# Decision Support Tool for Group Job-shop Scheduling Problems

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Abstract: This paper presents a new tool for group job-shop scheduling problems. The tool encompasses a dynamic Pareto-optimal method based on two criteria simultaneously: relative setup expenditure criterion and average orders utility criterion. In this method the concept of production intensity as a dynamic production process parameter is used. The software used allows scheduling for medium quantity of jobs. The result of software application is the set of non-dominant versions proposed to a user for making a final choice. Based on this model, a decision support tool (DST) called OptJobShop is used for scheduling optimization. The decision support tool provides for scheduling simulation with various initial parameters, comparison of different scheduling versions and choice of the final decision.



## 1 INTRODUCTION

Technological grouping of jobs assures low setup time for transition from a job to a job within a group. For instance, if it is necessary to perform a group of certain jobs (orders) to make one and the same product on a single machine, a set of orders turns into one batch for manufacturing. Such type of grouping is typical for cutting, punching, plastic details casting, etc., if the “make-to-order” manufacturing strategy is used. In the other case, a set of jobs may become a batch for manufacturing, when all jobs have to be executed simultaneously on a single machine (oven, bath).

Group scheduling is also applicable for the “make-to-stock” manufacturing strategy, which is typical for process manufacturing, production of hardware, fasteners, general-purpose tools, etc. For such production, as a rule, minimal product quantity that is jointly manufactured is equal to a “technical” lot. The latter depends on the machine volume, package size, truckload value and so on. From the economical point of view, it makes sense to merge technical lots into batches, which may be manufactured without a setup.

In the last two decades, a lot of papers dedicated to group scheduling have been published. Since group scheduling is a matter of great computational complexity, every group research, as a rule, was dedicated to a special scheduling case, and seeks a scheduling solution for the best value of certain criterion, for example makespan $C_{\max}$.

It is necessary to note, however, that the way a group scheduling problem is formulated as a problem with a single criterion contains an inherent contradiction. Indeed, the main reason of group scheduling is an attempt for rational tradeoff between a high customer service level and a low production cost. High customer service level may be achieved only by timely order completion. However, prompt order completion contradicts requirement of keeping production expenses low. Necessity to improve both characteristics simultaneously is known as the “dilemma of operation planning” (Nyhuis and Wiendal, 2009), and its solution is in principle impossible with a single criterion concept. More promising, but also more complicated, will be a direction of research seeking for Pareto-optimal diagrams on problem criteria.

Apparently, to get the best solution for “dilemma of operation planning”, one must design Pareto-optimal diagrams on the basis of criteria, which correspond to correlation between job execution expenses and efficiency. As it was shown in the paper by Mauergauz (2012), the criterion of relative setup expenses $U$ and the criterion of average orders utility $\bar{V}$ may be considered for group scheduling. These criteria are fundamental for computing of job-shop schedule

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both for “make-to-order” and “make-to-stock” manufacturing strategies. The scheduling simulation described in this paper provides a user with a set of Pareto solutions for a final decision.

The remainder of this paper is organized as follows. Section 2 provides a review of decision support systems for manufacturing. In Section 3 the problem is formulated, the function of direct expenses and the function of current orders utility are determined. Section 4 is dedicated for the structure of planning and decision support system. The example of group job-shop modeling and scheduling is described in Section 5. Section 6 includes discussion of results and outlook of investigations.

## 2 DECISION SUPPORT SYSTEMS FOR MANUFACTURING

As far as the author knows, the paper by Viviers (1983) was one of the early works, in which a decision support system for job-shop scheduling was used. To get suitable decision, the sequence of jobs completion was set by an interactive user interface. After a job was scheduled, a corresponding due date based on the scheduled lead time, was calculated. If work-in-process volume and lead time values were not high, the decision was supposed to be suitable.

Decision support systems designed in following years differed by direction, structure and simulation methods. The system’s goal is directly connected with hierarchical level of planning that the system is intended for. The most developed are decision support systems for tactical long time planning, when sales & operation plans are designed. For example, the paper by Lee and Lee (1999) was directed to coordination of production/marketing decisions.

Mansouri et al. (2012) studied some decision support problems in multi-criteria supply chain for the MTO strategy. Barfod et al. (2011) designed decision support system based on combining multi-criteria decision analysis with cost-benefit analysis both for production and transport aspects of supply.

A number of systems were designed for tactical long time planning on aggregated level. The hierarchical decision support system by Ozdamar et al. (1998) was integrated with MRP system through Master Production Schedule. This system had the interactive user interface for data input and visualization of elaborated decision versions. In the system designed for small companies by Silva Filho and Cezarino (2007) MS Access was used as a database. This system had a constrained linear stochastic production planning model. Silva et al. (2006) described the interactive decision support system for an aggregate production planning. A multi-criteria model with mixed linear programming was developed for three criteria: maximum profit, minimum late orders, and minimum work force level changes. In the work by Garcia-Sabater et al. (2009) the decision support system for aggregate production planning is concerned with determining the optimum production, work force, and inventory levels for each period of the planning horizon.

The important process in sales & operation scheduling is inclusion of a new order into the plan. In the paper by Okongwu et al. (2012) the systems are described for estimation of order inclusion expediency with regard to order influence on the whole supply chain. Kalantari et al. (2011) elaborated the decision support system for order inclusion within MTS and MTO strategies. The decision support systems review on order inclusion was made in the paper by Slotnik (2011).

Some systems are destined for decision support in Master Production Scheduling. Fonseca et al. (2005) designed the decision support system for Master Production Scheduling for mass production with the Just-in-Time. In the paper by Silva (2009) the decision support system named 'PHIL' was described, which was intended for regular week tasks in the synthetic fibre production industry. Sotiris et al. (2008) designed the system for weekly order releasing in metal forming industry**.**

Considerable number of decision support systems that have been designed recently is dedicated to daily scheduling. In these systems one can make order release decisions and select optimal parameters of production process. One of the early order release systems was described by Wang et al. (1994). In this paper, a neural network approach is developed for order acceptance decision support in job-shops with machine and manpower capacity constraints. The order acceptance decision problem was formulated as a sequential multi-criteria decision problem. Oguz et al. (2010) examined the order acceptance system, where the orders were defined by their release dates, due dates, setup times for a single machine.

Mahdavi et al (2010) elaborated the support system for scheduling based on discrete events simulation. The method "event – condition – action" was used for decision making. In the paper by Hasan et al. (2012) the decision support system for job-shop scheduling was described, which used genetic algorithm for makespan minimization.

In the more complex systems decisions are supported on various planning levels. Such systems may be divided into two groups. The systems related to the first group may be used in various industry fields; the systems related to the second group are niche. For example, the system VTT_GESIM (Heilala et al., 2010) has the general destination. This system is based on methods of Discrete Event Simulation. Such methods may be applied for all kinds of discrete production, including assembly and project production, and for supply chains as well. Simulation may be made at all production stages from design of the production lines and the manufacturing cells to daily planning. The feature of the system, which makes it possible to apply in various fields, consists in special parametrical files for database tuning. The system (Kargin and Mironenko, 2009) is the example of a niche system, which has the knowledge base and is destined for sheet cutting at primary operation shops.

Sometimes it is expedient to apply simpler systems, which may be named as the decision support tools. In the paper by Buehlmann et al. (2000) the simple decision support system for wood panel manufacturing is described. The system consists of MS Excel forms, which make it possible for a user in the shop to optimize the schedule, as terms of supply and material prices are changing. Novak and Ragsdale (2003) elaborated a decision support methodology for stochastic multi-criteria linear programming in MS Excel. Petrovic et al. (2007) designed the decision support tool using such linguistically quantified statements as *most*, *few* etc. for estimation of batch size influence, order importance and other parameters as measure of plane quality. They applied this tool in the pottery industry. In the paper by Sakalli and Birgoren (2009) the decision support tool for optimal receipt selection in brass casting industry was described.

Such simple systems are useful, when it is possible to use the available ERP-system for data input and work lists making. In these cases the decision support system has functions of scheduling simulation, modification of initial parameters for analysis and results visualization. This paper suggests such a decision support tool based on MS Excel for computing and final choice of a multi-criteria group schedule in job-shops.

# 3 MAIN DEFINITIONS AND PROBLEM FORMULATION

## 3.1 Utility Functions in Scheduling

The customer service level may be assessed by the current order utility function *V*. From the manufacturer's point of view, the order value increases proportionately to work amount $p_i$, since staff engagement increases. Besides, the more is the time reserve for completing an order, the more attractive is the order, since there is an opportunity to prepare for order execution. Eventually the order time reserve is decreasing, and the order value is diminishing. After all, if due date has expired, the order value becomes negative.

The manufacturer's attitude to the order changes in time and the appropriate function is named *production intensity* (Mauergaz, 2012):

$$H_i = \frac{w_i p_i}{G} \frac{1}{(d_i - t)/\alpha G + 1} \quad \text{at} \quad d_i - t \geq 0$$

and (1)

$$H_i = \frac{w_i p_i}{G}[(t - d_i)/\alpha G + 1] \quad \text{at} \quad d_i - t \leq 0,$$

where:

$\boldsymbol{p_i}$ = processing time of job *i*; $\boldsymbol{G}$= plan bucket duration; $\boldsymbol{w_i}$ = priority weight coefficient of job *i*; $\boldsymbol{\alpha}$ = "psychological coefficient"; $\boldsymbol{d_i}$ = due date; $\boldsymbol{t}$= current time.

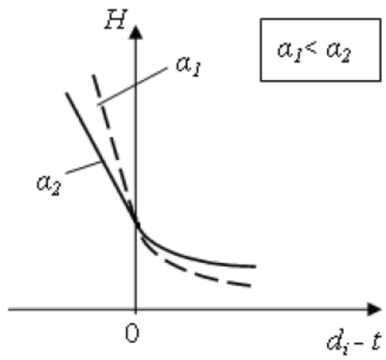


Figure 1: Production intensity diagrams.

On abscissa axes in Figure 1 the time reserve is measured. The reserve is equal to subtraction between due date and current time. In the positive part of the diagram ( $d_i > t$ ) the values of intensity with growth of available time reserve decrease in hyperbolic mode.

When the time reserve is negative ( $d_i < t$ ) and there is delay of order completion, the production intensity linearly increases. Since production intensity is dimensionless it has no physical sense, but it has psychological sense. Indeed, when this order parameter is augmenting, the nervousness about order execution is increasing. Two curves in Figure 1 differ in the psychological coefficient value. The higher is the $\alpha$ coefficient, the more placid is the attitude to delays and the lower is the intensity.

The production intensity concept may be used for determination of the current order utility function *V* (Figure 2).

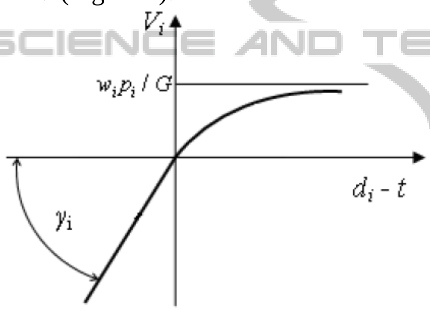


Figure 2: Current order utility function.

Assume that the current utility for an order $i$ is

$$V_i = \frac{w_i p_i}{G} - H_i . \quad (2)$$

The curve in Figure 2 for the positive value $d_i - t \geq 0$ tends to the horizontal asymptote,

$$V_i = w_i p_i / G . \quad (3)$$

In the negative part $d_i - t \leq 0$ the curve turns into the inclined straight line with

$$tg\gamma_i = \frac{w_i p_i}{\alpha G^2} . \quad (4)$$

If the order due date reserve is positive, the manufacturer usually intends to get some profit; if reserve is negative and job execution delays the manufacturer, as a rule, it incurs losses. There are a great number of papers dedicated to the utility changes as a function of available gain or loss. Results of such researches may be reduced to one of two versions depicted in Figure 3. On the abscissa axis in Figure 3 the gain value (anticipated profit $\Pi$ ) is set, on the ordinate axis the gain utility is set in the positive area of the abscissa axis, and the loss utility - in the negative area. The diagram 3a was named an S-mode curve as a result of a well-known research by Kahneman and Tversky awarded with the Nobel Prize on economics in 2002. Their research proved inclination of ordinary people to risk, when loss is probable (the left part of the diagram). The left part is concave, so a sign of corresponding second derivative is positive, and there is risk proneness.

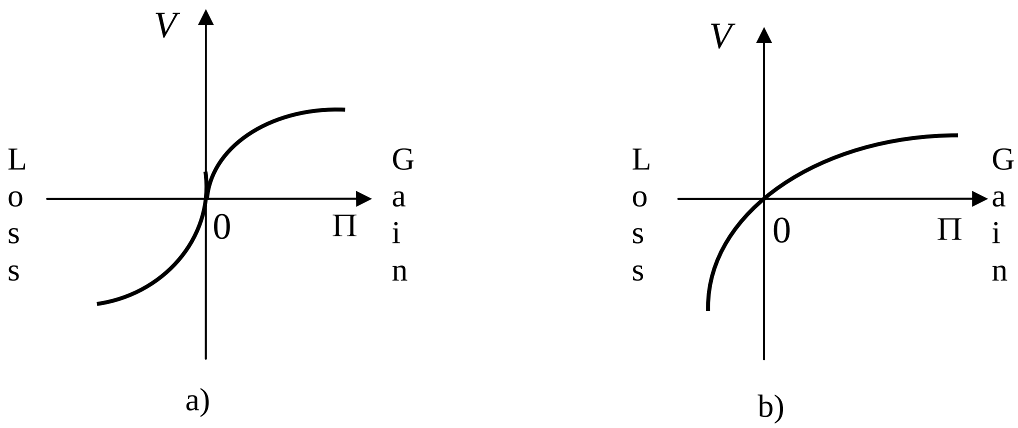


Figure 3: Possible diagrams of gain and loss utility; a) diagrams with risk averse and risk prone areas; b) diagrams only with risk averse area.

In contrast to the diagram 3a, the diagram 3b (Grayson-Bard utility function) shows risk aversion both for gain or loss perspectives. Difference of results in the diagrams 3a and 3b, most probably, were caused by choice of people circles for polling and by direction of money application. In the research by Kahneman and Tversky, modest people were interrogated, money amounts were negligible, and their purpose was consumption. On the contrary, Grayson-Bard function was designed for investments by large companies.

If we compare the curve in Figure 3 and the curves in Figure 2, we can see that the order time reserve is used as gain or loss. It seems to the manufacturer that the long-term order availability represents a considerable gain, but the rate of this gain growth goes down in proportion to the duration. In this positive field the order utility curve behaves entirely like the diagrams in Figure 3. The negative field in Figure 2 is similar to the loss field in Figure 3, but in contrast to the diagrams in Figure 3 there is linear diminution of order utility function in Figure 2. Accordingly, the function second derivative is equal to zero, and risk is neutral.

Due to the additivity property of production intensity and order utility function, it is possible to compute the average utility of the whole order set during a plan bucket. The value of this parameter describes timeliness of order completion and may be used as a criterion of scheduling.

Let us assume that a certain job that corresponds to the node of the scheduling versions tree at the level $l$ is completed at the moment of time $C_l$. Let us also assume that the job $k$ with processing time $p_k$ starts at the moment $t_k$, which is more than or equal to $C_l$. Then the average utility of the entire set of jobs $J$ from start until completion of the job $k$ in the node at the level $l+1$ equals

$$\bar{V}_{l+1,k} = \frac{1}{t_k + p_k} \int_0^{t_k+p_k} V dt = \frac{1}{t_k + p_k} (\bar{V}_l \times C_l + \int_{C_l}^{t_k+p_k} V_k dt) \qquad (5)$$

The function of negative expenses utility (loss function) may be used as the second criterion in the dilemma of operation planning. If the sequence number of planning job is $n$, then

$$U = \frac{1}{c}[c_s \sum_{l=0}^{n} s_l + c_i \sum_{l=0}^{n} (t_{kl} - C_l)], \qquad (6)$$

where:

$\boldsymbol{c}$= shift cost; $\boldsymbol{c_s}$ = hour setup cost; $\boldsymbol{c_i}$ = hour idle cost; $\boldsymbol{t_{kl}}$ = moment of job $k$ start after job $l$ completion; $\boldsymbol{s_l}$ = setup time for the next job with the sequence number $l$ in the specific schedule version.

## 3.2 Planning Problem to Be Considered

Let us consider the group job-shop problem. This problem may be considered as scheduling for several groups of parallel machines of various purposes. In this case every job consists of a set of operations, and every operation has to be executed on a machine with a corresponding availability. Let us assume that a set of jobs for manufacturing may be divided into groups of several types, and operation setup norms $s_{ij}$ depend on the corresponding machine group $j$ and job kind $i$.

According to a planning system, which is used at the plant, this problem has different versions. In the simplest case one may suppose that at the moment of planning the set of part batches to be manufactured within a plan bucket (1-5 working days) is known. In this case size of batches in process of treatment does not change, therefore release batches, transport batches and output batches are equal.

The situation is much more complex, when the kit planning system is applied. Within this system a shop has to manufacture the specified number of kits $n_k$ consisting of different parts during a plan bucket (for example, a working day). Besides, different sets may include parts of one type. It is also necessary to take into account that stocks for parts of different parts may arrive to the shop at various moments of time $r_i$. If available criteria of optimization are relative setup cost $U$ and average order utility $\bar{\boldsymbol{V}}$, in accordance with the well-known three-part scheduling classification, the considered problem is

$$J_j \mid prec, r_i, n_k, s_{ij} \mid U, \bar{V}, \qquad (7)$$

where:

$\boldsymbol{J_j}$ = machine quantity in a group *j*; $\boldsymbol{n_k}$ = needed kit quantity on a day; $\boldsymbol{r_i}$ = moment of stock arrival ; $\boldsymbol{s_{ij}}$ = setup time; $\boldsymbol{U}$ = setup cost criterion; $\boldsymbol{\bar{V}}$ = average order utility criterion; ***prec*** = the subsequent operation may be executed after all previous operations.

There are two target functions in the formula (7), and they may both be improved only within certain limits. The Pareto compromise curve serves as such limit, because in its points improvement (reduction) of the criterion $U$ is always related to deterioration (reduction) of the criterion $\bar{V}$ . To solve the problem (7), we should apply a MultiObject "Greedy" (MO-Greedy) algorithm (Canon and Jeannot, 2011), which at every step seeks a set of non-dominated solutions.

Examples of using this algorithm for group multi-criteria scheduling are described in the paper by Mauergauz (2013). With this approach for every level of search tree constructional nodes of non-dominated solutions should be found, and then new branches should grow from these nodes. Using the formulas (1, 2, 5) and the rules for integral calculations, we can compute the criterion $\bar{V}$ value in every node of the tree. The criterion $U$ value may be computed by the formula (6) in every node.

# 4 STRUCTURE OF PLANNING AND DECISION SUPPORT SYSTEM

The system to be considered consists of initial data input, data preparation for planning, the optimization model, the decision support tool and visualization of computed results. The system architecture and corresponding streams of information are shown in Figure 4. The initial data are being recorded on an MS Excel sheet by hand or are transferred from ERP system. The VBA program named OptJobShop provides the data actuality, when planning begins and start of macros with computer program for scheduling. The planning results depend essentially on a number of parameters. The simulation subsystem is the main module of decision support, which makes it possible to determine parameters influence.

The simulation parameters are input by a graphical user interface. Parameters of branching set constraints on nodes of the decision tree and are being fixed during the system tuning. It is possible to modify three main parameters of computing: the psychological coefficient, size of the transport batch and the planning horizon. The computation results for various simulation parameters are being recorded in an MS Excel sheet. After analysis of criteria set for all scheduling versions the Gantt diagram for selected version is being drawn. Parameters of the selected version may be transferred into the ERP system for generation of working tasks.

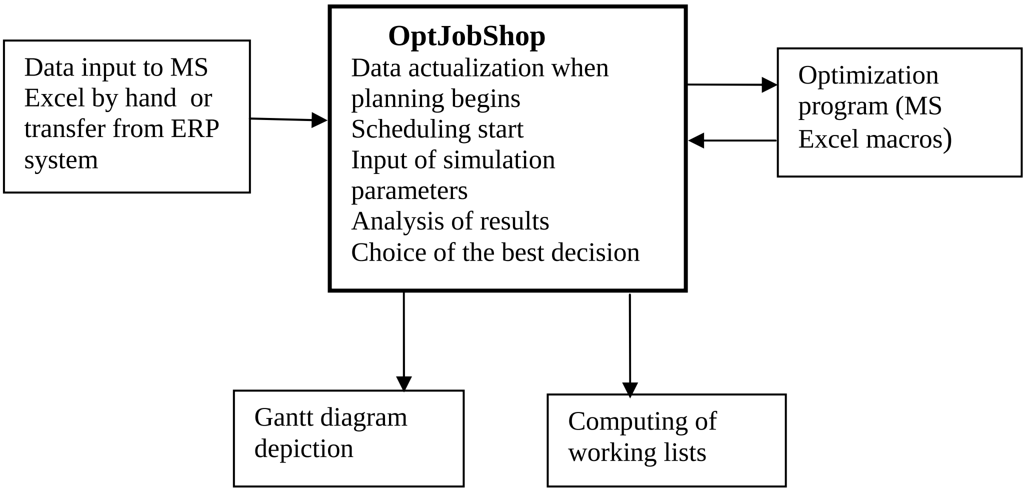


Figure 4: The system architecture and information streams.

## 5 EXAMPLE OF SYSTEM USAGE

Let us consider an example of system usage. Assume it is necessary to manufacture three types of part kits in a shop. Assume also that the shop must produce three kits of kind 1, one kit of kind 2 and two kits of kind 3 within a working day. Every kit consists of parts of six types in any number. In process of manufacturing parts of each type have to be subjected to various technological operations in a given sequence. Every operation may be executed on the corresponding machine which relates to a set of machines with similar technological functions.

Figure 5 shows the record of composition of sets and fragment of the operation table on the MS Excel sheet. Figure 6 shows the records of currents parts stocks and the records of parts batches, which are in manufacturing at the moment of planning.

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | | Structure of kits | | | | Technological operations | | |
| 2 | Kind of kit | Type of part | A number of parts | | Type of part | Operation number | Number of machine group | Process norm in hours |
| 3 | 1 | 1 | 2 | | 1 | 1 | 1 | 0.2 |
| 4 | 1 | 4 | 3 | | 1 | 2 | 2 | 0.3 |
| 5 | 1 | 3 | 1 | | 1 | 3 | 4 | 0.5 |
| 6 | 2 | 5 | 4 | | 1 | 4 | 3 | 0,1 |
| 7 | 2 | 1 | 3 | | 2 | 1 | 2 | 0.25 |
| 8 | 2 | 6 | 2 | | 2 | 2 | 1 | 0.15 |
| 9 | 3 | 3 | 4 | | 2 | 3 | 4 | 0.5 |
| 10 | 3 | 4 | 1 | | 2 | 4 | 3 | 0.15 |
| 11 | 3 | 2 | 3 | | 2 | 5 | 5 | 0.35 |
| 12 | | | | | 3 | 1 | 1 | 0.2 |
| 13 | | | | | 3 | 2 | 3 | 0.25 |

Figure 5: Structure of kits and the table of operations.



| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| 16 | | | Stocks on | 08.11.13 | | | | | |
| 17 | | Type of part | | 1 | 2 | 3 | 4 | 5 | 6 |
| 18 | | Designation | | P1 | P2 | Q1 | Q2 | R1 | R2 |
| 19 | | Minimal transport batch | | 6 | 6 | 6 | 6 | 6 | 6 |
| 20 | | Current stock | | 10 | 5 | 10 | 7 | 10 | 20 |
| 21 | | Backlog | | 0 | 2 | 0 | 0 | 2 | 0 |
| 22 | | Save stock | | 5 | 5 | 3 | 3 | 2 | 6 |
| 23 | Possible day of raw arrival | | | 0 | 1 | 0 | 0 | 0 | 0 |
| 24 | Number of the last batch | | | 43 | 26 | 17 | 57 | 13 | 45 |
| 25 | | Priority coefficient | | 1 | 1 | 1 | 1 | 1 | 1 |
| 26 | | | | | | | | | |
| 27 | Batches in manufacturing on | | | 08.11.13 | | | | | |
| 28 | | | | Type of part | Batch number | Quantity in a batch | Number of the last operation | Possible completion moment in hours | |
| 29 | | | | 1 | 44 | 10 | 3 | 0.5 | |
| 30 | | | | 3 | 18 | 5 | 1 | 0 | |
| 31 | | | | 2 | 27 | 10 | 2 | 0 | |
| 32 | | | | 1 | 45 | 10 | 1 | 1 | |

Figure 6: Parts stocks and batches in manufacturing at the moment of planning.

Apart from this data, information is recorded onto an MS Excel sheet about number of machines in each machine group, hour setup cost and hour idle cost of these machines, information on every machine setup on a moment of planning as well. Setup norms for each technological operation and working calendar for the several nearest days are also recorded into the sheet. Let us assume that during manufacturing every batch of parts is equal to the minimal transport batch, which is given in the stock table in Figure 6. After start of the program the non-dominated decision versions are being computed, and results have to be analyzed with the graphical user interface shown in Figure 7. For each version the average load coefficient and values of criteria are computed. The version numbers, which are recommended for decisions by Savage's method and Hurwitz's method, are automatically determined and displayed on the screen. Change of the simulation parameters results in changes of scheduling criteria values. The user can choose the version with criteria values that are optimal in current situation.

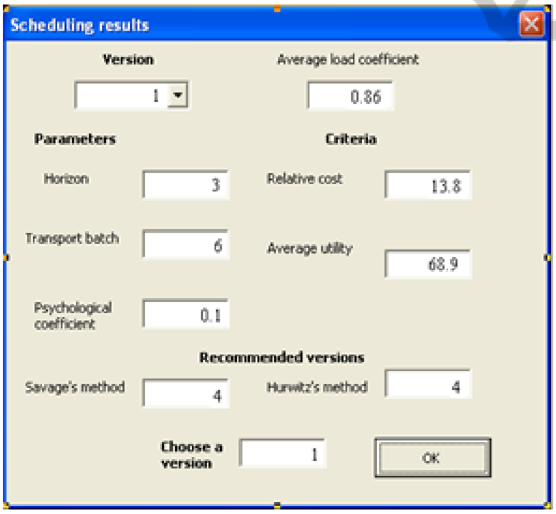


Figure 7: Dialog support decision interface.

In Figure 8 the Gantt chart for a selected version is shown. In this diagram the operations for batches with parts of type 3 are marked in black. At the beginning of scheduling in manufacturing there is the batch No. 18 (Figure 6) with parts of this type in amount of 5 pieces, and the last completed operation for this batch is operation 1. If one takes into account the available part stock, backlog and save stock, to manufacture the necessary kits within the horizon of 3 days, one must complete this batch No. 18 and additionally manufacture four transport batches of these parts. As it is follows from Figure 8, for this purpose the first operation has to be executed on the machine 1 with the release batch of 24 pieces. Then the operation 2 is scheduled on the machine 6 for the whole batch of 29 pieces.

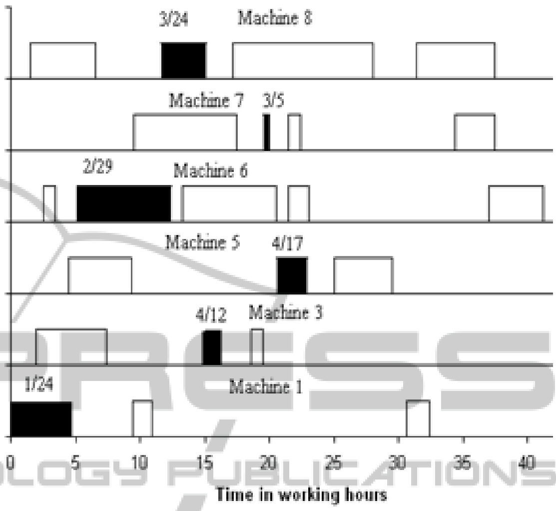


Figure 8: Gantt chart for selected scheduling decision.

The operation 3 begins without waiting for completion of all parts within the operation 2, so 24 parts are transported from the machine 6 to the machine 8. Then the remainder has to be transported to the similar machine 7. Some of parts, which has been through the operation 3 in amount of 12 pieces, must be transported to the machine 3 for execution of the operation 4, and all others in the amount of 17 pieces are joined on the similar machine 5. Thus, automatically the planning with parallel-consecutive treatment and parts grouping into batches is realized.

## 6 CONCLUSION

We designed the decision support tool for dynamic solution of the "operation planning dilemma" for a job-shop. The relative setup cost $U$ criterion and the average orders utility $\bar{V}$ criterion are used to define the correlation of "cost/efficiency" on the planning horizon. The average orders utility value is determined, depending on the production intensity $H_i$ of every order, which changes in time. To design a schedule, a set of Pareto-optimal solutions shall be calculated on the planning horizon, and the final decision will be made by the user.

The above results show that the group scheduling approach, based on applying the criterion of relative direct cost and the criterion of average orders utility, allows computing the satisfactory schedule versions. However, one cannot assert that any version is the best within a given set of versions and, all the more, within a whole possible set of versions. Moreover, when the planning horizon in the “make-to-stock” strategy is changed, the computed schedule versions change substantially as well. Quality of scheduling depends essentially on initial parameters: size of the transport batch, the planning horizon and the psychological coefficient.

Computations show that the order utility is great for a small transport batch. When the batch size increases, the order utility diminishes. For the numeral example in Section 5, in the interval from 6 to 12 pieces there is sharp decrease of the order utility, then utility increases again. Thus, in this case the optimal size of the transport batch is equal to 6 or 12.

When the planning horizon changes, the computed versions of schedule also change substantially. If the horizon increases, the system automatically offers the versions with larger groups of transport batches. Computations show that at the horizon that is named critical, the number of output batches for parts of any type begin to increase sharply. This horizon value may be considered as maximum possible for scheduling.

Scheduling is a regular process that repeats with certain, but not always constant cycle. For this purpose it is convenient to use new MS Excel sheets, where information from previous sheets may be contained. By changing or inserting of new data, the user can correct the previous plan or design a new one. The proposed decision support tool gives possibility for transition from previous date to subsequent one without serious changes in the scheduling methodology.

In real practice various additional constraints may be necessary for scheduling. For example, often it is needed to take into account the current device wear and tear, limited storage possibilities, general shipping terms, etc. In our opinion, it is not reasonable to take into account all such constraints in a single program. For each case it is necessary to create a special program with joint efforts of the user and the main developer. In the nearest future it is planned to elaborate some solutions, which correspond to listed problems.

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