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Heuristic Algorithms for Manufacturing and Replacement Strategies of the Production System

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Abstract: The paper highlights the problem of minimizing economic costs of making orders in the automated manufacturing system which consists of work centres arranged in a series. Each of them is equipped with tools which carry out defined manufacturing operations. Tools are replaced with new ones only when no manufacturing operation can be performed any more in order to minimize the residual pass. The equations of state of the production line are presented and heuristic control strategies are discussed in detail. The criterion is to minimize the number of replacement procedures which results in maximizing the use of tools in work centres. To prove the correctness of the presented approach the paper is supported with an extended simulation study based on implementing available combinations of either manufacturing or replacement strategies taking into account various configurations which come into being in the real manufacturing environment. The simulation results form the basis for the detailed analysis to meet the requirements of the applicable decision-making procedures.

Keywords: manufacturing system, optimization, heuristic algorithms, manufacturing strategy, computer simulation.
Categories: F.1.1, F.2.1, G.1.6, I.1.2

1 Introduction

The right decision-making approach is unavoidable in each complex manufacturing system. Manufacturing companies are currently facing very strong pressure in terms of cost, quality, flexibility, customisation and a product delivery time to the defined market. Production systems of these companies have to be flexible and able to react to changing production capacity requirements [Modrak and Pandian, 12]. There is an increasing emphasis put on improving production efficiency. One of the ways to achieve efficiency is through the use of automated manufacturing. Automated manufacturing is a production method that relies on the use of computerized control systems to run equipment in manufacturing environment. Human operators are not needed to control the assembly line or manufacturing floor because the system is able to handle both the mechanical work and the scheduling of manufacturing tasks [Kim and Lee, 2013], [Montoya-Torres and Bello, 2011], [Morris, 1994], [Surman and Morales, 2002].

The paper focuses on an automated manufacturing system represented by manufacturing lines which consist of work centres arranged in a series. The number of work centres can vary depending on order specification. Simple orders may need a few operations only however, more complex ones may require a big number of operations which results in the need to create an adequate system consisting of numerous work centres which is emphasized later in the paper. Each work centre is understood as an automated centre with the so-called robotic head equipped with tool seats. These systems are usually referred to as automated manufacturing robotic systems. A robotic system is an integrated system of devices that automate production and manufacturing of goods and services [Bajd et al., 2010]. Generally, the field of robotics may be more practically defined as the study, design and use of robot systems supporting achieving manufacturing goals.

As in other similar systems, management and optimization of these types of manufacturing systems plays a key role. The most important thing is to ensure the continuity of the manufacturing process e.g. in case of bringing a certain work centre to a technological standstill. The standstill may be caused by technological breakdown as well as a need to replace one or more elements of the robotic head. This leads to introducing methods based on the principle of minimizing either the total tool replacement time or manufacturing time. Moreover, it may prove advisable to alternate the route through which semi-products are passed in order to avoid the need to stop the manufacturing process or, in the worst case to minimize the interval of the system standstill. In other words, this case requires searching for the best ways of optimizing manufacturing systems. It seems that one of the ways allowing us to meet this goal is the need to implement the modelling and simulation methods [Banks et al., 05]. They enable us to solve the whole range of problems already mentioned and those ones which can come into being throughout the manufacturing process. By means of simulation it is possible to test and analyze routing the manufacturing process and its quantity and quality coefficients. Additionally, it is also possible to define different replacement strategies for products, charge material, labour force, etc. and the so-called replacement strategies for farm machinery [Edwards, 2008], [Li et al., 2009], on the basis of which we can define new topological architecture of manufacturing systems.

2 State of the Art

Modelling uses a wide range of methods and approaches. The basic assumption requires creating adequate models with the use for example process oriented approach [Šperka et al., 2013], value oriented approach [Shapiro, 2006], [Vymětal, 2009], multi-agent approach [Wooldridge, 2009], [Karageorgos et al., 2003], neural networks [Panella et al., 2013], discrete or continuous Petri-nets approach [Macias and De La Parte, 2004], fuzzy-multi objective approach [Dotoli et al., 2005] or heuristic algorithms which are responsible for meeting the set criterion [Bucki and Suchánek, 2012], business intelligence tools [Suchánek, 2011], genetic algorithms [Ventura and Yoon, 2013], [He and Hu, 2014], [Wang et al., 2013], and other mathematical and special approaches [Banik et al., 2012]. In many cases it is advisable and very effective to use a combination of different methods and approaches. The reason is quite simple. The general logistic system is usually too complex to be modelled mathematically, or the models are overly computation intensive to be applied in a real-time environment.

Optimization techniques have developed into a significant area concerning industrial, economic, business, and financial systems. With the increasing reliance on modelling optimization problems in practical applications, a number of theoretical and algorithmic contributions of optimization have been proposed. The approaches developed for treating optimization problems can be classified into deterministic and heuristic. Recent advances in deterministic methods for solving signomial programming problems and mixed-integer nonlinear programming problems are introduced in [Lin et al., 2012]. A number of important applications in engineering and management are also reviewed to reveal the usefulness of the optimization methods.

Modern optimization has played an important role in service-centred operations and manufacturing and as such has attracted more attention to this field [Vasant, 2012]. Multilevel production scheduling problem is a typical optimization problem in a manufacturing system which is traditionally modelled as several hierarchical sublevel problems and optimized at each level [Shi et al., 2010].

The modern methods of optimization include the use of heuristic algorithms [Michalewicz and Fogel, 2004]. Designed algorithms are tailored to accomplish a specialized task or goal and usually find a solution quickly and easily. Developing solutions with heuristic tools offers two major advantages: shortened development time and more robust systems [Lee and El-Sharkawi, 07]. Although heuristic algorithms were originally known as inaccurate, current approaches to the mathematical modelling and development of computer simulation completely changes scientific mind on these algorithms. Heuristic algorithms are thus increasingly used to optimize a range of sectors such as logistics [Niu and Tian, 2013], [Yun et al., 2013], [Zharfi and Mirzazadeh, 2012], finance [Lyra, 2010], [Mansini and Speranza, 1999], manufacturing [Quan-Ke et al., 2010], [Georgilakis et al., 2007], [Bensmaine et al., 2014] and in a big number of other professional and scientific works, for example [Xu et al., 2010], [Losada et al., 2013], [Rodriguez et al., 2009] and others.

As we can see from the preceding paragraphs, although there are various methods of optimization, even today in many cases heuristic approach is very conveniently applicable. [Vanderkam, 2007] emphasizes that heuristic algorithms are demonstrated to yield suboptimal networks in order to meet conservation goals. Although the degree of suboptimality is not known when using heuristics, some researchers have suggested that it is not significant in most cases and that heuristics are preferred since they are more flexible and can yield a solution more quickly.

Heuristic approach is widely implemented to control a manufacturing system especially to solve specific problems within the area of production planning and detailed scheduling i.e. repetitive manufacturing [Horn et al., 2006], [Shimizu et al., 2008], [Bankstona and Harnett, 2000], [Modrak et al., 2013]. The use of heuristic algorithms successfully meets e.g. the total time minimizing criterion. Moreover, the higher the system complexity is, the more effective they prove to be in terms of quickness of finding the required solution. Their correctness is proven by the simplex method which is a numerical method for solving problems in linear programming [Bucki and Marecki, 2006]. Hybrid search algorithms are used for scheduling flexible manufacturing systems. These algorithms combine heuristic best-first strategy with controlled backtracking strategy as discussed in [Xiong et al., 1996].

An alternative solution to cell scheduling by implementing the technique of Nagare cell is discussed by Muthukumaran and Muthu in [Muthukumaran and Muthu, 2012].

A simulation-based three-stage optimization framework for high-quality robust solutions to the integrated scheduling problem is presented in [Zhang, 2013]. It is considered to be a parallel machine scheduling problem with random processing/setup times and adjustable production rates. The problem of determining realistic and easy-to-schedule lot sizes in a multiproduct, multistage manufacturing environment is discussed by Ekinci and Ornek [Ekinci, 2007]. The developed model consists of two parts: the lot sizing problem and the scheduling problem.

There is a wide branch of manufacturing systems where manufacturing decisions are to be made immediately e.g. either regular parts or spare parts are manufactured in various series in the automotive industry. There are many specific details which make these systems complex. Decisions are more than often made after thorough simulation of the system in order to avoid disturbances in discrete manufacturing operations. This can be treated as searching for a satisfactory solution. Heuristics are particularly suitable for planning non-configurable products that are to be produced on simply structured lines (such as filling lines). With these heuristics it is possible to plan several resources (in repetitive manufacturing) or lines (in resources of type line) simultaneously. In this way manufacturing is possible on alternative resources (lines). Moreover, it is also possible to load products as necessary within finite planning.

3 Description of the Manufacturing System and General Assumptions

Let us assume that the discussed manufacturing system consists of serially arranged J work centers in which there are certain tool seats. The j-th work centre, $j = 1,...,J$ is equipped with I tool seats. Tools are placed in dedicated tool seats. Each tool seat is able to carry out a predefined manufacturing operation. The block scheme of the assumed manufacturing system is presented in Fig. 1.

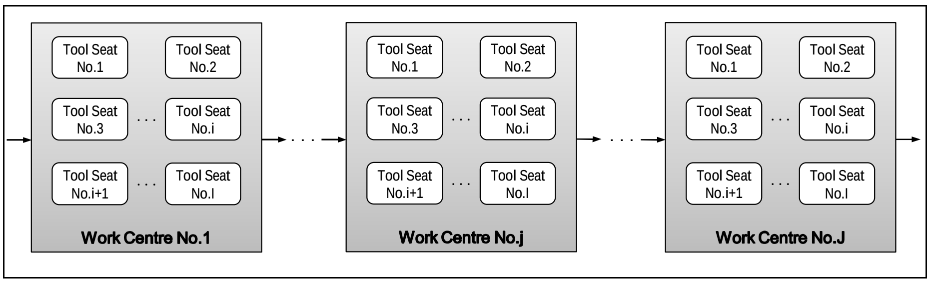

Figure 1: The block scheme of the assumed manufacturing system

It is assumed that operations are carried out subsequently in each j-th work center. Each tool seat can carry out only one operation at one time. Operations carried out by one tool in each work center are synchronized and their performance time is the same in all work centers. Moreover, it is assumed that the manufacturing process is treated as the continuous one (if there is a need to replace a tool in one work center, the whole system is brought to a standstill). A final product represents an order unit on which all pre-defined operations have already been carried out.

It is taken into account that M customers place N orders with a certain manufacturer and require them in time. It is necessary to make K decisions to manufacture all elements of the order.

Let us create a matrix of orders in the form (1):

$$Z^0 = \left[z^0_{m,n}\right] \text{ , } m=1,\ldots,M;\ n=1,\ldots,N \tag{1}$$

where $z^0_{m,n}$ is the number of units of the n-th product ordered by the m-th customer. Orders are to be made from the universal charge which means that any order can be made from any kind of charge. It is assumed that the manufacturing process is continuous which results from the fact that there are no buffer stores between work centers. The structure of the system is presented in the matrix form (2):

$$E = \left[e_{i,j}\right] \text{ , } i = 1,\ldots,I \text{ ; } j = 1,\ldots,J \tag{2}$$

where $e_{i,j} = 1$ if the tool in the i-th work seat of the j-th work center is in use, otherwise $e_{i,j} = 0$ (it means that it does not exist or is excluded from the production process).

It is further assumed that each tool seat is equipped with one dedicated tool which can be used only once. After it is totally worn out, it must be replaced with a new one. It is assumed that no regeneration procedures are required in the discussed logistic system. Moreover, it is taken for granted that there is a full supply of tools for replacement. The life of tools is defined in the life matrix (3):

$$G = \left[g_{i,j}\right] \text{ , } i = 1,\ldots,I \text{ ; } j = 1,\ldots,J \tag{3}$$

where $g_{i,j}$ is the life of the tool in the i-th work seat of the j-th work centre given in conventional units (if the tool does not exist or is excluded from the production process, then $g_{i,j} = -1$). Each n-th product ordered by the m-th customer is manufactured along its route defined in the vector of routes according to the form (4):

$$D_{m,n} = \left[d_{m,n,j}\right] \text{ , } m = 1,\ldots,M \text{ ; } n = 1,\ldots,N \text{ , } j = 1,\ldots,J \tag{4}$$

where $d_{m,n,j}$ specifies the number of a tool seat in the j-th work centre used for manufacturing the n-th product for the m-th customer. Let us establish the manufacturing rate matrix in the form (5):

$$V = \left[v_{m,n}\right] \text{ , } m = 1,\ldots,M \text{ ; } n = 1,\ldots,N \tag{5}$$

where $v_{m,n}$ is the number of units of the n-th product manufactured for the m-th customer within the time unit.

In the course of production tools get worn out. A worn out tool in the work seat can be replaced only if there is no other available route to carry out any manufacturing operation. The vector of replacement time is defined in the form (6):

$$T^{repl} = \left[\tau_j^{repl}\right] \tag{6}$$

where the variable τ_j^{repl} is the replacement time of all tools in the j-th work centre.

4 The State of the Manufacturing System

The state of the manufacturing system changes after every k-th decision to either make the next order or replace all worn out tools in a work centre. Let us introduce the matrix of state of the manufacturing system in the form (7):

$$S^k = \left[s_{i,j}^k\right],\ i = 1,...,I;\ j = 1,...,J;\ k = 1,...,K \tag{7}$$

where $s_{i,j}^k$ is the state of the i-th tool in the j-th work centre (the number of units already manufactured in the j-th work centre with the use of the i-th tool). The state of the system represents the number of units already manufactured in the specific work centre with the use of a dedicated tool. To enable the manufacturing process the state must meet the condition $s_{i,j}^k < g_{i,j}$, otherwise the j-th work centre is subject to replacing its tools.

The initial state S^0 is given. The general equation of state of the manufacturing system takes the general form (8):

$$S^k = f\left(S^{k-1}, x_{m,n}^k, c\right) \tag{8}$$

where c is the number of a work centre assigned to replacement of all its tools, and $x_{m,n}^k$ is the number of units of the n-th product ordered by the m-th customer manufactured in the k-th stage.

Let us introduce the flow capacity matrix of tools in the form (9):

$$PT^k = \left[pt_{i,j}^k\right],\ i = 1,...,I;\ j = 1,...,J;\ k = 1,...,K \tag{9}$$

where $pt_{i,j}^k$ is the flow capacity of the i-th tool in the j-th work centre. This variable specifies the number of units which still can be manufactured in the j-th work centre with the use of the i-th tool. It can be calculated according the formula (10):

$$pt_{i,j}^k = g_{i,j} - s_{i,j}^k \tag{10}$$

Let us introduce the flow capacity matrix of routes in the form (11):

$$PR_{m,n}^k = \left[pr_{m,n}^k\right],\ m = 1,...,M;\ n = 1,...,N;\ k = 1,...,K \tag{11}$$

where $pr_{m,n}^k$ is the flow capacity of the route responsible for manufacturing the n-th product for the m-th customer. This variable specifies the number of units of the n-th product ordered by the m-th customer which still can be manufactured in the discussed system. It can be expressed in the form (12):

$$pr_{m,n}^{k} = \min(pt_{d_{m,n,j},j}^{k}),\ j = 1,2,..,J \tag{12}$$

To allow the manufacturing process, the route flow capacity for at least one order must fulfill the condition $pr_{m,n}^{k} > 0$ and let us manufacture at least one unit of any order of the matrix element.

It is assumed that we can manufacture only the number of units of the n-th product ordered by the m-th customer which can be manufactured by the tool characterized by the minimal flow capacity, so it is necessary to calculate the number of units of the order $z_{m,n}^{k}$ which can be manufactured before the most worn out tool in its route cannot be used any more. It is possible to determine the number of units of the n-th product ordered by the m-th customer in the k-th stage according the form (13):

$$x_{m,n}^{k} = \min\left(pr_{m,n}^{k}, z_{m,n}^{k}\right),\ m = 1,...,M\ ,\ n = 1,...,N\ ,\ k = 1,...,K \tag{13}$$

The state of the i-th tool in the j-th work centre changes in case of the n-th product ordered by the m-th customer which is manufactured by the i-th tool in the j-th work centre throughout the k-th stage according to the form (14) otherwise $s_{i,j}^{k} = s_{i,j}^{k-1}$.

$$s_{i,j}^{k} = s_{i,j}^{k-1} + \min\left(pr_{m,n}^{k}, z_{m,n}^{k}\right) \tag{14}$$

The state of the manufacturing system changes in case of replacement according to the form (15) if all tools in the j-th work centre are replaced at the k-th stage, otherwise $s_{i,j}^{k} = s_{i,j}^{k-1}$.

$$s_{i,j}^{k} = 0 \tag{15}$$

As it can be seen above, the replacement of tools in the work centre brings about the opportunity for resuming further production.

The state of any element of the order matrix changes according to the form (16) if the specified number of units of the n-th product ordered by the m-th customer is made throughout the k-th stage, otherwise $z_{m,n}^{k} = z_{m,n}^{k-1}$.

$$z_{m,n}^{k} = z_{m,n}^{k-1} + x_{m,n}^{k} \tag{16}$$

The matrixes of life, state and flow capacity are given for all orders as it is assumed that no matter which one is manufactured, the production output is given in the same conventional units. The only difference which remains is the rate of the production process.

5 Heuristic Algorithms for Control of the Manufacturing System

The problem of scheduling versions of assembled objects is computationally difficult, i.e. it belongs to the NP class in terms of its computational complexity. It is possible to use various sophisticated methods of optimization of production systems to solve the problem formulated in such a way. However, sophisticated optimization techniques are implemented to solve problems characterized by polynomial computational complexity. Moreover, sophisticated optimization techniques consume a lot of hardware resources such as a CPU time consumption and its memory. On the other side, there exist problems characterized by at least exponential complexity that are difficult to solve. A nondeterministic polynomial (NP) type problem requires vastly more time to solve than it takes to describe the problem. Choosing the right method may ultimately determine the effectiveness of manufacturing processes. A heuristic approach was used due to the need for shortening the calculation time and search for an efficient real-time solution. The control of the discussed manufacturing system consists of implementing heuristic algorithms which choose an order for manufacturing and heuristic algorithms for replacement strategy.

5.1 Manufacturing strategies

The number of production heuristic algorithms proposed for manufacturing orders is optional, however, for illustration reasons, only a few, which have proved to be the most effective ones up till now, are put forward [Chramcov and Bucki, 2013], [Chramcov et al., 2013].

5.1.1 Strategy ς_1 - Maximal pass of routes

This algorithm assumes that in the phase between two successive stoppages of the production system most of the orders must be manufactured so there is a need to choose the route with the highest flow capacity $pr_{m,n}$ which allows manufacturing the biggest number of units of the order $z_{m,n}$. This strategy can be expressed in the form (17):

$$pr_{a,b}^{k} = \max\left(pr_{m,n}^{k}\right),\ 1 \le a \le M\ ,\ 1 \le b \le N \tag{17}$$

5.1.2 Strategy ς_2 - Relative pass of routes

This algorithm assumes that in the phase between two successive stoppages of the production system the routes with the maximal relative flow capacity must be subsequently eliminated so there is a need to choose the route with the maximal relative flow capacity which allows manufacturing the order $z_{m,n}$. This strategy can be expressed in the form (18):

$$pr_{a,b}^{k} = \max\left(\frac{pr_{m,n}^{k}}{g_{m,n}}\right),\ 1 \le a \le M\ ,\ 1 \le b \le N \tag{18}$$

5.1.3 Strategy ς_3 - Biggest order algorithm

This algorithm chooses the biggest order $z_{m,n}^k$ at the moment of making a manufacturing decision in order to balance the current state of ordered elements. It is possible to express it according to the form (19):

$$z_{a,b}^k = \max\left(z_{m,n}^k\right),\ 1 \le a \le M\ ,\ 1 \le b \le N \tag{19}$$

5.1.4 Strategy ς_4 - Relative order algorithm

This algorithm chooses the least worked out order $z_{m,n}^k$ at the moment of making a manufacturing decision in order to balance the state of orders proportionately. It is possible to express this strategy according to the form (20):

$$z_{a,b}^k = \max\left(\frac{z_{m,n}^k}{z_{m,n}^0}\right),\ 1 \le a \le M\ ,\ 1 \le b \le N \tag{20}$$

5.2 Replacement strategies

The number of replacement strategies is optional, however, for illustration reasons, four, which have proved to be the most effective ones up till now, are put forward [Chramcov and Bucki, 2013], [Chramcov et al., 2013]. It must be emphasized that any replacement strategy is implemented only when two or more work centers have completely worn out tools which makes the further manufacturing process impossible. If used worn out tools are detected only in one work centre, it becomes subject to replacement of all its tools. After replacing tools in a certain work centre, the manufacturing process is resumed till the manufacturing system is brought to a standstill again. Nevertheless, a work centre is subject to replacement of its tools when it is characterized by at least one completely worn out tool.

5.2.1 Strategy ζ_1 – Replacement of tools in the work centre with the lowest flow capacity

This strategy is based on choosing all tools for replacement in the work center which is characterized by the lowest flow capacity of tools (see the formula (21)):

$$\gamma_\nu = \sum_{i=1}^{I} p_{i,\nu}^k = \min\left(\sum_{i=1}^{I} p_{i,j}^k\right),\ 1 \le \nu \le J \tag{21}$$

5.2.2 Strategy ζ_2 - Replacement of tools in the work centers characterized by the defined coefficient of the work centre wear

This strategy is based on choosing all tools for replacement in centers characterized by a defined summary wear λ (see the formula (22)):

$$\frac{\sum_{i=1}^{I} s_{i,j}^{k}}{\sum_{i=1}^{I} g_{i,j}} > \lambda \,,\; 1 \le j \le J \tag{22}$$

It means that if the condition in the form (22) is valid for the specific work centre, then replacement of all tools in this work centre is carried out.

5.2.3 Strategy ζ_3 - Replacement of tools in the most worn out work centre

This strategy is based on choosing for replacement all tools in the most worn out work center. It is possible to define this strategy according to the formula (23):

$$\gamma_\nu = \sum_{i=1}^{I} s_{i,\nu}^{k} = \max\left(\sum_{i=1}^{I} s_{i,j}^{k}\right),\; 1 \le \nu \le J \tag{23}$$

5.2.4 Strategy ζ_4 - The biggest ready product amount till the subsequent standstill of the system

This strategy is based on choosing all tools for replacement in the work center which lets us manufacture the most units of the order matrix elements after the replacement process is carried out till the subsequent stoppage of the system.

6 Manufacturing criteria

Determined manufacturing criteria can be used to evaluate implemented control algorithms. In the discussed case, minimizing the total order making time, minimizing the system wear coefficient, maximizing the system usage factor, maximizing the system flexibility coefficient, minimizing the total tool replacement time or minimizing the number of manufacturing and replacement decisions are considered.

The total time of making orders is calculated from the equation (24):

$$T_C = T_E + T_R \tag{24}$$

where T_E is the effective manufacturing time and T_R is the replacement time.

It is possible to express the effective manufacturing time according to the formula (25):

$$T_E = \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{z_{m,n}}{v_{m,n}} \tag{25}$$

It cannot be alternated within the course of production so the searching for the sequence of replacement procedures which minimize the total manufacturing time remains the core issue of the presented modelling problem. It is assumed that the total manufacturing time can be minimized only by finding such a sequence of manufacturing decisions which leads to minimizing the replacement time of tools. The effective manufacturing time (the operation time) of a tool placed in adequate seats cannot be either accelerated or slowed. Additionally, it is assumed that tools are replaced with new ones only and no regeneration procedures are required in the discussed system. The replacement time is defined in the form (26):

$$T_R = \sum_{k=0}^{K}\sum_{j=1}^{J} y^k \cdot \tau_j \tag{26}$$

where τ_j represents the replacement time of tools of the j-th work centre. If the replacement procedure is carried out, then y^k=1, otherwise y^k equals zero.

On the basis of the above assumptions it is possible to introduce the system usage factor in the form (27):

$$\vartheta = \frac{T_E}{T_C} \tag{27}$$

Let us introduce the system wear coefficient in the form (28):

$$\theta^k = \frac{\sum_{j=1}^{J}\sum_{i=1}^{I} s_{i,j}^k}{\sum_{j=1}^{J}\sum_{i=1}^{I} g_{i,j}} \tag{28}$$

This variable represents the summary wear of tools in all work centers at the k-th stage. If $\theta^k = 0$, it means that all tools are completely new. Consequently, on this basis the flexibility coefficient can be calculated according to the formula (29):

$$\rho = \sqrt{\vartheta \cdot \theta} \tag{29}$$

It is possible to implement these criteria individually or they can be used to create a multi-criterion model. In fact, in the case of only one manufacturing system, it means minimizing the values of these criteria. However, after using more than one parallel manufacturing plant, there is a need to minimize the values of these criteria in each additional plant.

7 Simulation study

In order to prove the correctness of the assumptions presented in the paper the simulation process is carried out for various configurations which can come into being in the real manufacturing environment. For the simulation purposes a dedicated simulation tool was implemented [Gruszka, 2003].

The aim of this simulation study is to find the most suitable manufacturing and replacement strategy for the discussed manufacturing system. For this reason it was decided to create 12 various sets of edge values taking into account the following:

- the number of work centers,
- the maximal number of tool seats in the work center,
- the maximal and minimal values of life of tools (expressed in general time units),
- the maximal replacement time of a tool (expressed in general time units),

- the maximal production rate (number of units manufactured in the time unit),
- the maximal number of order units.

The data for drawing procedures are presented in Table 1. The simulation study assumes manufacturing systems with different structures. It is assumed that the system is equipped with 3, 5, 7 or 9 work centers. Each work center is equipped with 3, 4 or 5 different tools maximally. The simulation experiments are carried out for big orders (set 1 - 6) or small orders (set 7 –12). All orders are manufactured in each work center. Work centers are arranged in a series. Simulation experiments are carried out for different numbers of orders.

Set no.	Number of work centers [-]	Number of tool seats [-]	The minimal value of a tool life [time unit]	The maximal value of a tool life [time unit]	The maximal value of the replacement time [time unit]	The maximal value of the manufacturing rate [number of units per time unit]	The maximal number of order units [-]
1	3	5	100	500	10	10	5000
2	7	5	100	500	10	10	5000
3	5	3	100	500	10	10	5000
4	7	3	100	500	10	10	5000
5	5	5	100	500	10	10	5000
6	9	4	100	500	10	10	5000
7	5	3	20	80	8	5	500
8	7	5	20	80	8	5	500
9	3	5	20	80	8	5	500
10	7	3	20	80	8	5	500
11	5	5	20	80	8	5	500
12	9	4	20	80	8	5	500

Table 1: Sets of assumed data for simulation experiments

Ten replications were carried out for each defined set of data. The given set is characterized by the number of work centers. Other parameters of the manufacturing system are generated at random for the given drawing intervals. The matrix of orders, the structure matrix, the life matrix of tools, the route vectors, the manufacturing rate matrix and the vector of time replacement are generated randomly. The simulation experiments are evaluated for all combination of manufacturing and replacement strategies. The value of replacement time is namely monitored. The analysis of results is outlined in Tables 2-6.

8 Results of simulation experiments

This section reports results of the performed simulation experiments. Firstly, the relative deviation of the replacement time for the specific combination of manufacturing and replacement strategies from the best result (the best combination of strategies) is tracked for each replication of the given set of data. The average values of this deviation are presented in Table 2. The best and the worst results for each set of data are highlighted.

Combination of strategies	The set number of the simulation process data												Average
	1	2	3	4	5	6	7	8	9	10	11	12	
$\varsigma_1\zeta_1$	6.89%	3.78%	1.97%	5.31%	5.58%	4.12%	4.31%	3.45%	4.37%	6.39%	7.70%	4.10%	4.83%
$\varsigma_1\zeta_2$	6.66%	3.81%	1.79%	5.25%	5.74%	4.09%	4.25%	3.66%	4.48%	6.29%	8.36%	3.39%	4.81%
$\varsigma_1\zeta_3$	6.97%	6.12%	4.45%	4.29%	5.26%	3.55%	3.73%	5.66%	5.78%	6.34%	6.61%	4.50%	5.27%
$\varsigma_1\zeta_4$	1.91%	1.97%	1.59%	0.57%	1.20%	0.96%	1.44%	1.20%	2.20%	1.76%	1.79%	1.51%	1.51%
$\varsigma_2\zeta_1$	4.70%	3.94%	2.06%	5.33%	5.53%	4.32%	4.15%	3.69%	3.18%	5.35%	6.88%	4.14%	4.44%
$\varsigma_2\zeta_2$	4.64%	3.91%	1.92%	5.27%	5.62%	4.29%	4.09%	3.99%	3.29%	4.97%	6.01%	3.61%	4.30%
$\varsigma_2\zeta_3$	5.48%	5.48%	4.03%	4.26%	5.38%	3.28%	3.24%	5.69%	3.77%	5.96%	5.62%	4.89%	4.76%
$\varsigma_2\zeta_4$	1.49%	1.75%	0.89%	0.60%	0.96%	0.91%	1.43%	1.52%	2.32%	1.49%	1.27%	0.98%	1.30%
$\varsigma_3\zeta_1$	3.33%	2.66%	1.64%	3.72%	5.78%	4.53%	4.64%	3.83%	3.15%	5.33%	5.20%	4.21%	4.00%
$\varsigma_3\zeta_2$	3.29%	2.58%	1.25%	3.72%	5.28%	4.43%	4.06%	3.85%	3.15%	5.51%	4.90%	3.90%	3.83%
$\varsigma_3\zeta_3$	3.26%	4.98%	3.18%	3.14%	4.75%	2.88%	2.39%	5.15%	3.16%	5.45%	4.88%	4.03%	3.94%
$\varsigma_3\zeta_4$	0.66%	2.06%	0.61%	1.07%	0.75%	1.46%	0.85%	1.50%	2.25%	1.64%	1.05%	1.03%	1.24%
$\varsigma_4\zeta_1$	2.83%	2.19%	1.84%	3.79%	5.85%	4.42%	4.54%	4.04%	3.05%	5.26%	5.25%	4.33%	3.95%
$\varsigma_4\zeta_2$	2.95%	2.17%	1.47%	3.73%	5.85%	4.31%	4.04%	3.85%	3.05%	5.17%	5.42%	3.81%	3.82%
$\varsigma_4\zeta_3$	3.01%	4.81%	3.97%	4.02%	4.58%	2.73%	2.16%	5.09%	3.97%	6.23%	4.46%	4.08%	4.09%
$\varsigma_4\zeta_4$	0.85%	2.17%	1.02%	1.14%	0.55%	1.59%	1.64%	1.10%	3.05%	1.52%	0.92%	0.86%	1.37%

Table 2: The values of the average relative deviation of the replacement time from the best result for each set of data

The presented results show that the best combination from the point of the minimal average value of the monitored deviation (see the last column of Table 2) is the combination of the manufacturing strategy no. 3 and the replacement strategy no. 4. In addition, a more detailed analysis shows a very good result of any manufacturing strategy and the replacement strategy no. 4. On the other hand, the worst results are achieved by means of implementing the manufacturing strategy no. 1 and the replacement strategy no. 3.

Another important aspect of analysis should be the numbers of replications in each data set where the value of the replacement time differs from the best result by less than 2% or more than 7%.

Tables 3 and 4 present this analysis. It is visible that implementing the combination of the manufacturing strategy no. 3 and the replacement strategy no. 4 is best to control the discussed manufacturing system.

The value of the replacement time differs from the best result in 76.67% cases less than 2% and never does this value differ from the best result by more than 7%. More similar results are also achieved in case of the combination of the manufacturing strategy and the replacement strategy no. 4.

However, there are only 50% cases with the deviation lower than 2% and more than 20% cases with the deviation higher than 7%.

Combination of strategies	The set number of the simulation process data												Sum	Effectiveness
	1	2	3	4	5	6	7	8	9	10	11	12		
$\varsigma_1\zeta_1$	4	2	7	4	3	3	3	3	5	1	2	4	41	34.17%
$\varsigma_1\zeta_2$	4	2	7	4	3	3	3	2	4	1	3	5	41	34.17%
$\varsigma_1\zeta_3$	2	2	4	4	1	3	4	3	3	2	2	2	32	26.67%
$\varsigma_1\zeta_4$	6	6	8	10	8	9	7	8	5	6	6	7	86	71.67%
$\varsigma_2\zeta_1$	5	1	7	5	2	3	4	3	5	3	2	4	44	36.67%
$\varsigma_2\zeta_2$	5	1	7	5	2	3	4	1	4	4	4	4	44	36.67%
$\varsigma_2\zeta_3$	2	2	6	4	1	3	5	1	2	2	2	0	30	25.00%
$\varsigma_2\zeta_4$	6	8	9	9	8	9	7	7	6	7	7	8	91	75.83%
$\varsigma_3\zeta_1$	6	4	7	6	2	4	4	2	5	4	3	3	50	41.67%
$\varsigma_3\zeta_2$	6	4	8	6	3	4	5	2	5	4	3	4	54	45.00%
$\varsigma_3\zeta_3$	6	4	7	4	2	4	6	3	5	2	2	2	47	39.17%
$\varsigma_3\zeta_4$	8	7	9	9	8	6	9	7	6	7	8	8	92	76.67%
$\varsigma_4\zeta_1$	7	4	7	6	3	4	4	1	3	3	3	3	48	40.00%
$\varsigma_4\zeta_2$	7	4	7	6	3	4	5	1	3	3	4	4	51	42.50%
$\varsigma_4\zeta_3$	5	4	5	4	3	5	6	3	4	2	2	1	44	36.67%
$\varsigma_4\zeta_4$	7	6	8	9	9	6	7	8	5	6	8	7	86	71.67%

Table 3: The number of replications where the value of the replacement time differs from the best result by less than 2%

Combination of strategies	The number of set of the simulation process data												Sum	Effectiveness
	1	2	3	4	5	6	7	8	9	10	11	12		
$\varsigma_1\zeta_1$	4	1	1	4	4	2	2	1	2	5	5	1	32	26.67%
$\varsigma_1\zeta_2$	4	1	1	4	4	2	2	1	2	5	5	1	32	26.67%
$\varsigma_1\zeta_3$	4	2	3	2	3	1	2	3	3	3	3	2	31	25.83%
$\varsigma_1\zeta_4$	0	1	0	0	0	0	0	0	0	0	1	0	2	1.67%
$\varsigma_2\zeta_1$	4	1	1	4	4	2	3	1	1	3	5	1	30	25.00%
$\varsigma_2\zeta_2$	4	1	1	4	4	2	3	1	1	3	5	1	30	25.00%
$\varsigma_2\zeta_3$	4	1	2	2	4	1	2	2	1	3	3	1	26	21.67%
$\varsigma_2\zeta_4$	0	1	0	0	0	0	0	0	0	0	0	0	1	0.83%
$\varsigma_3\zeta_1$	3	0	1	3	3	2	3	1	2	5	4	1	28	23.33%
$\varsigma_3\zeta_2$	3	0	1	3	3	2	3	1	2	4	3	1	26	21.67%
$\varsigma_3\zeta_3$	3	2	2	1	2	0	1	1	1	2	3	1	19	15.83%
$\varsigma_3\zeta_4$	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
$\varsigma_4\zeta_1$	2	0	1	3	5	2	3	1	1	4	3	1	26	21.67%
$\varsigma_4\zeta_2$	2	0	1	3	5	2	3	1	1	4	3	1	26	21.67%
$\varsigma_4\zeta_3$	2	2	2	2	2	1	1	2	3	5	2	1	25	20.83%
$\varsigma_4\zeta_4$	0	0	0	0	0	0	0	0	2	0	0	0	2	1.67%

Table 4: The number of replications where the value of the replacement time differs from the best result by more than 7%

Table 5 sorts results in each data set by the value of the average relative deviation from the best result of the replacement time. The combination of manufacturing and replacement strategies with the best result has the smallest number and the worst result is represented by the biggest number. The last two columns show again that the best results are achieved by implementing the combination of any manufacturing strategy and the replacement strategy no. 4. Moreover, the combination of the manufacturing strategy no. 3 and the replacement strategy no. 4 reached the third place at worst in each set of results. Definitely, the worst results are given by the combination of the manufacturing strategy no. 1 and the replacement strategy no. 3.

Combination of strategies	The set number of the simulation process data												Sum	Average
	1	2	3	4	5	6	7	8	9	10	11	12		
$\varsigma_1 \zeta_1$	15	9	11	15	11	10	14	5	14	16	15	11	146	12.17
$\varsigma_1 \zeta_2$	14	10	8	13	13	9	13	6	15	14	16	5	136	11.33
$\varsigma_1 \zeta_3$	16	16	16	12	7	8	8	15	16	15	13	15	157	13.08
$\varsigma_1 \zeta_4$	4	2	6	1	4	2	3	2	1	4	4	4	37	3.08
$\varsigma_2 \zeta_1$	12	12	12	16	10	13	12	7	10	9	14	12	139	11.58
$\varsigma_2 \zeta_2$	11	11	10	14	12	11	11	11	11	5	12	6	125	10.42
$\varsigma_2 \zeta_3$	13	15	15	11	9	7	7	16	12	12	11	16	144	12.00
$\varsigma_2 \zeta_4$	3	1	2	2	3	1	2	4	3	1	3	2	27	2.25
$\varsigma_3 \zeta_1$	10	8	7	6	14	16	16	8	7	8	8	13	121	10.08
$\varsigma_3 \zeta_2$	9	7	4	6	8	15	10	9	7	11	7	8	101	8.42
$\varsigma_3 \zeta_3$	8	14	13	5	6	6	6	14	9	10	6	9	106	8.83
$\varsigma_3 \zeta_4$	1	3	1	3	2	3	1	3	2	3	2	3	27	2.25
$\varsigma_4 \zeta_1$	5	6	9	9	15	14	15	12	4	7	9	14	119	9.92
$\varsigma_4 \zeta_2$	6	5	5	8	15	12	9	10	4	6	10	7	97	8.08
$\varsigma_4 \zeta_3$	7	13	14	10	5	5	5	13	13	13	5	10	113	9.42
$\varsigma_4 \zeta_4$	2	4	3	4	1	4	4	1	6	2	1	1	33	2.75

Table 5: The sequence of results sorted by the value of average relative deviation of the replacement time from the best result in each data set

Combination of strategies	The number of set of the simulation process data												Sum	Effectiveness
	1	2	3	4	5	6	7	8	9	10	11	12		
ς_1 OR ζ_x	7	8	10	10	8	10	8	9	7	8	8	7	100	83.33%
ς_1 AND ζ_x	1	0	3	4	1	1	3	0	2	0	0	2	17	14.17%
ς_2 OR ζ_x	8	9	10	9	8	10	9	8	8	9	8	8	104	86.67%
ς_2 AND ζ_x	1	0	5	4	1	0	3	0	1	0	0	0	15	12.50%
ς_3 OR ζ_x	10	10	10	9	9	10	10	8	10	8	9	9	112	93.33%
ς_3 AND ζ_x	4	1	5	4	1	1	3	0	3	0	1	0	23	19.17%
ς_4 OR ζ_x	10	9	9	9	10	10	10	8	8	8	9	9	109	90.83%
ς_4 AND ζ_x	3	1	5	4	0	1	2	0	2	0	0	0	18	15.00%
ς_x OR ζ_1	7	5	8	6	4	4	4	3	8	4	3	4	60	50.00%
ς_x AND ζ_1	4	1	6	4	1	3	3	1	2	1	2	3	31	25.83%
ς_x OR ζ_2	7	5	8	6	4	4	5	3	7	5	4	5	63	52.50%
ς_x AND ζ_2	4	1	6	4	1	3	3	1	2	1	2	3	31	25.83%
ς_x OR ζ_3	6	4	7	4	4	6	7	3	6	2	5	4	58	48.33%
ς_x AND ζ_3	1	2	3	4	1	2	3	1	1	2	0	0	20	16.67%
ς_x OR ζ_4	8	9	9	10	10	9	9	10	7	9	9	9	108	90.00%
ς_x AND ζ_4	6	5	8	7	6	5	6	4	3	4	5	5	64	53.33%

Table 6: Effectiveness of the manufacturing and replacement strategies separately

Table 6 presents the effectiveness of strategies separately. Each strategy is observed from two different points of view. First of all, the number of repetitions was found in each set when the implemented strategy reached at least in one combination the difference from the best result lower than 2%. In the second case, the number of repetitions in each set is searched for when all combinations of strategies reached the difference from the best result lower than 2%.

In terms of manufacturing, the best results were achieved by the strategy no. 3 whereas the worst ones by the strategy no. 1. Results in Table 6 show that if strategy no. 3 is used for controlling the manufacturing system, then 93.33% of the cases include results which differ from the best one by less than 2%. Moreover, there is no need to solve the problem of the replacement strategy in 19.17% of all cases. The results delivered by individual manufacturing strategies are very close in nature. The difference between the best and the worst results equals only 10%.

In case of replacement, the best results were achieved by the strategy no. 4 whereas the worst ones by the strategy no. 3. The result for the replacement strategy is more emphasized than in case of the manufacturing strategy. The difference between the best and the worst cases equals more than 40%. The result shows that controlling the system by means of strategy no. 4 delivers the solution which differs from the best one by less than 2%. Moreover, the solution does not depend on the manufacturing strategy type in 53.33% cases.

9 Simulation experiments of more extended systems

The previous conclusions are verified by means of more extended (complex) production systems. Further experiments were conducted. Specifically, 10 extra simulation experiments were carried out for the system with thirty and fifty work centers as well as 10 simulation experiments for fifty work centers. In the first case a manufacturing machine has 5 various tools at its disposal. The results are presented in the following tables.

Combination of strategies	Average of basic sets of data	System with 30 work centers	System with 50 work centers
$\varsigma_1 \zeta_1$	4.83%	6.41%	4.55%
$\varsigma_1 \zeta_2$	4.81%	6.34%	4.55%
$\varsigma_1 \zeta_3$	5.27%	7.76%	3.46%
$\varsigma_1 \zeta_4$	1.51%	1.64%	1.94%
$\varsigma_2 \zeta_1$	4.44%	6.61%	4.86%
$\varsigma_2 \zeta_2$	4.30%	6.62%	4.68%
$\varsigma_2 \zeta_3$	4.76%	7.80%	2.41%
$\varsigma_2 \zeta_4$	1.30%	0.82%	1.97%
$\varsigma_3 \zeta_1$	4.00%	6.59%	4.43%
$\varsigma_3 \zeta_2$	3.83%	6.60%	4.43%
$\varsigma_3 \zeta_3$	3.94%	7.09%	3.42%
$\varsigma_3 \zeta_4$	1.24%	0.80%	1.25%
$\varsigma_4 \zeta_1$	3.95%	5.96%	4.37%
$\varsigma_4 \zeta_2$	3.82%	6.24%	4.37%
$\varsigma_4 \zeta_3$	4.09%	7.68%	3.17%
$\varsigma_4 \zeta_4$	1.37%	1.41%	1.99%

Table 7: The values of average relative deviation of the replacement time from the best result

The tables always show the comparison with the current result achieved on the basis of the preceding simulation experiments for 12 basic sets of data. Firstly, the comparison of the relative deviation of the replacement time for the specific combination of manufacturing and replacement strategies from the best result (the best combination of strategies) is tracked. The results of simulation experiments of more extended manufacturing systems confirm the general conclusion that the best combination from the point of the minimal average value of the monitored deviation is the combination of the manufacturing strategy no. 3 and the replacement strategy no. 4. Tables 8 and 9 present the comparison of the numbers of replications in each data set where the value of the replacement time differs from the best result by less than 2% or more than 7%. Again, the results are consistent with the conclusions which were based on the results of the simulation experiments of relatively smaller manufacturing systems.

Combination of strategies	Average of basic sets of data	System with 30 work centers	System with 50 work centers
$\varsigma_1 \zeta_1$	0.34	1	3
$\varsigma_1 \zeta_2$	0.34	2	3
$\varsigma_1 \zeta_3$	0.27	0	5
$\varsigma_1 \zeta_4$	0.72	7	6
$\varsigma_2 \zeta_1$	0.37	0	2
$\varsigma_2 \zeta_2$	0.37	1	2
$\varsigma_2 \zeta_3$	0.25	0	6
$\varsigma_2 \zeta_4$	0.76	9	6
$\varsigma_3 \zeta_1$	0.42	1	2
$\varsigma_3 \zeta_2$	0.45	1	2
$\varsigma_3 \zeta_3$	0.39	1	3
$\varsigma_3 \zeta_4$	0.77	9	8
$\varsigma_4 \zeta_1$	0.40	2	4
$\varsigma_4 \zeta_2$	0.43	1	4
$\varsigma_4 \zeta_3$	0.37	0	4
$\varsigma_4 \zeta_4$	0.72	7	6

Table 8: The number of replications where the value of the replacement time differs from the best result by less than 2%

Combination of strategies	Average of basic sets of data	System with 30 work centers	System with 50 work centers
$\varsigma_1 \zeta_1$	0.27	6	2
$\varsigma_1 \zeta_2$	0.27	6	2
$\varsigma_1 \zeta_3$	0.26	7	2
$\varsigma_1 \zeta_4$	0.02	0	1
$\varsigma_2 \zeta_1$	0.25	6	2
$\varsigma_2 \zeta_2$	0.25	6	2
$\varsigma_2 \zeta_3$	0.22	6	1
$\varsigma_2 \zeta_4$	0.01	0	1
$\varsigma_3 \zeta_1$	0.23	5	2
$\varsigma_3 \zeta_2$	0.22	5	2
$\varsigma_3 \zeta_3$	0.16	5	1
$\varsigma_3 \zeta_4$	0.00	0	0
$\varsigma_4 \zeta_1$	0.22	4	2
$\varsigma_4 \zeta_2$	0.22	5	2
$\varsigma_4 \zeta_3$	0.21	7	1
$\varsigma_4 \zeta_4$	0.02	0	0

Table 9: The number of replications where the value of the replacement time differs from the best result by more than 7%

10 Conclusions

The paper presents the way of searching for available manufacturing and replacement strategies in order to minimize the replacement time of tools. Four manufacturing and four replacement heuristic strategies are taken into account. All combinations of these strategies are implemented to control the discussed manufacturing system. Results of simulation experiments showed that the combination of manufacturing strategy no. 3 (the appropriate algorithm chooses the biggest order) and replacement strategy no. 4 (the biggest ready product amount till the subsequent standstill of the system) delivers the best result. It proves that it is most suitable to choose the biggest order at the moment of making a manufacturing decision and to replace all tools in the work center which lets us manufacture the most units of order after the replacement procedure is carried out till the subsequent stoppage of the system.

In case of evaluating strategies separately it is possible to emphasize different results for manufacturing and replacement strategies. Whereas differences between discussed individual manufacturing strategies tend to be minimal, the results for replacement strategies are clear. This separate analysis shows that very good results can be achieved by combining any manufacturing strategy with replacement strategy no. 4 which is based on choosing all tools for replacement in the work center which lets us manufacture most units of order vector elements after the replacement process is carried out till the subsequent stoppage of the system.

It may be argued that more sophisticated optimization techniques guarantee to reach the global minimum, but the computational burden can become early exaggerated for most practical problems. That computational burden is strictly related to the shape of the error surface, and particularly to the presence of local minima. Hence, it turns out to be very interesting to investigate the presence of local minima and particularly to look for conditions that guarantee their absence. However, sophisticated optimization techniques are implemented to solve problems characterized by polynomial computational complexity. Moreover, sophisticated optimization techniques consume a lot of hardware resources: CPU time and memory. On the other side, there exist problems characterized by at least exponential complexity that are difficult to solve. A nondeterministic polynomial (NP) type problem requires vastly more time to solve than it takes to describe the problem. Choosing the right method may ultimately determine the effectiveness of manufacturing processes.

Nondeterministic polynomial hard problems are solvable in polynomial time only if they are on par with polynomial problems. Solving an NP-hard problem requires worst case exponential time. Polynomial-time approximation algorithms are implemented for optimization problems, yielding a worst-case upper bound of the ratio between the cost of an approximate solution and the cost of optimal solution. Unfortunately, these guaranteed approximation ratios are unrealistically high.

Modern problems tend to be very intricate and relate to analysis of large data sets. Even if an exact algorithm can be developed its time or space complexity may turn out unacceptable. In reality it is often sufficient to find an approximate or partial solution. Such admission extends the set of techniques to cope with the problem. Heuristic algorithms are able to suggest some approximations to the solution of optimization problems while solving complex problems.

In probabilistic analysis problem instances are drawn from simple probability distributions. Often one can prove excellent performance on the average. However, the probability distributions may not correspond to real-life instances.

Heuristics are typically evaluated empirically on examples drawn from, or representative of real-life instances. Heuristics are often “unreasonably effective,” for reasons not well understood.

Simulation of this type of the manufacturing system is also important in real time. In this case it is possible to determine when the last order unit leaves the manufacturing system. Moreover, the operator of the manufacturing system knows exactly which part of the order is made at the specified moment of the manufacturing process. It will be interesting to extend this work by including the manufacturing algorithm of the order unit to be chosen at random. It could be possible to choose the elements of the order matrix at random by implementing of the pseudorandom generator. This process can be carried out an optional number of times (e.g. 100000 times or more) and, as a result, the best result is shown and compared with other results for the subsequent analysis.

Further work should be devoted to the extension of other types of production systems. It seems unavoidable to invent appropriate heuristic control algorithms which could deliver a satisfactory solution. The results will have to be compared with other optimization methods also, in terms of the computation time.

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