decision models, which integrate pricing and production decisions. They showed through numerical analyses that price and lead times flexibilities are, in general, complementary and that price flexibility is useful in all environments.

(c) Order acceptance and scheduling

Today, the procedure of responding to an enquiry is approached as a multistage-multicriteria decision-making process. The most common support for this process is to develop an appropriate decision support system (DSS). In this kind of decision-making structure, the initial decision is to determine whether to accept or not the order based on a prescreening process.

Gharehgozli et al. [24] present a comprehensive decision-making structure composed of two phases and dedicated to manage the incoming orders. The incoming orders are checked in the first phase for acceptance on the basis of their due dates. In this purpose, they apply the backward method proposed by Kingsman and Hendry [25] and calculate the completion date, the earliest release date, and the latest release date of the orders. In the second phase, the accepted orders are ranked according to a multiple criteria decision-making methodology, which combines two techniques, the analytical hierarchy process and the technique for order performance by similarity to ideal solution. The ranked orders are then finally accepted based on manufacturing system capacity. Xiong et al. [26] propose a DSS approach that helps SMEs to make appropriate responses to customer enquiries. There are three phases in the workflow for processing enquiries. Oduoza and Xiong [27] showed that none of the existing decision support systems had the capability to instantly relate customer enquiries, during the enquiry stage, with capacity, process capability, inventory, potential profit to be derived and material requirement planning. Ebadian et al. [28] propose a new comprehensive decision structure for the order entry stage in order to improve the production planning framework in MTO environments, by taking into account all affected parties of the supply chain: customers, the MTO company, suppliers and subcontractors. Ebben et al. [29] investigated the importance of the workload based order acceptance method in over-demanded job shop environments. Their approaches integrate order acceptance and resource capacity loading. Herbots et al. [30] investigate dynamic order acceptance and capacity planning under limited regular and non-regular resources aiming to maximize the profits of the accepted projects within a finite planning horizon. Ivanescu et al. [31] investigated the selectivity property of two acceptance policies. The first uses simulated annealing techniques and an empirically determined slack to estimate the realized makespan of an order set. The second uses regression techniques to estimate the realized makespan. Slotnick [32] present a literature overview on researches regarding order acceptance and scheduling. The author considers that taxonomy of research in order acceptance and scheduling includes single/multiple machines and deterministic/stochastic approach. The objectives are maximum profit, maximum thruput, maximum value of accepted orders, minimum cost, maximum percent of time utilization, and net present value.

(d) Manufacturing process planning

Many papers discuss the problem of integrated process planning and scheduling, defined as: giving the N jobs which have to be processed on M machines, by finding an operations–machines sequence and schedule for each job, which is optimal with respect to some criteria. The main approaches of this problem are agent and algorithm based. The goal is always the implementation of CAD/CAPP/CAM integration [33].

One example is provided by Lihong and Shengping [34] that propose an algorithm-based solution, consisting in (a) development of a representation of flexible process plans, (b) formulation of some objective functions to evaluate the performance of each plan, (c) formulation of specific restrictions, and (d) development of an improved genetic algorithm, to select de best plan. Approaching the same problem, Kafashi [35] developed another presentation of the process plan, whose setups (defined by machine, tool, and tool approach direction), operations, and operation sequencing are the process plans generators. Raman and Marefat [36] proposed an interesting idea regarding process plan representation. According to this idea, recognition of part features is based on those tool/process capabilities that stay at the base of each feature generation. Another interesting idea proposed by Chang and Chen [37] consists in the fact that process planning and scheduling take into account that with a job release, just a part of the floor is available. Sormaz and Khoshnevis [38] solve the problem of alternative process plans generation in the integrated manufacturing environment by selecting alternative machining processes, clustering and sequencing of machining processes, and generating a hierachical process plan network.

(e) Production activities scheduling

Authors of the papers [39, 40] studied single-machine scheduling problems with past-sequence-dependent setup times and time-dependent learning effect. They proved that the makespan minimization problem, the total completion time minimization problem, and the sum of the quadratic job completion time's minimization problem could be solved by the SPT (processing time first) rule. In paper [41] a single-machine scheduling problem with setup times and learning considerations is solved. The setup times are proportional to the length of the already scheduled jobs. The paper [42] is a review of scheduling research involving setup times or costs.

Scheduling problems with deteriorating jobs and learning effects including proportional setup times are studied in the paper [43]. The authors considered a new scheduling model in which job deterioration, learning, and past-sequence-dependent setup times exist simultaneously. The objective of the paper [44] is to find a schedule to minimize the total completion times. The authors developed a branch-and-bound algorithm for the optimal solution. Then they proposed a simulated annealing heuristic algorithm for a near-optimal solution.

The majority of the studied papers addressed sequence-independent setup times because dealing with sequence-dependent setup times is more difficult. The common solution methods are branch-and-bound algorithms, mathematical programming formulations, dynamic programming algorithms, heuristics, and meta-heuristics.

(f) Performance measurement

Frequently, the performance measurement systems of manufacturing companies are based on cost evaluation. In present manufacturing environment, these systems do not capture the relevant performances issues. Assessment results are used for monitoring, control, and improvement of manufacturing operations. So, many researchers suggested new performance measurement approaches in order to provide to managers and operators relevant information to support daily activities. However, there are few papers referring to measurement of manufacturing systems performance, most researchers being focused on financial and managerial accounting measures in order to determine organization performance.

For example, in [45] a new performance measurement model is proposed. It includes four indicators, each one with a given weight. Haskose et al. [46] take as consistent for make-to-order environment the following performance measures: work in progress, manufacturing lead time, and utilization of workstations. Lee et al. [47] studied the relationship between the managed earnings (defined as the illegal practice when a company projects a higher profit margin to attract investors) and firms earnings performance and proposes a new performance measure, namely earnings quality, defined as the proportion of true economic earnings in total reported earnings. Ratore et al. [48] take in consideration the total productivity as an important measure of performance.

In this paper, we propose a method to control the entire production process performed by a MTO manufacturing system, from customer enquiry up to product delivery. The following aspects could be highlighted regarding the proposed method.

Firstly, the control achieved by implementing the proposed method includes the modeling of cost and time, two very important elements of manufacturing process performance criteria.

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 analytical modeling, neural modeling, or *k*-nearest neighbor regression. Each of these techniques cover a range of specific cases. Thus the analytical technique covers the cases with known regularities. The technique based on neural modeling regards the cases when a large number of similar products are manufactured, slightly different. The *k*-NN regression technique is appliable in the cases when there is too little data to produce a model.

Secondly, the order acceptance problem is usually treated in literature by considering the single resource case with deterministic processing time. In addition, the acceptance is based on capacity-driven approach. This is why we cannot take into consideration that company performance is essentially dependent on the measure in which the accepted orders are appropriate to the characteristics of manufacturing system components. In accordance to the method proposed in this paper, the order acceptance is earning power-driven, while workload, due date, and price are considered as restrictions.

Thirdly, the machine control is conceived as independent to order features, such as the price of performed operation, for example. This is why, although the machine local control is optimal, the order performance level is not maximum. The method proposed in this paper removes this disadvantage in that the machine control is based on simultaneous optimization of all manufacturing processes performed for order fulfillment.

Finally, nowadays, the problems of (1) order acceptance, (2) planning and scheduling of the production process, and (3) machine control are solved separately. In this paper, we propose an integrated control method for all three aspects where earning power is used as decision criterion.

The paper is structured as it follows. Section 2 presents the conceptual flowchart of the proposed method. Section 3 presents a case study where three time and cost modeling techniques—namely analytical, neural, and *k*-NN regression techniques—are applied. The models of earning power at operation, job, and order level are further built and analyzed. In Section 4, the main conclusions of this paper are summarized.

2 Method proposed

2.1 Key ideas

This new method is based on the folowing key ideas:

- Manufacturing system control should be based on an integrated approach of (a) the two production process stages, namely order acceptance and order fullfilment; (b) all operations which should be executed in a given period, be they administrative, commercial, or manufacturing type; and (c) all resources of the manufacturing system, irrespective they consist in material or information processing.
- Tradeoff between cost and time should be obtained by using the earning power as assessment criterion in all the decision-making actions. This way, instead of several specific criteria, a unique, synthetic, and general criterion is used.
- The product–process assembly should be identified, using simple and efemeral type models instead of the general and perenial ones. On the other hand, all the data corresponding to the past operations, executed by the manufacturing systems workstations, should be recorded in a database. Using this database, the product-process assembly is online identified and the models obtained are applied for the current assessment of manufacturing operation.
- All the variables describing the proces and product should be considered as discrete so the modeling, planning, programming, and control actions might be reduced to solving a combinatorial optimization problem. The accuracy will be achieved by proper setting of the meshing step.

2.2 Manufacturing system

In order to implement the idea of integrated approach, the manufacturing system is here defined as all the resources that have been designed to fullfil the orders of a certain class. An order may consist in several jobs. A job may include operations of various kinds (manufacturing, commercial, or administrative, for example).

The basic cell of a manufacturing system is the resource. A resource can execute only operations of a particular type. The resource will be further generically called *workstation*, not only when executing manufacturing operations (machining, ansembling, etc.) but also when they perform administrative operations (such as monitoring, planning, and scheduling) or commmercial ones (supply, for example). In other words, this name will be used regardless of whether the cell is processing materials or information.

Currently, the manufacturing system workstations are used to perform those operations, which compose the order released manufacturing jobs, be they of manufacturing, commercial, or administrative type.

Figure 1 shows the MTO manufacturing system configuration. The ith order is released out from the order entry pool. This order consists in manufacturing jobs and non-manufacturing jobs. Manufacturing jobs are released in production from manufacturing jobs pool to several workstations.

Let us consider that ij job includes $ij1$, $ij2$, and $ij3$ operations. For $ij1$ operation, the ij job will wait for workstation *M2*. After processing it goes for $ij2$ operation on *M3* workstation. The $ij3$ operation performed on workstation A is an assembling operation of the ij, $i(j-1)$ manufactured parts and $i(j+1)$ non-manufactured part. The $i(j-1)$ job consists in $i(j-1)1$ operation performed on *M6* workstation. After processing, the part $i(j-1)$ will result. We supposed that the groups of non-manufacturing workstations includes a supply workstation for parts unsuitable to be processed, as an example, the $i(j+1)$ part.

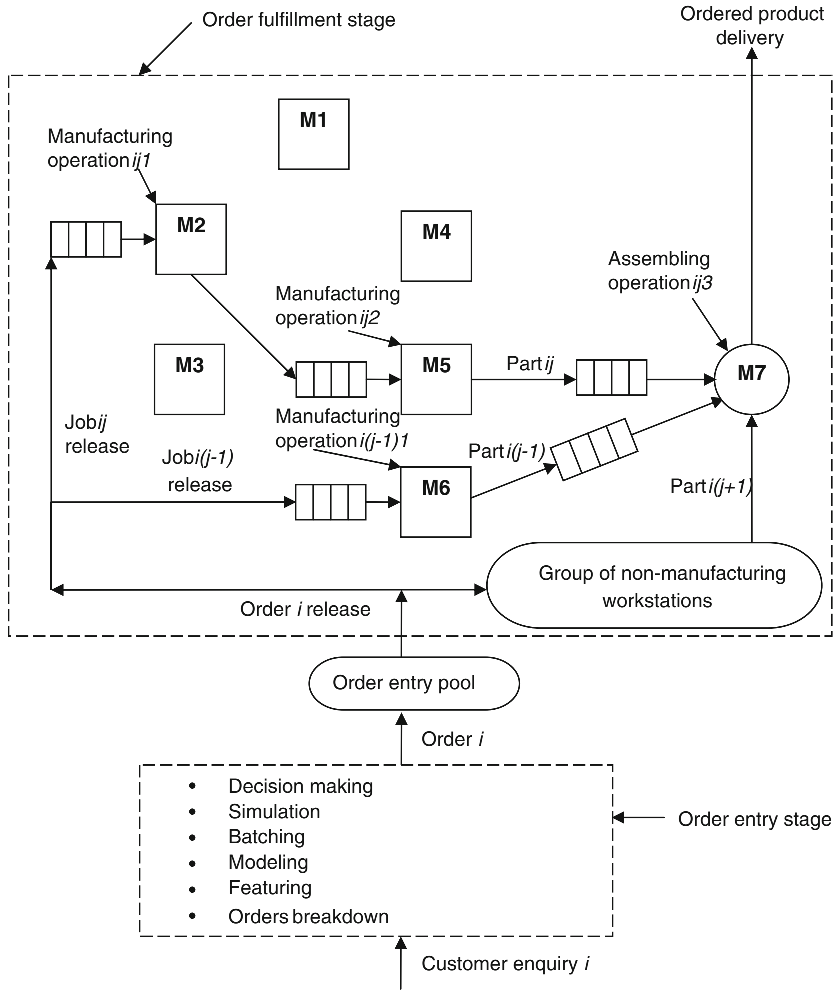


Fig. 1 Scheme of the manufacturing system

2.3 Earning power

As novelty, we propose the earning power (EP) as performance criteria for better representing the manufacturing system goal. It is both synthetic (because it reflects the essential motivation of manufacturing process) and compliant with the most important five performance aspects selected by researchers after their importance, namely profitability, conformance to specifications, customer satisfaction, return on investment, and materials/overhead cost.

By definition, earning power is the operating income divided by total assets. Operating income is the income resulting from a firm primary business operations, excluding extraordinary income and expenses. It gives a more accurate picture of firm profitability than the gross income.

By asset, we mean something that an entity has acquired or purchased, and has money value (its cost, book value, market value, or residual value). An asset can be (a) something physical, such as cash, machinery, inventory, land, and building; (b) an enforceable claim against others, such as accounts receivable; (c) a right, such as copyright, patent, trademark, or an assumption, such as goodwill.

For calculation of earning power, the cost, time, asset, and price must be estimated. Earning power is defined at operation, job, order, or manufacturing system level.

At *operation level,* earning power is defined by considering the operation as the processing of a batch of samples using one workstation from the manufacturing system. In case of the operation k belonging to job j of the order i, we will define earning power EP_{ijk} as follows:

$$\mathrm{EP}_{ijk} = \frac{P_{ijk} - c_{ijk}\left(p_{ijk}\right)}{A_{ijk} \cdot t_{ijk}\left(p_{ijk}\right)} \quad \left[\frac{\text{euros}}{\text{euros} \cdot \text{min}}\right] \tag{1}$$

where:

$c_{ijk}(p_{ijk})$ Expenses corresponding to operation k that belong to job j of the order i and which depend on parameters vector p_{ijk} [euros]

A_{ijk} The asset of that workstation which performs the operation k from job j in order i [euros]

$t_{ijk}(p_{ijk})$ The time for processing the batch of samples when the workstation performs the operation k from job j of order i [minute]

P_{ijk} The price for operation k that belongs to job j of order i [euros]

This price can be calculated with the following relation:

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

where:

α The share of profit, which we seek to obtain during negotiations. It is constant, for all operations and jobs, corresponding to a certain order

The price of order, P_i, is distributed on all jobs and operations that compose the order, according to the following relation:

$$P_i = \sum_j \sum_k P_{ijk} \tag{3}$$

At *job level,* the earning power is defined by taking into consideration the fact that a job consists in several operations. Knowing for each operation the price P_{ijk}, cost c_{ijk}, asset A_{ijk}, and time t_{ijk} , we can calculate the earning power at job ij level as follows:

$$\mathrm{EP}_{ij} = \frac{P_{ij} - \sum_k c_{ijk}\left(p_{ijk}\right)}{\sum_k A_{ijk}\cdot t_{ijk}\left(p_{ijk}\right)} \quad \left[\frac{\text{euros}}{\text{euros}\cdot\text{min}}\right] \tag{4}$$

At *order level,* the earning power is defined by considering that a customer's order can include several jobs. Knowing for each operation the price P_j (13), the cost c_{ijk}, the asset A_{ijk}, and time t_{ijk}, we can build the order model, as follows:

$$\mathrm{EP}_i = \frac{P_i - \sum_j \sum_k c_{ijk}\left(p_{ijk}\right)}{\sum_j \sum_k A_{ijk}\cdot t_{ijk}\left(p_{ijk}\right)} \quad \left[\frac{\text{euros}}{\text{euros}\cdot\text{min}}\right] \tag{5}$$

At *manufacturing system level*, the earning power is defined as follows:

$$\mathrm{EP}_{\text{system}} = \frac{\sum_{\text{performed operations}} \left(P_{ijk} - c_{ijk}\left(p_{ijk}\right)\right)}{A_{\text{system}}\times t_{\text{period}}} \quad \left[\frac{\text{euros}}{\text{euros}\cdot\text{min}}\right] \tag{6}$$

where A_{system} is the asset of the whole manufacturing system, while t_{period} is the time between two succesive planned moments for reactive scheduling (Fig. 4).

2.4 Method algorithm

The eight steps of the method algorithm, along with its linkage tree are shown in Fig. 2.

I. Breakdown of the current enquiry

In this first step, each enquiry is considered as a potential order, even if a decision regarding its acceptance was not taken yet. To take such a decision, this potential order is processed for enabling to generate its network routings.

Processing consists in identifying all the alternatives regarding order decomposition in jobs and operations. Each operation is defined so that it can be accomplished by using one of the manufacturing system resources. Definition includes the resource that will be used and the product status before and after the operation execution. The result is the routings network diagram of the order, associated with the definitions of all operations.

Figure 3 shows the routings network diagram of the order i, which consists in two jobs: job *i1* having three routings and job *i2* having two routings. The routings network diagram is associated with the definitions of all operations that appear in the five routings, namely 7 operations related to job $i1$ and 3 operations related to job $j2$.

II. Featuring the order routings network operations

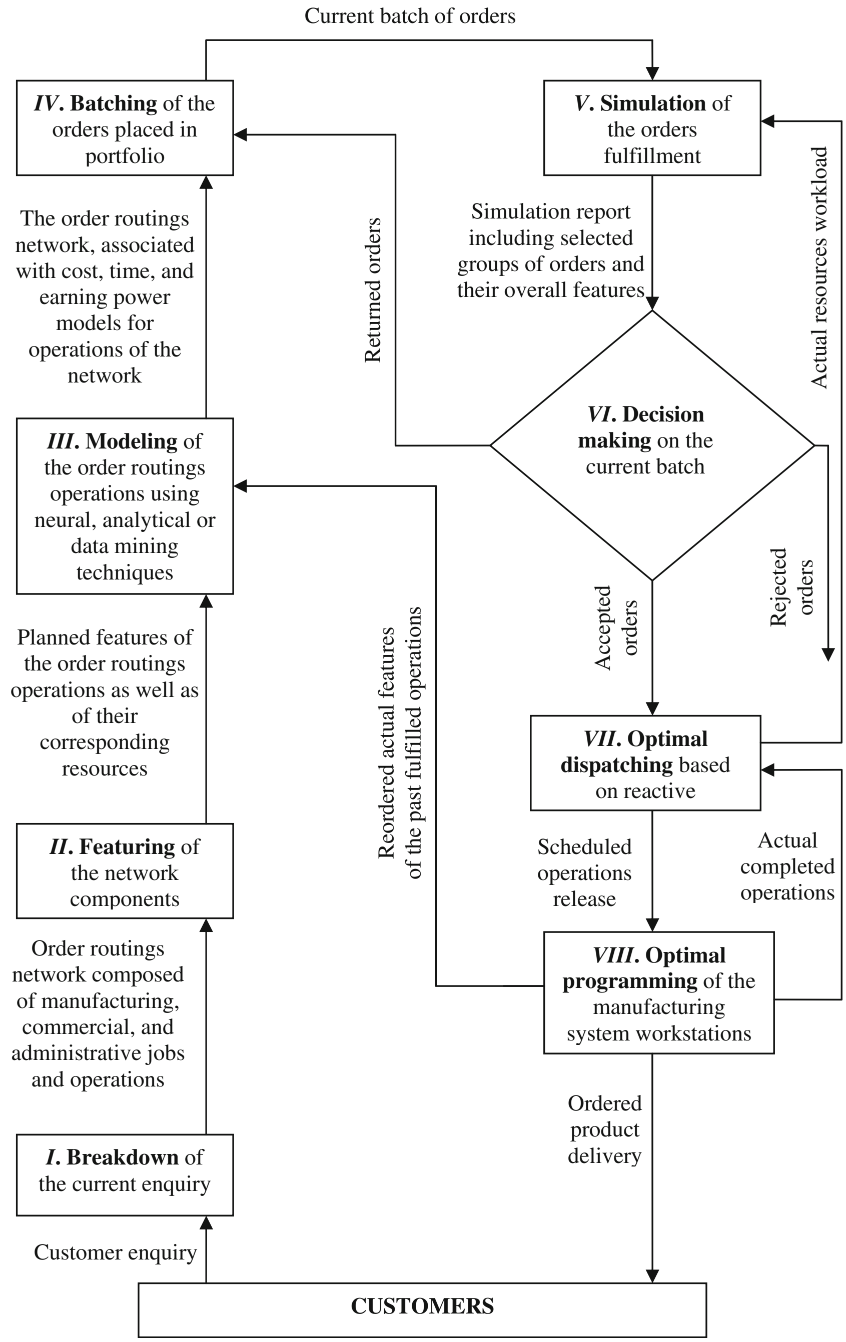
For every manufacturing system resource, a set of features was a priori and definitively established. These features represent the potential input variables of the model, which describes every operation that such a resource will perform. During this stage, for each operation that appears in the routings network diagram of the current order, the values of the corresponding set of features are established, based on the operation definition.

III. Modeling the network operations

This step consists in modeling the order routings operations, by using a proper technique (such as for example neural modeling). For every manufacturing system resource, one of these modeling techniques was a priori and definitively selected. Each operation is modeled by using the resource previous selected technique. As model output variables are considered the cost, the time, the earning power, and the asset (the same for all the operations) while the input variables are selected from the resource's set of features, in order to obtain the best operation model.

In addition, a resource-dedicated dataset containing the resource past experience is permanently updated by registering the actual data resulted after completion of the current performed operation. Depending on the modeling technique, some data are extracted from this dataset. Finally, the order routings network associated with the cost, time, earning

Fig. 2 Method flowchart



power, and asset models of all operations are obtained and placed in a portfolio.

IV. Batching the orders flow

For concurrent order processing, the orders existing in portfolio are grouped periodically, this way forming the current batch of orders. Only the enquiries found in the portfolio are considered for batching. They are either newcomers or returnees. Batching rule can be (1) first N_e enquiries, while the others are postponed, or (2) all enquiries found in portfolio. Period size is set according to orders flow and the due dates. Depending on company policy, the batching can take place either at certain dates or at regular intervals.

V. Orders fullfilment simulation

The current batch of orders is analyzed in order to divide the orders in three groups: accepted, rejected, and returned to portfolio. In this purpose, for each order, the earning power is firstly evaluated by using the operations models prepared at step III. The orders belonging to current batch are further ranked according to their earning power values.

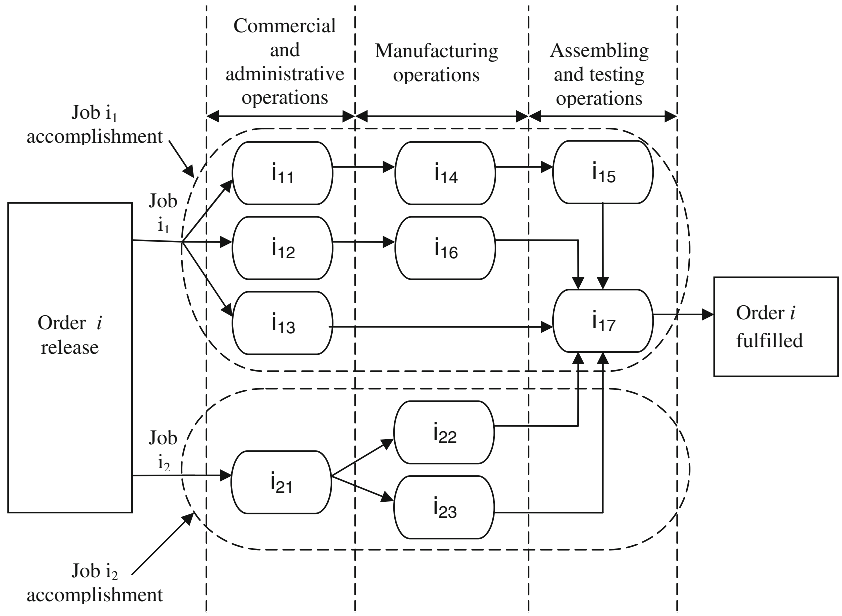


Fig. 3 Diagram of the order *i* routings network

Then, one or several order groups are prepared. Such a group order contains those orders, which could be accepted; the orders that are not included in the group will be either rejected or returned back to portfolio.

Orders grouping algorithm contains two generic actions, namely the group making up and the performance evaluation. For making up a group, successively, in decreasing order of the earning power value, the acceptance of each order is simulated, by taking into account the resources available workload and the due date of each included order. The performance criterion is the earning power, evaluated at the level of the entire manufacturing system and for the whole current period. Restrictions are the orders due dates.

The prepared orders groups (i.e., theirs content and performance) are finally transmitted to the management, for taking a decision at the next step.

Figures 4 and 5 show an example of the scheduling diagram before and after simulation. For before simulation case (Fig. 4), let us consider the moment when the precedent period is finished and a new batch of orders is coming for simulation. In progress there are the remaining two orders, namely order 1 with the four jobs 11, 12, 13, and 14 and due date DD1=21; and order 2 with the two jobs 21 and 22 and due date DD2=19. Workload of the six workstations, namely F, R, S, T, G, and A can be seen in the diagram.

On the other hand, the new batch of orders consists in accomplishment of four orders, namely orders 3, 4, 5, and 6, before the following due dates: DD3=29, DD4=22, DD5=28, and DD6=23.

Taking into account the order 3 routings network, it was established that the maximum earning power could be obtained when this order will consist in jobs 31, 32, and 33, which can be accomplished by completion of the operations shown in diagram. Similarly, the jobs and theirs operations, corresponding to the orders 4, 5, and 6 were established. The maximum values of the earning power (EP) for the four new orders (namely EP3=3.432, EP4=3.336, EP5=2.568, and EP6=2.542), as well as their ranking are shown in the diagram.

VI. Decision making on current batch

Two alternatives were highlighted as a result of the previous step. According to the first alternative, orders 3 and 5 are accepted, while orders 2 and 4 are rejected. According to the second alternative, order 3 is accepted, orders 2 and 4 are rejected, while order 5 is returned to portfolio (for being included in the next batch of orders). The first alternative has been adopted because, inter alia, the earning power evaluated at level of the entire manufacturing system and for the whole current period is higher (EP=2.952). Scheduling diagram, resulting from simulation of this alternative, is shown in Fig. 5.

VII. Optimal dispatching of the orders fulfillment

The pool of orders consists in the orders 1, 2, 3, and 5, as consequence of the previous step. Their operations should be fulfilled according to the scheduling diagram shown in Fig. 5.

If a deviation from this diagram appears, during actual production process, at a given moment, then a new scheduling diagram is elaborated. The start point is the state at the given moment while the scheduling technique is the same as in simulation. In this way, the optimal dispatching is implemented on the base of reactive scheduling.

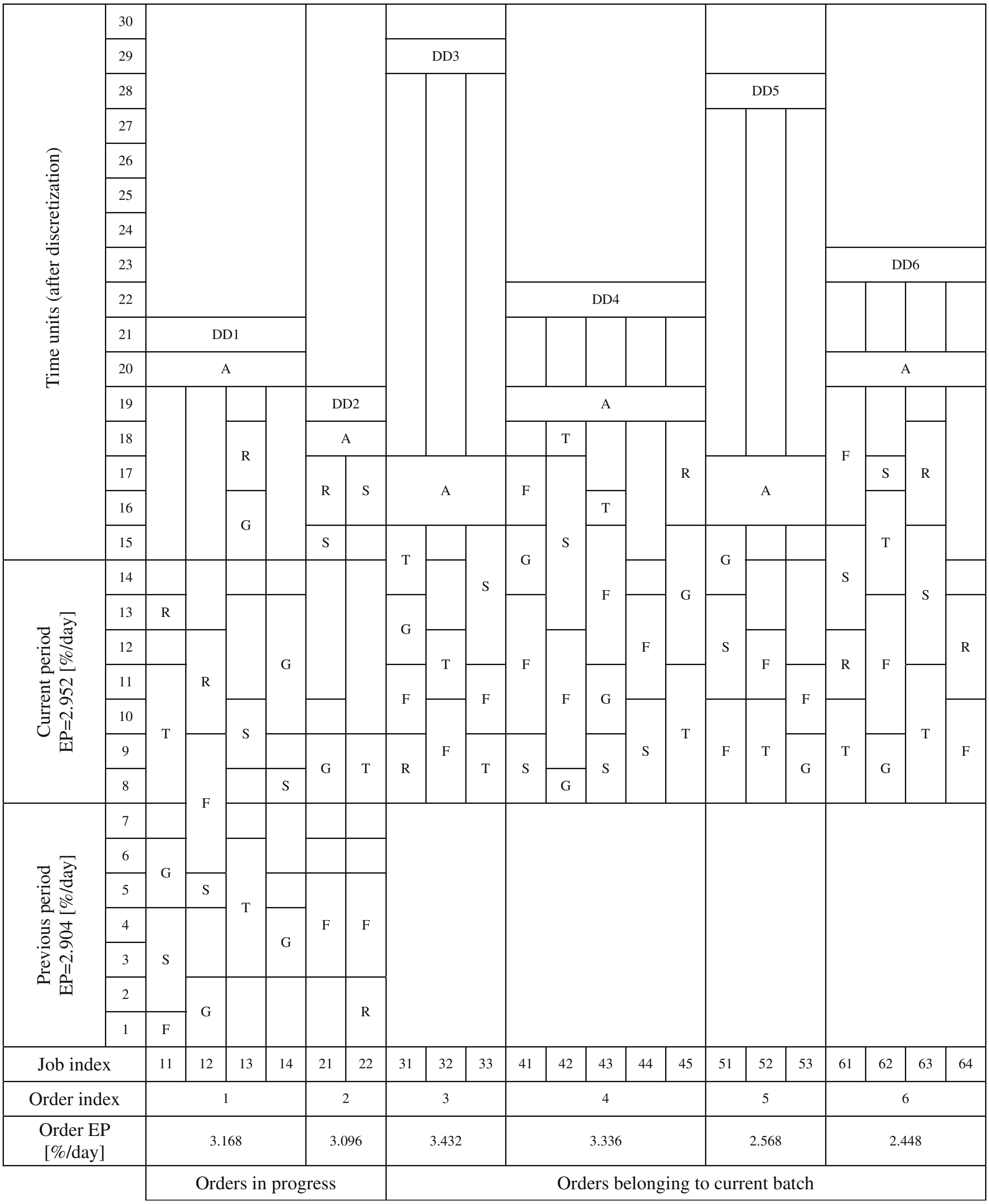


Fig. 4 Scheduling diagram—before simulation case. *F* milling, *R* grinding, *S* turning, *T* thermal treatment, *G* drilling, *A* assembling

VIII. Optimal programming of the manufacturing system's workstations

For many among system's workstations, the cost and time depend on the process intensity. The latter is set during the workstation programming. On the other hand, let us consider that the tradeoff between cost and time will result by considering EP as criterion for performance evaluation. Finally, we may observe that EP depends on the product price.

These aspects lead to the opportunity of EP maximization through such a workstation programming that would be adequate to level of the product price is. The action developed in this last step of the proposed method is to elaborate on these bases the workstation work program.

For example, let us consider the case of a workstation that performs a certain machining operation. The development of the part-program dedicated to this operation

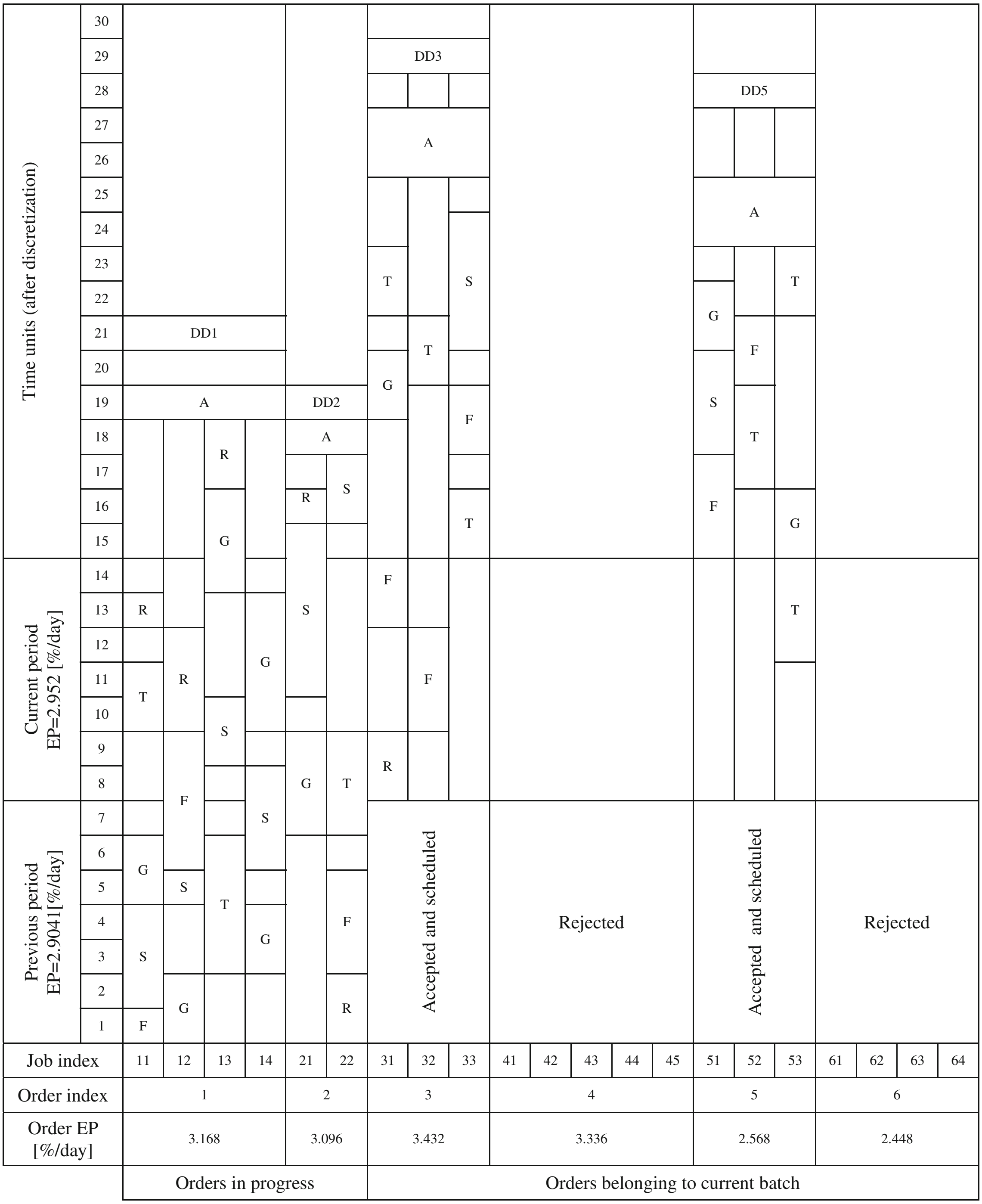


Fig. 5 Scheduling diagram—after simulation case. *F* milling, *R* grinding, *S* turning, *T* thermal treatment, *G* drilling, *A* assembling

includes determining those values of the cutting parameters that, taking into account the price of product, lead to maximum value for earning power.

2.5 Decisional support system of the new method

The four generic decision-making actions that make up the method decisional support system are the following: order routings networking, online modeling, reactive scheduling, and optimal programming of the manufacturing system resources.

Order routing networking is an action performed by specialists knowing the manufacturing system capabilities. Currently, there are no adequate solutions for performing this action automatically. However, the facilities offered by current CAPP systems can be considered as support.

Conversely, *online modeling* can be performed automatically if a software would implement the modeling algorithm. The algorithm should be specific to each resource. In addition, it should include the data obtained from monitoring and management of the resources operation.

Reactive scheduling is an action with a strong general nature. It appears in two of the eight steps of the method, namely steps VI and VII. In addition, this action appears many times. Therefore, despite it could be performed manually, when the number of operations is small, however, it is preferable to use an appropriate software.

Optimal programming of the manufacturing system resources is performed mainly when issuing the part-program for each operation. In particular, when a CAM system is used, the subroutine for calculating the cutting parameters can implement the algorithm of this action.

3 Case study and discussions

The case study objective was to exercise the main actions of the decision support system corresponding to the new method, namely *online modeling* and *optimal programming*. These two actions were approached at *operation*, *job*, and *order* level.

We consider the order consisting in manufacturing N samples of the product presented in Fig. 6.

The order breakdown results are job 1 (rod 1, Fig. 6) and job 2 (plate 2, Fig. 6). Job 1 consists in a turning operation. Job 2 consists in two operations, namely drilling and welding.

3.1 Operation level

(a) Turning operation

The analytical technique that consists in composing elementary analytical models to achieve a dedicated mathematical model was applied to model the turning operation.

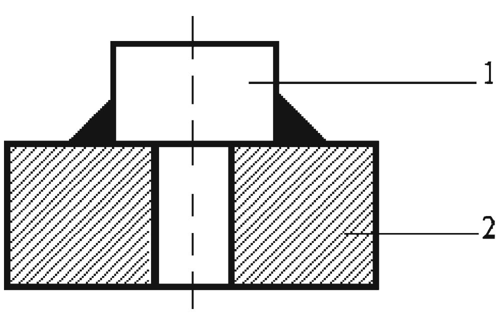


Fig. 6 Manufacturing part. *1* rod, *2* plate

If regarding to the cost, the analytical model of the turning operation is the following:

$$c_{ijk} = C_{am\,ijk} + C_{p\,ijk} + c \cdot S_{ijk} \cdot N_{ijk}\ [\text{euros}] \tag{7}$$

where:

C_{amijk} Auxiliary labor costs for process operation k from job j (4)

$$C_{am\,ijk} = \frac{C_{m\,ijk} \cdot N_{ijk}}{4}\ [\text{euros}] \tag{8}$$

C_{mijk} Labor costs for process operation k from job j
C_{mijk} 2.75 euros
N_{ijk} The number of processed samples (batch size)
C_{pijk} Preparation costs [euros]. C_{pijk}=2.7 euros

On the other hand,

$$c = \frac{c_\tau}{10vs} + \frac{\tau_{sr}c_\tau + c_s}{10Tvs} + \frac{d \cdot c_{mat}}{10} + \frac{K_e c_e}{10{,}000vs} + \frac{C_M}{10K_M} v^{\alpha-1} s^{\beta-1} d^{\gamma}\ [\text{euros/cm}^2] \tag{9}$$

where in the case of the turning operation:

c_τ The cost for 1 min of using the job place; c_τ=0.45 euro/min
τ_{sr} The time for worn tool changing [minute]; τ_{sr}=10 min
c_s The tool expenditure between two consecutive tool changes; c_s=20 euro
c_{mat} The cost of removing 1 cm^3 of detached material; c_{mat}=0.008/cm^3
c_e The cost for 1 kWh of electric power; c_e=0.23 euro/KWh
K_e The energy coefficient [watt-hour per minute]; K_e=15 Wh/min
K_M The machine tool coefficient; K_M=5.4 10^6
C_M The machine tool cost [euros]; C_M=100,000 euros
v The cutting speed [meters per minute]
s The feed rate [millimeters per revolution]; s=0.15 mm/rev
d The depth of cut [millimeters]; d=3 mm
α =β=γ=0.5
T The tool durability [minute]

$$T = \left[\frac{470}{v}\right]^{2.5}\ [\text{min}] \tag{10}$$

S_{ijk} The area of the processed surface [square centimeter]; S_{ijk}=281.34 cm^2

Table 1 The EP variation with cutting speed, *v*, and number of samples, *N*

Cutting speed [m/min]	Earning power [%/h]			
	N=2	N=5	N=10	N=50
10	−0.0064094	0.00514917	2.13E−02	0.03786275
20	−0.0022102	0.034395173	0.058611	0.084846858
30	−0.000766	0.045188262	0.072918	0.103554941
40	−0.0002898	0.049159054	0.078426	0.111060697
50	−0.0002994	0.049666294	0.079419	0.112742971
60	−0.0006035	0.048084724	0.077688	0.110900855
70	−0.0011076	0.04510273	0.074139	0.106716533
80	−0.0017582	0.041114966	0.069297	0.100879791
90	−0.0025219	0.036371053	0.063496	0.093831976
100	−0.0033759	0.031041101	0.056962	0.08587579
110	−0.0043037	0.025247933	0.04986	0.077230167
120	−0.0052929	0.019084342	0.042314	0.068060043
130	−0.0063338	0.012622973	0.034422	0.058493614
140	−0.0074185	0.005922319	0.026261	0.04863292

The loading time t_{ijk} for a workstation performing operation k of job j of order i is:

$$t_{ijk} = t_{p\,ijk} + t_{a\,ijk} \cdot N_{ijk} + \tau \cdot S_{ijk} \cdot N_{ijk}\,[\mathrm{min}] \tag{11}$$

where:

t_{pijk} Means the time to prepare the operation; t_{pijk}=60 min

t_{aikj} The operation auxiliary time; t_{aikj}=4.4 min

$$t_{a\,ijk} = 0,2 \cdot t_{u\,ijk}\,[\mathrm{min}] \tag{12}$$

t_{uijk} The unitary time to perform the operation

t_{uijk} 22 min

For time calculation, the analytical model of turning operation is

$$\tau = \frac{T + \tau_{sr}}{10 \cdot T \cdot v \cdot s}\,[\mathrm{min/cm^2}] \tag{13}$$

where:

τ The specific time necessary to remove 1 cm^2 of material

We can observe that the cost c_{ijk}, and time t_{ijk} are dependent on several variables, namely c_τ, τ_{sr}, c_s, c_{mat}, c_e, K_e, K_{M}, C_{M}, v, s, t, α, β, and γ.

Some of these variables depend on the workstation (K_{M} and C_{M}), others on the tool (τ_{sr} and c_s), or on the process (v, s, d).

To study the optimal programming of the turning operation, we will take into consideration two categories of model

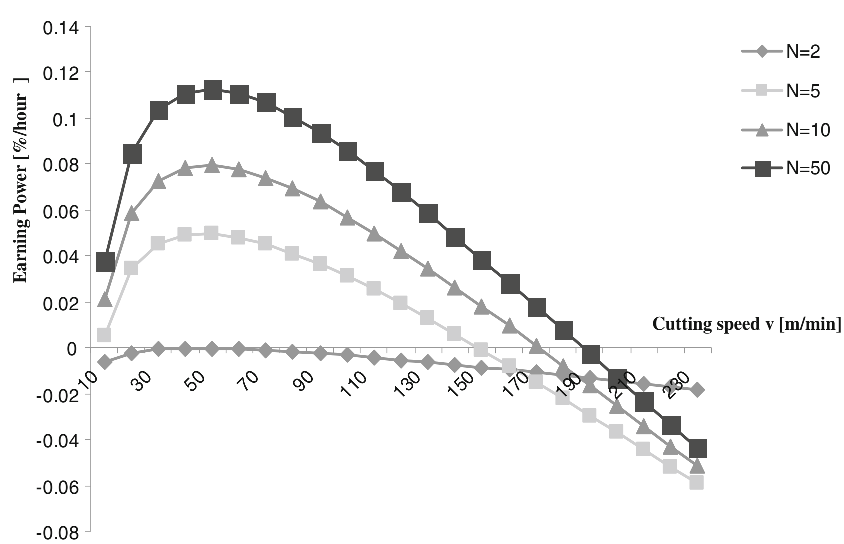


Fig. 7 The variation of the earning power with cutting speed and the batch size

Table 2 Excerpt from the drilling workstation dataset

State number	Material type v1	Hole diameter [mm] v2	Number of holes v3	Drilling speed [mm/s] v4	Drilling feed[mm/s] v5	Number of pieces v6	Drilling time [s] v7	Energy consumption [kW/h] v8	Operation cost [euros] v9	Waste quantity [Kg] v10
6	OL 37	17.55	8	3.2	0.75	77	2,459	13.17	158.10	75.89
14	OL 37	28.6	6	3.2	0.45	65	2,410	29.53	265.8	127.60
31	OL 37	32.6	7	5.1	0.2	70	4,011	41.32	433.9	208.30
38	OL 37	22.5	8	4.15	0.45	73	11,243	20.53	246.3	118.26
47	OL 37	20.5	7	6.2	0.65	68	2,983	15.87	166.6	80.01
60	OL 37	22.55	9	6.25	0.42	132	2,459	37.29	503.9	241.64
73	OL 37	29.5	13	6.1	0.67	77	3,998	37.22	725.9	348.44
83	OL 37	21.55	10	2.2	0.5	73	10,256	18.83	282.5	135.60
92	OL 37	18.6	13	5.05	0.9	43	8,201	8.26	161.1	77.35

variables: (1) variables that remain unchanged during this study, and (2) the rest of variables (namely cutting speed *v* and number of samples *N*), which will change during this study. By these variables changing, we can study the process, because they can influence the value of EP so that it becomes maximal.

The results presented in Table 1 and Fig. 7 show that EP reach a maximum value for a specific optimal value of the cutting speed. As example, if $N=2$, the maximum value of EP is 0.0002898 %/h for $v=40$m/min; if $N=5$, the maximum value of EP is 0.0496663 %/h, for $v=50$m/min; if $N=10$, the maximum value of EP is 0.079419 %/h for $v=50$ m/min; and, finally, if $N=50$, the maximum value of EP is 0.112742971 %/h for $v=50$ m/min.

(b) Drilling operation

Because, in this case, an experimental database is available, 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

Table 3 States that have the lowest common distances

v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	Common distance
OL 37	17.55	8	3.20	0.75	77	2,459	13.176	6,324.318	75.892	9.434
OL 37	29.50	13	6.10	0.67	77	3,998	37.227	29,037.342	348.448	9.950
OL 37	21.55	10	2.20	0.50	73	10,256	18.834	11,300.461	135.605	11
OL 37	20.50	9	5.20	0.65	73	10,976	17.043	9,203.475	110.442	11.091
OL 37	22.50	8	4.15	0.45	73	11,243	20.531	9,854.999	118.260	11.358
OL 37	16.55	8	4.15	0.19	73	6,856	11.108	5,331.969	63.983	11.358
OL 37	29.50	4	2.20	0.55	77	4,645	37.227	8,934.567	107.215	12.369
OL 37	35.50	12	3.20	0.67	70	5,432	49.010	35,286.999	423.444	13.416
OL 37	24.50	7	4.20	0.50	90	5,432	30.012	12,605.250	151.263	13.784
OL 37	32.60	7	5.10	0.20	70	4,011	41.329	17,358.314	208.301	13.784
OL 37	16.55	10	3.20	0.40	92	9,245	13.999	8,399.677	100.796	14.697
OL 37	20.50	7	6.20	0.65	68	2,983	15.876	6,667.967	80.016	15.297
OL 37	28.60	6	3.20	0.45	65	2,410	29.537	10,633.480	127.602	18.138
OL 37	8.55	4	4.15	0.67	94	6,066	3.817	916.218	10.994	18.439
OL 37	28.60	5	2.05	0.20	63	2,459	28.628	8,588.580	103.063	20.273
OL 37	16.55	4	5.20	0.28	63	4,011	9.586	2,300.781	27.609	20.809
OL 37	10.60	5	6.20	0.95	55	3,404	3.433	1,029.967	12.359	27.331

Table 4 Earning power values for several values of drilling speed

Drilling speed [rpm]	Earning power [%/h]
100	0.15414
180	0.193682
227	0.207301
273	0.206644
318	0.182055
364	0.120791
410	0.009412

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 2.

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:

$$\begin{aligned} v7 &= a_0 + a_1 v2 + a_2 v4 + a_3 v5 \\ v9 &= b_0 + b_1 v2 + b_2 v3 + b_3 v4 \end{aligned} \tag{14}$$

As consequence, earning power EP is depending on $v2$, $v3$, $v4$, and $v5$.

In this case study, the customer requirements were: $v1$=OL 37, $v2$=21, $v3$=6, and $v6$=82. For states clustering, the lowest common distances against these requirements are given in Table 3.

By taking the drilling speed (variable $v4$ in the dataset) as control parameter, we present in graphical form the earning power variation depending on the drilling speed, drawn on the base of data from Table 4 (Fig. 8).

One can see that in case of drilling operation, the maximum EP is obtained for the drilling speed of 227 rpm.

(c) 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 5), 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.

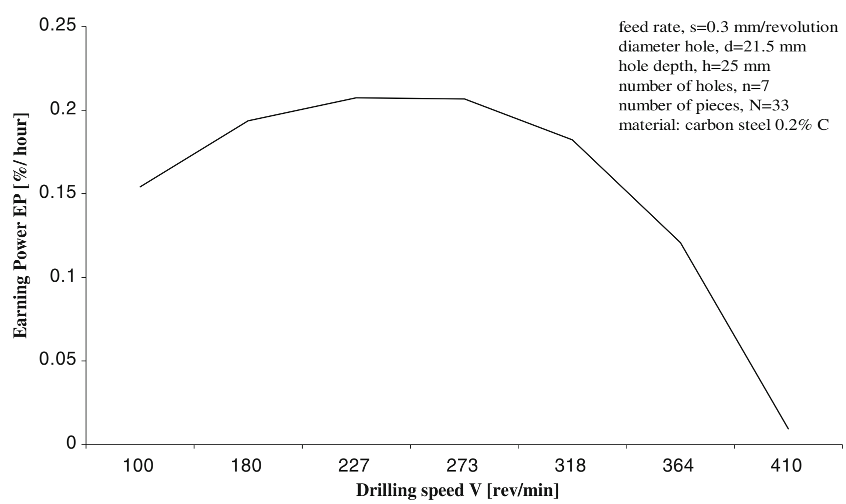


Fig. 8 Variation of the earning power with drilling speed

Table 5 Sequence from the table of welding operation variables

Item number	Material type	Welding type	Length of welding seam [mm]	Number of passes	Current intensity [A]	Rate of welding [mm/s]	Quantity of welded wire [m]	Number of pieces	Welding time [s]	Energy consumption [KW/h]	Operation cost [euros]	Waste quantity [kg]
	$v1$	$v2$	$v3$	$v4$	$v5$	$v6$	$v7$	$v8$	$v9$	$v10$	$v11$	$v12$
1	OL 52	Corner	501	3	200	10.2	4.2	63	1,375	10.521	78.9	15.781
21	OL 37	Corner	503.5	9	204	5.1	4.85	103	6,758	52.898	388.9	77.791
40	OL 52	Corner	490	4	197	8.2	4.60	59	11,243	12.656	96.3	19.273
52	OL 42	Corner	515	10	188	9.2	5.20	52	2,459	27.970	223.1	44.633
64	OL 52	Corner	521	11	191	8.15	4.1	92	6,066	55.947	439.3	87.875

The result will be two clusters of variables, namely ($v11$, $v3$, $v4$, $v6$, and $v8$) for cost modeling, and ($v9$, $v3$, $v4$, and $v6$) 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. If adopting the rate of welding as parameter, the values from Table 6 result. Fig. 9 shows these data in graphical form.

One can see that for a certain welding rate, the earning power is maximum.

3.2 Job level

By considering the fact that a job consists in several operations and by knowing the price P_{ijk}, cost c_{ijk}, asset A_{ijk}, and time t_{ijk} for each operation we can build the job model.

For job 1 containing a single operation, EP job is just the EP for turning operation (Table 1).

For job 2 containing welding and drilling operations, EP is calculated according to the following formula:

$$EP_{i2} = \frac{(P_{i21} + P_{i22}) - (c_{i21} + c_{i22})}{A_{i21} \cdot t_{i21} + A_{i22} \cdot t_{i22}} \quad \left[\frac{\text{euros}}{\text{euros} \cdot \text{min}}\right] \tag{15}$$

where: P_{i21}, c_{i21}, A_{i21}, t_{i21}, P_{i22}, c_{i22}, A_{i22}, and t_{i22}, are provided in Tables 7 and 8.

By numerical simulation for the cases of 11 drilling speed values and 13 rate of welding values, the EP for job 2 we got 143 cases. The maximum value for EP was obtained in the case of the optimal drilling speed, v=200 rpm and of the optimal rate of welding v=5.2 mm/s. The maximum value for EP is $1.12 \cdot 10^{-7} \left[\frac{\text{euros}}{\text{euros} \cdot \text{min}}\right]$.

Evaluation of the job EP is an effective tool for taking decisions about accepting or outsourcing the job. The company will keep only those jobs that bring favorable EP, the other ones being given to others for execution. Thus, the manager can easily select the most favorable jobs for its company.

Table 6 EP values for different rate of welding

Rate of welding [mm/s]	Earning power [%/h]
2.2	0.005206
3.2	0.028903
4.2	0.038126
5.2	0.039392
6.2	0.036163
7.2	0.030261
8.2	0.022651
9.2	0.013768
10.2	0.003928
11.2	−0.00673
12.2	−0.01816

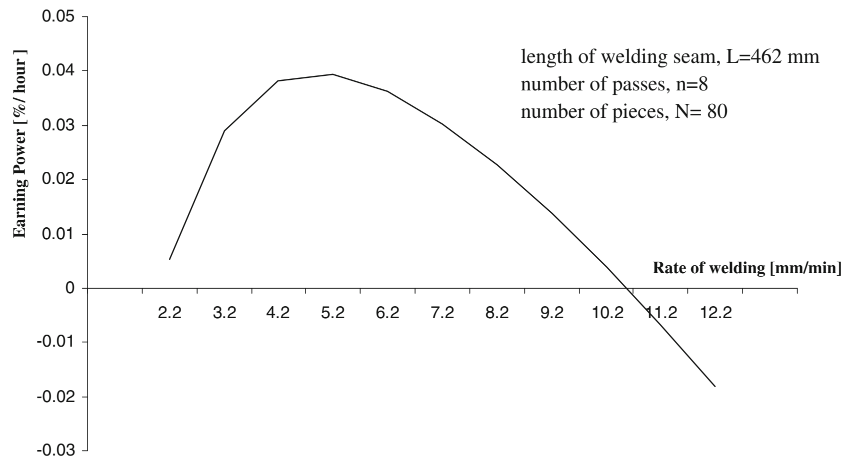


Fig. 9 The variation of the earning power depending on rate of welding

3.3 Order level

A customer order can include several jobs.

By knowing the price P_j , cost c_{ijk}, asset A_{ijk}, and time t_{ijk} values, we can build the order model.

Based on EP$_i$ 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.

The relationship (5) will be used aiming to evaluate the order EP and if this is adapted to order i it becomes:

$$\mathrm{EP}_i = \frac{P_i - \sum_j \sum_k c_{ijk}\left(p_{jkn}\right)}{\sum_j \sum_k A_{ijk} \times t_{ijk}\left(p_{jkn}\right)} = \frac{(P_{i11} + P_{i21} + P_{i22}) - (c_{i11} + c_{i21} + c_{i22})}{A_{i11} \times t_{i11} + A_{i21} \times t_{i21} + A_{i22} \times t_{i22}} \quad \left[\frac{\text{euros}}{\text{euros} \cdot \text{min}}\right] \tag{16}$$

where P_{i11} is the turning operation price, c_{i11} is the turning operation cost, A_{i11} is the turning operation asset, and t_{i11} is the time needed to perform the turning operation.

By numerical simulation in the cases of 14 cutting speed values, 11 drilling speed values, and 13 rate of welding values, 2,002 EP values resulted. The maximum value for EP was obtained for the turning speed v=50 m/min, the drilling speed, v=200 rpm and the welding speed, v=*5.2* mm/s. The maximum value for EP is $7.25 \times 10^{-8}\ \left[\frac{\text{euros}}{\text{euros}\cdot\text{min}}\right]$.

We can also calculate the EP for the other orders in the order entry pool in a similar manner. In the end, all EP values of all orders must be ordered in a decreasing sequence. The

Table 7 Data for welding EP evaluation

Rate of welding [mm/s]	Welding cost, c_{i21} [euros]	Welding time, t_{i21} [s]	Welding price, P_{i21} [euros]	Welding asset, A_{i21} [euros]
1.2	207.025	257,978	150	1,875
2.2	143.075	255,409	150	1,875
3.2	111.95	252,761	150	1,875
4.2	100.35	250,036	150	1,875
5.2	99.275	247,236	150	1,875
6.2	103.975	244,363	150	1,875
7.2	111.95	241,418	150	1,875
8.2	121.875	238,405	150	1,875
9.2	133.125	235,325	150	1,875
10.2	145.25	232,182	150	1,875
11.2	158.025	228,979	150	1,875
12.2	171.35	225,718	150	1,875
13.2	185.05	222,404	150	1,875

Table 8 Data for drilling EP evaluation

Drilling speed [rpm]	Drilling cost, c_{i22} [euros]	Drilling time, t_{i22} [s]	Drilling price, P_{i22} [euros]	Drilling asset, A_{i22} [euros]
110	6.575	6,703	13.75	2,500
200	6.725	5,223	13.75	2,500
250	7.125	4,602	13.75	2,500
300	7.875	4,094	13.75	2,500
350	9.1	3,678	13.75	2,500
400	10.95	3,338	13.75	2,500
450	13.55	3,060	13.75	2,500
500	16.975	2,833	13.75	2,500
550	21.175	2,648	13.75	2,500
600	25.775	2,497	13.75	2,500
625	28.125	2,432	13.75	2,500

orders with a maximum calculated EP that brings economical effect to the company should be kept. It results that the manager will have an overview of the order EP to make a decision on the order acceptance. The order acceptance will be decided after an evaluation of maximal EP values and after selecting only those orders that may bring profit to the company.

By analyzing data from Table 9, the manager can decide whether to perform all jobs necessary to achieve order in the company or not, according to the maximum value of EP. If obtaining a value unsatisfactory of EP for the company, the manager may choose to outsource those operations. Thus, if the company would run only drilling and outsource the other two operations, then it would be observed that this case is the most profitable (EP=$57.5\cdot10^{-8}$ euros/euros·min). If they would perform only the welding operation then the worst EP (EP=$6.09\cdot10^{-8}$ euros/euros·min) will be get.

4 Conclusions

This paper targets to develop a method for control of the MTO manufacturing systems in accordance to the present market dynamics. In order to survive in a complex and unpredictable environment, MTO manufacturing system must be able to react rapidly in terms of favorable market position. Acquiring and maintaining this capacity is the most difficult because it involves many endogenous and exogenous factors and the process is continuous, dynamic, and difficult to predict.

Manufacturing system performance depends on how it is working. In several specialized papers, the reference is made to the relationships between processing parameters and technical performance of the manufacturing system (i.e., purely technical aspects), while in others, as many are referred to the relationship between product made by the system manufacturing and market (i.e., economical relations) and requiring an intervention in the manufacturing system to achieve favorable economic effects. There were not reported in the literature any attempts to address the whole manufacturing-market system. As result, there are significant resources for performance improvement that are not used, because of addressing to the technical and to the economical aspect separately.

The proposed method is based on using the earning power as evaluation criterion for orders accepting or rejection. Thus, there are accepted those orders whose EP, evaluated at manufacturing system level, have the maximum value. As regards the order jobs, a job selection takes place, meaning that those jobs with a favorable economical effect are kept and the others

Table 9 Order EP maximum

Order price [euros]	Order operation			Order EP maximum [euros/euros·min]
	Turning	Drilling	Welding	
150	x	x	x	$7.256\cdot10^{-8}$
136.25	x		x	$6.11\cdot10^{-8}$
22.5	x	x		$14\cdot10^{-8}$
141.25		x	x	$7.4\cdot10^{-8}$
127.5			x	$6.09\cdot10^{-8}$
8.75	x			$6.26\cdot10^{-8}$
13.75		x		$57.5\cdot10^{-8}$

are outsourced to other companies. For an operation, the optimal process parameters will be selected so that the maximum value of EP will be obtained. Thus, the manufacturing process will be optimally programmed.

The results of numerical simulations for the method proposed in this paper proved the importance of order analyzing by EP criterion.

The method efficiency was assessed by a case study. Following order breakdown, the three operations comprising the order were modeled by means of different techniques: turning, by analytical method; drilling, by *k*-NN regression technique; and welding, by neural network technique. The value of the maximal EP was determined, the optimal values of the process parameters resulting then. Thus, for turning operation EP decreases by 34 %, for a number of 5 pieces, if v=100 m/min in the case when $v=v_{\mathrm{optimal}}$=50 m/min.

In the case of the drilling operation, when the speed is v=100 rpm, EP decreases by 30 % compared to the case when the optimal work speed is v=227 rpm.

In the case of the welding operation, if the process is performed with the speed v=2.2 mm/s then the value of EP will decrease 78 times relative to the case when $v=v_{\mathrm{optimal}}$= 5.2 mm/s. It follows that for an operation, the optimal operation control can be made by knowing the maximal EP.

The manager can decide whether to perform all operations to accomplish the job within the company or not, depending on the maximum value of the order EP. The manager can choose to outsource those operations that EP does not have a positive effect. Order acceptance will be made only after evaluating the maximal values of EP and selecting those orders that could be positive for the company.

For the simulated order, if the company would perform only the drilling operation and would outsource the other two operations, the effect on the company will be a positive one (EP= $57.5\cdot 10^{-8}$ euros/euros·min). If the company would perform only the welding operation, then it will get the worst EP (EP= $6.09\cdot 10^{-8}$ euros/euros·min). Therefore, the manager will have an overview on the order EP in order to perform the order acceptance.

On one hand, this analysis will help the manager of a MTO company to accept or not an order and, on the other hand, it will enable to perform an optimal control of the manufacturing system.

Acknowledgment The authors gratefully acknowledge the financial support of the Romanian Ministry of Education, Research, Youth and Sports through grant PN-II-ID-795/2008.

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