DYNAMIC PLANNING AND MULTICRITERIA SCHEDULING OF TURNED PARTS' PRODUCTION

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Original scientific paper

Technical innovations in the area of manufacturing logistics are being introduced partially and thus not exploiting their full potential. In order to optimise the efficiency of turning manufacturing processes, the process has been analysed and fundamentally re-engineered. All data from production (operations, quantities, date, time duration of operations, etc.) are now located in ERP system. It provided the necessary condition for the establishment of a robust dynamic planning model. An update was required for the whole lifecycle of products and means of work. The paper presents the information support and an algorithm for a dynamic planning model, based on a genetic algorithm. Continuous data capturing and planning in real time are a breakthrough in the management of the process. Presented are a generalised dynamic planning model and a case example from the production of turned parts, which take account of the singularities of a real environment. Production capacities have to be linked up with the supply chain and customers. The presented dynamic planning model can be adapted to various types of production.

Keywords: Integrated process planning and scheduling, genetic algorithm, multicriteria scheduling

Dinamičko planiranje i terminiranje uz više kriterija u proizvodnji tokarenih dijelova

Izvorni znanstveni članak

U području proizvodne logistike tehničke se inovacije uvode parcijalno te se ne koristi njihov puni potencijal. U cilju poboljšanja efikasnosti proizvodnih procesa tokarenja, postupak se analizirao i u potpunosti preradio. Svi se podaci iz proizvodnje (operacije, količine, datumi, vrijeme trajanja operacija itd.) sada nalaze u ERP sustavu. On je osigurao potrebne uvjete za stvaranje modela dinamičkog planiranja. Tražili su se ažurirani podaci o cijelom radnom vijeku proizvoda i sredstvima za rad. U članku se predstavlja informatička podrška i algoritam za dinamički model planiranja, zasnovan na genetskom algoritmu. Stalno dobivanje podataka i planiranje u realnom vremenu predstavljaju važan napredak u upravljanju tim procesom. Predstavljen je generalizirani model dinamičkog planiranja i primjer iz proizvodnje tokarenih dijelova gdje se uzimaju u obzir specifičnosti stvarnog okruženja. Proizvodni se kapaciteti moraju povezati s nabavnim lancem i kupcima. Ovaj se model dinamičkog planiranja može adaptirati različitim tipovima proizvodnje.

Ključne riječi: genetski algoritam, planiranje i terminiranje integriranog procesa, terminiranje uz više kriterija

1 Introduction Uvod

In traditional approach, planning and scheduling are two separate and successive operations. The process planning phase is mostly about the physical aspect of planning, where a product range, production quantities, machines, tools, material and accessories are selected. The emphasis in the second, scheduling phase, is on the time aspect. The plan is the basis to determine the sequence of operations across available machines in a way that provides maximum machines utilisation and timely manufacturing. Differences between planning and scheduling criteria often lead to conflict situations or even opposition between respective goals.

Master production schedule (MPS) and capacity requirement planning (CRP) in the environment of manufacturing resources planning (MRPII) are the most frequently applied traditional methods in practice. This system is characterised by a hierarchical approach from the top to the bottom. Goals and restrictions at the lower level are determined by the results at the higher level. Such planning method rarely takes account of the scheduling problem. Separate treatment of planning and scheduling often results in plans having to be manually modified. It leads to significant rearrangement costs and supply delays. Nowadays, such planning does not provide efficient business operations as customers and the market require flexibility and quick response.

A solution for such problems is the integration of planning and scheduling processes. The article presents a solution on the case example of planning the production of turned parts. Presented is a dynamic planning model and its advantages, compared to the existing method of work in the turned parts' production. A genetic algorithm was used to optimise scheduling. The updated process planning improved the efficiency of production and reliability of supplies. The proposed integrated model is presented in section 4, user interface is presented in section 5. The genetic algorithm and the target functions are described in section 6 and experimental results in section 7.

2

Literature review Pregled literature

The change of planning was triggered by the requirement for flexibility and quick response to the market and consumers' needs. J. Errington [1] presented the advantages of Advanced Planning and Scheduling (APS), compared to traditional methods. Here, individual steps of the traditional approach are merged in the way that they allow automatic transition. Tasič et al. [2] presented advanced scheduling methods, such as priority rules, useful also for sophisticated systems.

Computer Aided Process Planning (CAPP) has been recognised to play a key role in Computer Integrated Manufacturing (CIM) [3]. Traditionally, nearly all computer aided process plannings (CAPP) suppose that manufacturing is of secondary importance and that the workshop has unlimited resources. It triggers unrealistic plans that are unworkable in the manufacturing process.

Planning and scheduling functions often have opposing goals, which makes their separate treatments less efficient. The other deficiency of separate treatments is not taking account of the dynamic manufacturing environment. Time delay between process planning and the actual beginning of the plan can cause the plan to become unworkable. Fixed plans lead to bottleneck situations. Researches have shown that as much as between 20 to 30 per cent of all plans have to be modified in order to adjust them to the dynamic manufacturing environment [4].

Integration between planning and scheduling process is therefore vital as this is the only way to create more realistic plans and schedules. Only this will result in a real computer integrated manufacturing (CIM) [5]. The integration creates a single space for solutions and provides the basis for efficient integrated solutions that are in the interests of both planning and scheduling [6]. It contributes to improved efficiency of manufacturing resources, shorter throughput times, scheduling times and shorter delays. The integration of planning and scheduling is much more complex and more difficult to do in practice. The main contribution of this article is to show on a case example the rules and methods how to introduce dynamic planning and scheduling into practice. The basis for our work was the existing ERP (Enterprise Resource Planning) information system.

Larsen [13] and Alting [7] arranged different approaches to integrated process planning into three types: concept of non-linear process planning (NLPP) or flexible process planning, closed loop process planning (CPP) and distributed process planning (DPP).

The concept of non-linear process planning is typical of integrated process planning and scheduling (IPPS). According to this model, all alternative plans for a product are determined, which is called MPP (multiple process plans) [8]. All these plans are defined regardless of the current situation on the shop floor. A large number of products and alternatives can make individual plans unworkable, and so an optimum result is not possible to be achieved through integration.

Closed loop process planning (CLPP) generates plans by means of a dynamic feedback from the shop floor. It is better than NLPP because plans are generated with a view to realistic conditions in the manufacturing environment. With this method, the realistic conditions are vital and the dynamic feedback is important for the scheduling process.

Distributed process planning (DPP) performs process planning simultaneously with the scheduling of manufacturing. Process planning is divided into two phases. The first phase is the initial phase where product requirements are analysed according to its shape, tools, machines etc. When all requirements are clear, the second phase or final planning begins. During this phase, the required manufacturing resources and the available resources are matched. The flexibility of this approach increases if the required resources are given as alternatives. Examples of such approach are L. Wang and W. Shen [9] and IPPM system by H-C. Zhang [10], followed by IPPS by S. H. Huang et al. [5].

Matching individual planning models has shown that DPP is the best approach. However, it still requires high performance hardware and software. NLPP involves alternative plans, which allows better scheduling flexibility. Such method can be introduced in enterprises without the need for their reorganisation, compared to DPP and CLPP that would require reorganisation of planning and scheduling departments. This is due to CLPP and DPP requiring merging of different separate processes within an enterprise.

Several researchers merged individual approaches in order to remove the deficiencies and come up with optimum plans. L. Gao et al. [11] presented an integrated process planning and scheduling model, based on taking the advantages of NLPP (alternative plans) and DPP (hierarchical approach) models. The model is based on the principles of concurrent engineering, where computeraided planning and scheduling are performed simultaneously. Usher and Fernandes [3] presented a system, called PARIS (Process Planning Architecture for Integration with Scheduling), which divides the dynamic process planning into two phases, the static one and the dynamic one. Each phase has its objectives that should be met. A. Jain et al. [8] and M. R. Razfar et al. [12] tackled the task in a similar way, by dividing the problem into two modules.

Nowadays, modern manufacturing systems should be adapted to the changes on the market. They all have the same objective – the lowest possible manufacturing costs. On the other hand, they wish to meet customers' quality and timely delivery requirements. M. Starbek et al. [14] developed a method whereby it is possible to predict the delivery time of a new product on the basis of actual throughput times of previous products. The suggested procedure also allows changes of the calculated delivery time with regard to confidence and risk level. J. Kopač et al. [15] presented modern techniques together with methods for the reduction of throughput times and improved quality.

The importance of artificial intelligence has grown due to increased complexity of planning problems. Methods, based on a genetic algorithm, for example, are very efficient for difficult problems. They do not always yield the best absolute solution but they find an approximation, good enough for practice. J. Balič et al. [16] used genetic algorithms in order to arrange machines and apparatuses in a flexible processing system. They used variable transferable costs as their target function. Yan and Zhang [17] developed a uniform planning and scheduling optimisation model for the management of a three-tier manufacturing system. In order to solve the problem, they opted for heuristic approach, based on genetic algorithms. They developed an algorithm where they determined the optimum size of a batch. Park and Choi [18] suggested the use of genetic algorithms (GA). The target function was the shortest production time of all products, while taking account of alternative machines and alternative sequence of operations. Using genetic algorithms, A. Kimms [19] solved mixed integer program formulation which he had developed for multi-level, multi-machine scheduling. Zhang and Yan [20] defined the planning and scheduling problem as nonlinear mixed integer program model. For the purpose of simultaneous optimisation of production plan and scheduling, they presented an improved hybrid genetic algorithm (HGA). To improve the results, they also used heuristic rules, i.e. the shortest production time (SPT) and the longest processing time (LPT). Lee and Kim [21] suggested simulation with a genetic algorithm, linked with a simulation module that calculates the success rate of planning, based on combinations between process plans. Total production time and delivery date were used as target functions. To solve the single machine scheduling problem, Valente and Goncalves [22] suggest genetic algorithm approach with linear earliness penalty and quadratic tardiness penalty. They suppose that there is no dead time on a machine. L. Gao et al. [11] suggest the use of a modified genetic algorithm where each function (process planning and scheduling) was given a different chromosome representation. Minimum throughput time of all products was used as the target function. For the integrated model

they used a mathematical model, which they solved with genetic algorithms [23]. Lestan Z. et al. [24] developed a simple genetic algorithm for a job-shop problem. They used makespan as a target function and the solution is searched without the help of heuristic rules.

2.1

A survey of the current situation and new approach to dynamic planning

Postojeće stanje i novi pristup dinamičkom planiranju

In order to achieve optimum plans in a dynamic manufacturing environment, it is necessary to take account of the current situation on the shop floor, which traditional CAPP neglects. Most researchers have focused on a sole target function, such as throughput time of all products, delivery time, effective utilisation of machines. Manufacturing costs and effective utilisation of machines were rarely considered. It is important to consider effective utilisation of machines in order to cover high investment costs and reap economic benefit from them [6]. Researchers are mostly focused on scheduling algorithms and on narrow problems. Missed are introduction methods and examples of dynamic planning in the industrial environment.

An integrated process planning and scheduling model is presented and described in detail for production of turned parts.

A planning model has been developed which comprehensively covers production planning. Constructing the model has shown that planning should also include materials and tools purchase as well as product sales. This model has served as a basis to determine a satisfactory plan based on genetic algorithms. Several target functions and criteria are present in the optimisation procedure. With the genetic algorithms we improved productivity, utilisation of machines and delivery times. Presented are also experimental results and comparison with other authors.

3

Problem description: Planning and scheduling in the production of turned parts

Opis problema: Planiranje i terminiranje u proizvodnji tokarenih dijelova

Planning and scheduling of products in the production of turned parts ranks among complex problems. An nnumber of products should be scheduled across an mnumber of machines in the way that they are manufactured and delivered to the customer in time. Each product has at least one alternative plan that includes several operations. It also represents the end product. Each operation is performed on a single machine. Currently, plans are made manually and everything depends on a single person who relies on his or her experiences. Some products are subjected to planning according to MRP system. It is a known fact that such system does not always lead to workable plans, which makes it almost unusable in a dynamic environment. For this reason planners extend product's throughput time and thus deliberately extend delivery times. In turn, it creates longer queues, less flow through the production, less effective utilisation of machines and higher production costs. Current planning does not provide any feedback on the situation of manufacturing resources and response to any change on the shop floor (machine failure, urgent order) is poor. The

Because process planning and scheduling are closely related functions, their integration in such environment is vital for the creation of an optimum plan. A dynamic process planning and scheduling model is presented below.

4

Integration of process planning and scheduling functions

Integriranje funkcija planiranja i terminiranja procesa

Fig. 1 shows the whole dynamic process planning and scheduling model. It is basically divided into two parts - the part where all alternative plans for each product are determined and the optimisation part with the genetic algorithms approach. The first part could be termed as a static part or pre-planning phase, with the emphasis on specifying various plans according to available resources and specifying production quantities and material needs. The second part involves all dynamics, which is why this part is called the dynamic part or the final planning phase, where target functions as well as realistic conditions in the manufacturing environment are considered. It means that the available resources are matched with the required ones. If current capacity does not meet the requirements, an extra plan should be included in the process. In practice it means that a product is being manufactured simultaneously on two machines.

First, all orders are collected, followed by making a rough plan by means of gathering the information on the available capacity of regular orders that are always manufactured on a single machine. For other orders, alternative plans are prepared according to other available resources. This is followed by specifying material needs and capacity for all production quantities.





When alternative plans, manufacturing procedure (sequence of operations), required quantities of material and tools are available, the second phase begins, for which these are the input data. This is called the scheduling phase and its key role is to schedule all product operations across machines in the way that scheduling criteria are met. Prior to detail planning, materials and tools stocks are checked in the system. Detailed planning of manufacturing plan is subject to timely delivery of materials and tools by suppliers. Specifying the optimum plan, the target function is the minimum throughput time of all products and minimum total costs. At the same time, another aim is to achieve the most effective utilisation of machines, reduction of set-up times for the first operation and to minimise order delays.

Once the satisfactory schedule has been completed, it is considered as a working frame. If urgent orders arrive after the schedule had been completed, certain tasks are given higher priority. If an order has been cancelled or there is an equipment failure, a new schedule should be created. Due to the above-mentioned reasons it again functions as a frame. If there are no modifications, the optimum schedule should take place on the shop floor

The following assumptions have been specified for the solution of such problem:

- Only one product can be produced on one machine at the same time
- Each product can be machined independently from the other products
- Each product has from one to three alternative plans (different CNC machines)
- The sequence of operations is predefined for each product in the alternative plan.
- The size of a batch is divided into equal smaller units, such as packaging units which are tracked throughout the manufacturing process.

4.1

Advantages and disadvantages of dynamic planning Prednosti i nedostaci dinamičkog planiranja

The integration of process planning and scheduling has led to the shift from manual scheduling to automated, computer-aided planning. Defining a detailed time when the manufacturing process of an order will start and when it will end, including delivery time, is the biggest advantage. Each operation on a product has a specified start time and end time. For example, it is specified when and how many products should be ready for galvanic coating. A planner is now able to check in any given moment which products are being produced on which machines and how many of them are on each operation. Such planning method gives a planner a more supervisory role as he or she can follow via the information system what is going on at the shop floor and is informed whether an order is behind or ahead of schedule.

Manual method included a lot of verbal communication with the shop floor, physical checks of machines on the progress of the work, which is now no longer necessary. Automated planning and scheduling system also allows control over finished products, material and tools. Dynamic planning requires consistency in the monitoring of products on each operation throughout the manufacturing process. This information allows an accurate prediction of how many products can be finished in a short period of time. This is important in case of increased demand for a product by a customer. The most important thing for managing a

efficient response to changes, such as machine failure, maintenance work, and urgent orders. This means, if the machine is broken, then the new borders are put into the planning system. Products which have already been put on the machine have the status "in progress" and they cannot be canceled, but the products with the status "plan" can be rescheduled. This status is written in ERP system. Likewise is with the urgent orders. This can be done any time, response time to get a new plan is 15 minutes on average. Information from the production is automatically updated in ERP system every 30 minutes. Managing changes of materials and tools delivery dates

Managing changes of materials and tools delivery dates by suppliers could be a drawback of dynamic planning. If materials and tools are out of stock or they are not supplied on the planned date, the plan is unworkable and should be delayed by at least one day, which can trigger delays in the supply of end products.

dynamic manufacturing environment is a quick and

5

User interface between ERP system and schedule optimisation software

Korisničko sučelje između ERP sustava i programa za optimizaciju terminiranja

Manufacturing information system is the backbone for the planning and managing of production, which is why the existing information system within the dynamic planning model has been complemented rather than replaced. All data are stored in the ERP information system. In order to calculate the optimum plan and schedule, data are exported and optimisation of the plan with genetic algorithms is performed. The collected data are then returned to the information system. The whole system of data management and integrated process planning and scheduling is shown in Fig. 2.



Figure 2 Data flowchart Slika 2. Dijagram toka podataka

Data are exported from the information system with the Oracle Discoverer 4.1. application. Process planning and scheduling is performed once a day or at a request into a purpose built software application (relational base MS Access, Visual Basic). Later, transition to Oracle base and C++ is planned. A genetic algorithm was used and it proved very fast, with good conversion results. This local base is



the groundwork for planning on the basis of the data from the basic information system. The optimisation procedure results in a detailed plan and schedule of products manufacturing. It serves as input information and enables the planner to generate manufacturing product tasks within the ERP system.

The Oracle Discoverer application allows access to the data base, located in the information system. Each ERP session has a table with data that are also visible in the session itself. Necessary tables (information) for the integrated planning method are specified in the Oracle Discoverer application. Besides, the application also allows data filtering, additional equations-based restrictions, similar data pooling etc. The selected data are exported into the local relational base that functions as the basis for planning and scheduling. The relational data base is created in MS Access. The whole relational database set-up procedure was subjected to normalisation, which was used in order to establish relationships between the data and to determine links between the attributes from different tables. The links were of both simple (1:1) and complex (N:1) type. Fig. 3 shows the relational database that serves as the basis for the plan. Each field is written in the same way as in the table in the ERP (Baan) system. The same goes for tables names.

A purpose application has been created for the optimisation process. On the basis of the ERP information system it schedules the activities on the shop floor in real time. Genetic algorithms have proved to be an efficient method for product scheduling. The presented planning and scheduling method is performed once a day or at the request of the planner.

6

Genetic algorithm-based approach for production scheduling

Pristup terminiranju proizvodnje baziran na genetskom algoritmu

Genetic algorithms (GA) are a method of evolutionary computation. Evolution can be defined as the optimisation process where living organisms are becoming increasingly adapted to the environment where they live. Evolution can be simulated on a computer and used to solve problems in a variety of fields. Genetic algorithms are a random search technique, not requiring detailed knowledge about a problem that is being optimised.

Fig. 4 shows the application of genetic algorithms procedure. The CAPP system initially specifies all alternative plans and other information of any importance for the calculation of the optimum plan of integrated process planning and scheduling. Other data include delivery dates, stock information, materials and tools supply. In the next step, a population is randomly generated. It consists of a large number of different possible plans. On the basis of target functions and restrictions, each chromosome of the initial population is evaluated. The evaluation process is then carried out, with better and better solutions being sought on the basis of selection, reproduction, crossover and mutation until the required condition is reached. When the goal is reached, the optimum schedule for each task is also completed.



Figure 4 Course of the application of genetic algorithms Slika 4. Tok primjene genetskih algoritama

Genetic algorithms represent solutions of problems in structures, called chromosomes. The collection of chromosomes is called a population and specific chromosomes in the population are individuums. A population in any given time is called a generation. The goal of genetic algorithms is to create new generations. Although the population can change from generation to generation, the size of the population and the structure of chromosomes remain the same. They operate with characters, representing parameters. Proper specification of parameters or chromosome syntax is an important step. It has an effect on subsequent work with genetic algorithms and on the share of workable solutions in the search area in terms of a large number of plans and restrictions. The literature has so far presented the chromosome in a number of ways [25]. Below are presented the chromosome, the evolutionary function with restrictions and genetic operators. The chromosome has been adapted to the needs of the production of turned parts.

5.1 Chromosome representation Predstavljanje kromozoma

Job-based representation of chromosome has been chosen to represent the chromosome of the given problem. The manufacturing type in the company is by orders. One product is represented by one gene in the chromosome. The gene is represented by two pieces of information, with the first one being the number of the alternative plan according to which the product will be manufactured while the other one specifies whether tools presetting will take place (number 1) or not (number 0). The gene can be extended to other characteristics. The chromosome is shown in Fig. 5. The chromosome is made up of a group of genes. In our case this is the schedule of all products to be manufactured. It means that the chromosome represents permutation of tasks. Representation of the chromosome by products belongs to direct approaches, where the solution is built in the chromosome. Genetic algorithms are used for the creation of the chromosomes whose objective is to find a better schedule. First, operations of the first product in the chromosome are scheduled across machines. They are followed by the second product's operations and so on to the last one in the chromosome.



When the target function of the chromosome is calculated it has to be decoded back to the solution of the problem, which means the schedule of products. During the encoding it is of utmost importance to keep the subsequent solution of each chromosome decoded within the possible space of the given problem. This feature is called feasibility. When the generated chromosome cannot be decoded into a solution, correcting techniques are applied. They change an illegal chromosome into a legal one. This feature is called illegality. For permutations, the technique with a PMX operator is very useful. It is basically a two-point crossover with the correction procedure.

The relational database contains information on products that is used for the purpose of orders scheduling. The list of genes or the chromosome represents one possible schedule on the shop floor. Using GA, a satisfactory schedule, as close to the optimum as possible, should be found. The GA principle is similar to natural evolution. Only the strongest individuals survive, creating a new and more advanced population of descendants by means of genes mutations and their crossover.

5.2 Evaluation functions Evaluacijske funkcije

The shortest makespan and minimum manufacturing costs were set as target functions and manufacturing restrictions and customers' requirements were considered. Delivery time is the most important of the customer's requirements. Other restrictions and criteria are described later on. Special emphasis is on the products where one of the operations is performed at an outsourcer. Together with the making itself, the manufacturing time also involves machine set-up and finishing times. Total costs consist of manufacturing costs, labour costs and depreciation costs.

While choosing an alternative manufacturing plan for a product, heuristic priority rules can be of assistance. The shortest processing time (SPT) was used for the initial schedule. Later, the rule saying that products with the earliest due date (EDD) are scheduled first is also applied. If two products are scheduled for the same machine, the product with the earlier due date is manufactured first.

- Mathematical model symbols:
- N Number of orders or work orders
- A Number of items on the bill of material
- M Number of machines on the shop floor
- P_i Number of alternative plans for product i
- G_{il} –Number of operations for product's *i* plan *l*
- o_{ilk} -k-operation for product's *i* plan *l*
- Q_{ai} Ordered quantity of product *i*
- $Q_{p,i}$ Quantity of product's *i* workpieces, overlapping with the next operation
- $t_{po,ilkj}$ -Time of operation's o_{ilk} overlap on machine j
- $t_{t,ilkj}$ Technological time for the production of one product *i* for operation o_{ilk} on machine *j*
- $t_{w,ilkj}$ Processing time for operation o_{ilk} on machine j
- $t_{op,ilkj}$ Time of the performance of operation o_{ilk} on machine j
- $t_{pz,ilkj}$ Set-up and finishing times of machine *j* for operation o_{ilk}
- $t_{es,ilkj}$ -The earliest beginning of operation o_{ilk} on machine j
- $t_{ef,ilkj}$ The earliest end of operation o_{ilk} on machine $j(d_{f,ilkj})$
- $t_{p,i}$ Product's *i* throughput time
- t_{pj} Throughput time for all operations, performed on machine *j*, i.e. total time when a machine is engaged in the performance of all planned operations
- $t_{s,ilkj}$ Set-up time of machine *j* for operation o_{ilk}
- $t_{mo,ilkj}$ Time of interoperational hold-up for operation o_{ilk} on machine j
- w_i Product *i* priority
- $d_{d,i}$ Scheduled delivery date of product *i* to the customer
- $t_{p,\max}$ -Maximum time on a machine among all machines
- $c_{ssc,i}$ Manufacturing costs for one piece of product *i* (all operations, materials, tools)
- c_d Labour costs
- c_{ai} Depreciation cost for machine j
- $c_{s,ilkj}$ Cost of machine *j* for operation o_{ilk}
- $c_{pz,ilkj}$ Cost of operation's o_{ilk} set-up and finishing time on machine j

 c_{wi} – Total cost for processing all operations for product *i*

 $c_{p,i}$ – Total costs for product *i*

 \tilde{C} – Total costs for all products

 mnu_i – Non-utilisation of machine j

MU-Maximum utilisation of all machines

- D Large positive integer
- Z_i Delivery delay of product *i* (in the number of days)
- cwf-Combined weighted function
- λ -Weight of delay
- δ -Costs of 1 day delay of the delivery date
- $\alpha_{ii'j} = \begin{cases} 1; \ 1 \text{ alternative plan for product } i \text{ IS selected} \\ 0; \ 1 \text{ alternative plan for product } i \text{ IS NOT selected} \end{cases}$ 1; product *i* appears before product *l* on machine *j*
- $\beta_{il} = \langle 0; \text{ product } i \text{ DOES NOT appear before product } i \text{ on }$ [machine j
- $\gamma_{ilk} = \begin{cases} 1; \text{ operation is performed simultaneously} \\ 0; \text{ operation is performed sequentially} \end{cases}$

Target functions:

a) Minimum throughput time of all tasks and operations on a single machine:

$$\min t_{p,\max} = \max \left\{ t_{p,1}, t_{p,2}, t_{p,j}, \dots, t_{p,M} \right\}; j = 1, \dots, M$$

$$t_{p,j} = \sum_{i=1}^{N} \left(\sum_{l=0}^{P_i} \sum_{k=1}^{G_{il}} \left(t_{op,ilkj} \cdot \beta_{il} \right) \right).$$

$$(1)$$

Time of the performance of operation:

$$t_{op,ilkj} = t_{pz,ilkj} + t_{w,ilkj} = t_{pz,ilkj} + t_{t,ilkj} \cdot Q_{o,i}.$$

Overlap time:

 $t_{po,ilkj} = t_{t,ilkj} \cdot Q_{p,i}.$

b) Timely delivery with minimum delays:

$$\begin{aligned} & \operatorname{Min} Z_{\max} = \operatorname{Max} \left\{ Z_1, Z_2, Z_i, ..., Z_N \right\}; i = 1, ..., N \end{aligned} \tag{2} \\ & \text{if } d_{d,i} > d_{f,i \mid G_{il}} \end{aligned}$$

$$Z_{i} = \begin{cases} 0 \quad ; \text{ if } d_{d,i} > d_{f,ilG_{il}} \\ d_{f,ilG_{il}} - d_{d,i}; \text{ otherwise} \end{cases}$$

 $d_{f,ilG_{il}} = t_{ef,ilG_{il}j}.$

c) Minimum total manufacturing costs for all products:

$$C = \operatorname{Min} \sum_{i=1}^{N} c_{pi},$$

$$c_{p,i} = \sum_{l=0}^{P_{i}} \sum_{k=1}^{G_{il}} \sum_{j=1}^{M} \left(\left(c_{pz,ilkj} + c_{s,ilkj} \right) \beta_{il} \right) + c_{w,i}.$$
(3)

Processing costs:

$$c_{w,i} = c_{ssc,i} \cdot Q_{o,i}; i = 1,...,N.$$

Machine costs:

 $c_{s,ilkj} = t_{op,ilkj} \cdot c_{a,j}.$

Set-up and finishing time costs:

$$c_{pz,ilkj} = t_{pz,ilkj} \cdot c_d \,,$$

d) Maximum utilisation of all machines:

$$MU = \left(\frac{1}{\min\sum_{j=1}^{M} mnu_j}\right),$$

$$mnu_j = \left(1 - \frac{\sum_{i=1}^{N} t_{wilkj}}{t_{\max,j}}\right); \quad j = 1, ..., M.$$
(4)

e) Combined weighted function

$$cwf = \sum_{i=1}^{N} (c_{p,i} + c_{z,i}),$$

$$c_{z,i} = (\lambda^{\wedge} Z_{i}) \cdot Z_{i} \cdot \delta.$$
(5)

All restrictions have to be considered for a satisfactory manufacturing schedule of turned parts. They are listed above. Below, they are presented in a mathematical form. Restrictions:

a) Only one product can be processed on each machine at the same time:

If
$$d_{d,i} < d_{d,i'}$$

then $t_{p,i'l'k'j} - t_{p,ilkj} + D \cdot (1 - \alpha_{ii'j}) \ge t_{w,i'l'k'j}$. (6)

b) Sequence of operations is predefined for each product in the alternative plan:

$$t_{es,ilkj} + t_{w,ilkj} + t_{pz,il(k+1)j'} \le t_{es,il(k+1)j'}$$
(7)
 $i = 1,...,N; \ l = 0,...,P_j; \ k = 1,...,G_{ij}; \ j,j' = 1,...,M.$

c) Only one alternative plan can be selected for one product.

Assumption: $w_{il} > w_{i(l+1)}$

$$\sum_{l=0}^{P_i} \beta_{il} = 1 \quad \forall i \in [1, N].$$

$$\tag{8}$$

d) Operation is performed simultaneously or sequentially. Product's throughput times change because operation can be performed simultaneously or sequentially.

Throughput time for product i where operations are performed sequentially:

$$t_{p,i} = t_{ef,ilG_{il}j} - t_{es,il1j} = \sum_{k=1}^{G_{il}} \left(t_{op,ilkj} + t_{mo,ilkj} \right).$$
(9)

Throughput time for product i where operations are performed simultaneously:

$$t_{p,i} = \sum_{k=1}^{G_{il}-1} \left(t_{pz,ilkj} + t_{po,ilkj} + t_{mo,ilkj} \right) + t_{op,ilG_{il}j};$$

$$t_{mo,ilkj} = t_{es,il(k+1)j'} - t_{ef,ilkj}.$$
(10)

e) Throughput times for each operation and product costs have to equal or exceed 0:

$$t_{pilkj} \ge 0; c_{pi} \ge 0 \tag{11}$$

$$i = 1, ..., N; l = 0, ..., P_i; k = 1, ..., G_{il}; j = 1, ..., M.$$
 (12)

Target functions equations are written from (1) to (5). Taking account of all objectives can be termed as a multiobjective problem. The most important objectives to achieve are minimum throughput time (1), timely delivery (2) and minimum total costs (3). It is necessary to achieve the highest possible efficiency of machines (4), which reduces dead time on a machine. Combined weighted function (5) is composed of total costs and delays.

Restrictions that appear in the algorithm are written from (6) to (10). Equation (6) determines that a machine can produce only one product at a time. The sequence of operations for two different products on the same machine depends on the delivery date. It applies to all operations for all products. Equation (7) determines that the sequence of operations is fixed for each product. It further increases the complexity of the problem. Only one alternative plan can be used for each product, which is shown in equation (8). The technological process with the highest priority is used as the initial plan. Choosing only one possible plan automatically means that only one machine is designated for the performance of a single operation because the machine is hidden in the plan. Equations (8) and (9) determine product's throughput time according to the way of operations performance. The algorithm also takes account of the fact that some operations take place consecutively and others simultaneously. Equation (10) determines that each operation's throughput time and all product costs should equal or exceed 0.

5.3

Genetic operators Genetski operatori 5.3.1 Selection Odabir

Tournament-type selection was used. For this selection type, a certain number of chromosomes is selected, which then take part in the tournament. Two individuums are matched and the chromosome with the best value is selected. If the number of chromosomes to be matched increases in an algorithm, the pressure on the selection is increased. Inferior chromosomes are not selected and thus do not take part in the creation of the next generation while at the same time good individuums also do not dominate the reproduction process.

5.3.2 Crossover Prijelaz

Two-point crossover was chosen as the crossover operator. Selected from the population are two parents who form two offsprings. Two random points are selected in the chromosome, as shown in Fig. 6. The material between both points is exchanged between the parents. This always creates feasible solutions. The crossover operator is



Slika 6. Operator prijelaza

subjected to the probability that determines the use of the crossover chromosome.

5.3.3 Mutation Mutacija

F

A mutation is about introducing new genetic material in the existing chromosome. It introduces variety in the population and broadens the search area. A mutation as well as crossover is subjected to some probability. For the existing problem, the uniform mutation was selected. This mutation is about each gene in a chromosome being attributed a random number, which is then matched with the probability of mutation. If the random number is smaller, the gene is subjected to a mutation. This is shown in Fig. 7.

Before Mutation	1 1	1 1	1 0	1 0	2 1	11	10	1 1	2 0	1 0
prob_mut: 0,01										
Random numbers	0,51	0,04	0,93	0,009	0,12	0,89	0,41	0,75	0,003	0,98
After Mutation	1 1	1 1	1 0	2 1	2 1	11	10	1 1	3 1	1 0
Figure 7 Mutation Slika 7. Mutacija										

Genetic operators were selected on the basis of a systematic comparison between the results of optimising and the necessary calculating time.

6 Experimental results Rezultati eksperimenta

During the development of genetic algorithm, several set-ups and approaches were systematically tested. Tests showed that with roughly 1000 evaluations it is possible to find a satisfactory solution for a plan. The size of the population was limited to 60. Larger population extends the calculation time while there are no significant savings with the population sizes of 80 and 120 (Fig. 8).

The optimum selection was determined after comparing selections without the use of crossover and mutation operators. The roulette and tournament selections proved to be the best.

Two-point crossover with one-point mutation quickly converges towards a good solution but it also calms down





	Processing time/h									
Jobs		Operation 1		Operation 2	Operation 3	Operation 4				
	Plan 1	Plan 2	Plan 3	Operation 2	Operation 5					
J1	30,3	/	/	0,8	2,8					
	(M13)	/	/	(M19)	(M27)					
J2	35,1	33,6	33,6	1,21	1,04	17,42				
	(M10)	(M8)	(M15)	(M19)	(M22)	(M26)				
J3	92,1	/	/	1,3	11,1					
	(M13)			(M19)	(M27)					
J4	10,8	8,9	/	0,3	0,3					
	(M10)	(M12)	/	(M19)	(M27)					
J5	9,6	8,7	1	0,3	0,4					
	(M10)	(M12)	/	(M19)	(M27)					

Table 1Processing time of all operations for a job with alternative plansTabela 1.Obradno vrijeme svih operacija za posao s alternativnim planovima

Tabela 2 Rezultati inicijalnog planaTable 2. Results from the initial plan

	Total costs/EUR	Throughput time/h	Makespan/h	Sum of delays/day	Maximum utilisation of all machines/%	Combined weighted function/EUR
Initial plan	146 269,6	4 386,27	1 257,58	83	23	452 567,5

quickly and is unable to look further for better solutions. A random mutation is looking for solutions to a larger extent and the convergence of the population towards better solutions is slower but the final solution is very good. For these reasons, two-point crossover with random mutation is used in the final version. The crossover probability is set at 0,9 and the mutation probability at 0,01.

For the purpose of determining the optimum solution for the production of a product or a product range, several alternative plans were used for each product. These plans are entered in the information system and their numbers of operations and designated machines for each operation are already specified. Thirty products were scheduled onto eighteen CNC machines in the case study. There are thirty machines and ninety-five operations all together. There can be up to four operations on a particular product and up to three alternative plans. Planned time in hours and machines for particular operations is shown in Tab. 1. In the case of alternative plans additional machines are specified as at products J2, J4 and J5.

For each target function almost optimal solution was found with genetic algorithms. Solutions are good enough – satisfactory for production scheduling. There exist better optimal solutions but with no significant difference which does not pay additional calculation time. The objective is to find the almost optimum or satisfactory manufacturing plan out of the alternative plans in order to achieve a good result of the fitness function.

The results of different target functions are summarized in Tab. 3. Size of population was set to sixty and number of generations to fifty. Calculation time on a middle class personal computer was 280 seconds for each target function from table 3. The almost optimal solutions for particular target functions are marked with shadow. Other values in the same line are given for comparison between different target functions. Each target function achieves the best result in the colon – it is according to expectations. Special attention was given to deliver products on due dates and to control costs at the same time. We have made a combined weighted function that considers both criteria: due date and costs. In the comparison between the first and the second target function it can be seen that the results are very similar. Because of the bigger makespan the function Throughput time has more delays and bigger additional costs. In that case products are not well scheduled on the machines.

According to the minimum of delay criteria the fourth target function is the best choice. Products enlarge the throughput time in this case and total costs although combined costs are at acceptable level. The delays are only 6 days. The last one of the target functions is a combined

Target function	Total costs/EUR	Throughput time/h	Makespan/h	Sum of delays/day	Maximum utilisation of all machines/%	Combined weighted function/EUR
Total costs/EUR	116 849,2	3 565,60	421,55	29	51	161 489,5
Throughput time/h	125 131,9	3 533,68	461,08	36	49	193 800,8
Makespan/h	126 840,1	3 753,66	421,55	33	52	180 927,5
Sum of delays/day	138 955,9	4 001,91	443,98	6	53	146 468,9
Non-utilization of all machines/%	153 241,1	4 139,53	443,98	48	58	259 471,8
Combined weighted function/EUR	124 658,7	3 816,34	439,98	7	51	134 035,1

Tabela 3 Usporedba vrijednosti ciljnih funkcija Table 3. Comparison between the values of target functions



Target function: Total costs





Slika 10. Utjecaj ciljne funkcije kombinirana ponderirana funkcija





weighted function. It represents the compromise between total costs and delays. The value of this target function from Tab. 3 is not optimal, but it represents a good solution acceptable for the practice.

Attention was also paid to the busiest machines on the shop floor and utilization of the machines. At the maximum

utilization target function, where the result is 58 %, the order of products on machines gives the biggest delay. The reason is probably in the order of the products on the machines. All products together give very good utilization, but some products will be delayed because of this.

Figs 9 to 11 show the comparison between three target

functions. The conditions stabilize after 30 generation. From the other researchers it is known that 1200 evaluations with genetic algorithm represent a good enough solution that could be put into practice. In our case there have been made 3000 evaluations. Beside the target function presented are also the results from the other two target functions in Figs. 9 to 11. This means, in Fig. 9 are beside the Total costs of target function also given the total costs from the target function.

After all these results the specific solution for the turned parts' production has been made. We decided that the combined weighted function gives the satisfactory solution. From the sale department's point of view the minimum delays are the top priority, while from the production department and the management's one the minimum costs are the top priority. The combined weighted target function could satisfy both.

7 Conclusion

Zaključak

On the example of the production of turned parts, the article has shown how to combine process planning and scheduling into an integrated and thus more efficient system. Each criterion or target function works very convincing, which could take us on a blind road. The need is therefore to check some combinations of different target function, like in the combined weighted function. The proposed criterion for turned parts' production includes total costs and delays. For the lowest common costs, additional delays will have to be accepted.

At the end we could compare the results from the chosen target function and the initial plan given in Table 2. It has been put on the machine in the same order they came into our company and for each product or job, first alternative plan was chosen. The costs of combined weighted function drop by 69,1 %. 15,6 % are the total costs, the rest is because of the right choice of the machines. The makespan moves from 1257,58 hours to 439,98 hours. The amount of the saving is because we have a big emphasis on delays. For that reason the special weight has been developed.

Besides planning and scheduling of manufacturing activities, the presented model also allows optimisation of manufacturing plans and machines. In this case the solution area is much larger due to the fact that all available machines are varied within each operation of the plan. It is possible to take account also of the machines that are not yet present in the existing plans or exist only in investment plans. Calculation time is by a factor of ten or more.

Further researches will focus on the introduction of group turning technology on CNC machines. Geometrically similar products require minimum machine set-up time for the transition from one product to another. The introduction of the group technology principle in the presented planning model will be made possible on the basis of genetic algorithms. First, it will be necessary to provide reliable information on the association with a group for each product and enter it in the information system.

Acknowledegment

Zahvala

These researches are supported by the Ministry of Higher Education, Science and Technology under the project P-MR-08/88. Operation part is financed by the European Union, European Social Fund.

8

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