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Sequence of Production Orders Optimisation, its Benefits and Implications

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Abstract Manufacturing of products take place in an environment that is continually changing. The intensity of competition becomes stronger and the variety of customer demands is on the rise. One important factor of business success and customer satisfaction is responsiveness to customer requirements - i.e. the ability to deliver the product in the shortest possible time without compromising on costs, quality, maintenance and reliability. This ability is significantly supported by production management support systems. The article deals with the role and application of Advanced Planning and Scheduling system for flexible scheduling of production orders. The introduction outlines the substance of optimisation of production orders sequencing. A digital model of a production system is designed for this purpose, and simulation of production order sequencing and optimisation is carried out using a genetic algorithm. The article follows with describing the general benefits of APS systems, the key impact of production on competitiveness and strategic position of a firm and the strategic importance of reducing lead time for business success and customer satisfaction.

Keywords sequence of production orders, advanced planning and scheduling, simulation, optimization, genetic algorithm

1. INTRODUCTION

In recent years the business environment has undergone considerable changes. Customers are no longer satisfied with "standard", mass-produced products that are more or less the same. They want products with a high degree of customisation, for the same price as standard products, and they want them as fast as possible. These requirements are inherently contradictory. The increase in customisation results in production batches becoming smaller and, in some cases, single piece flow is required. Moreover, as the existing infrastructure is not designed for this production profile, production becomes more complicated and lengthy. In no way can such products be sold for the same prices as standard products.

This, of course, makes it increasingly difficult for businesses to be successful. However, difficult does not mean impossible. Transition from inflexible planning, in most cases using ERP systems, to flexible production planning, or scheduling, is of primary importance in this context. This can be done with APS (Advanced Planning and Scheduling) software, or with software for discreet event simulation of production systems such as Tecnomatix Plant Simulation. Both types of software are linked to the ERP system and work with data entered into them. Unlike the ERP system they allow for a relatively easy (flexible) modelling of the current condition of the production system (such as temporary shutdowns, the state of orders, the presence of workers, etc.). They also make it possible to simulate the scheduling of planned orders and optimise it according to given criteria (minimisation of costs and production lead time, a combination of these criteria, etc.).

This article intends to point to the importance of good optimisation in the context of the changes in the business environment. Specifically, it focuses on optimisation of order sequencing in a model production system and on describing some of its potential benefits and implications. The second chapter describes the model production system. The third chapter focuses on the digital model of the system and on simulation of the process of executing orders as they come from customers. The fourth chapter deals with optimisation of order sequencing by means of a genetic algorithm (GA). The fifth and the sixth chapter explains some general potential benefits and implications of optimization.

2. DESCRIPTION OF THE PRODUCTION SYSTEM

For this article we have designed a model production system based on a real-life system. The system consists of six stations that are interconnected by some 50 metres long accumulating pallet conveyor for carrying the products. A simplified chart of the situation is in Fig. 1.

One of the six stations is assembly and it is placed at the system entry point. Depending on the sequence of orders coming from customer's four types of product (Product 1, Product 2, Product 3 and Product 4) are fastened to empty pallets held in a buffer adjacent to the station. Each pallet always carries only one piece.

Dismantle is another station where the finished product is removed from the pallet. This unit is at the system exit point next to the assembly. A buffer is placed between the two stations and it holds the pallets from which the finished product has been removed. The assembly and dismantle stations are connected to the main conveyer by means of a short, three-metre conveyor that also serves as a buffer.

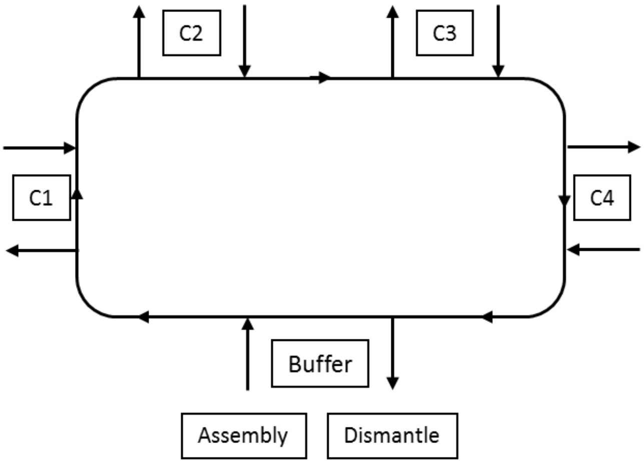

Fig. 1: Production system chart

The remaining four stations are productions cells C1 to C4. There the individual products (Product 1 to 4) are manufactured in line with prescribed production processing (a sequence of manufacturing operations). For example, Product 2 starts in C4, then moves to C4, from there it proceeds to C1 and, finally, to C3 where it is completed. For other manufacturing operations see Tab. 1.

Tab. 1: Product manufacturing operations

	Product1	Product2	Product3	Product4
Manufacturing operation 1	C1	C4	C2	C2
Manufacturing operation 2	C2	C1	C1	C4
Manufacturing operation 3	C3	C3	C3	C1
Manufacturing operation 4	C4		C4	C3

The production cells are connected to the main conveyor by means of two short, three-metre conveyors that also serve as a buffer. One is for entry and one is for exit from the cell. The main conveyor is equipped with sensors that direct the pallet with the product to the entry conveyor where it is heading in line with the operating procedures.

As mentioned earlier, there are 4 types of product manufactured within the system. The size of the production batch for each product is always determined by the customer order. Each new order comes to the end of the order line according to the FIFO (First In, First Out) principle, and then enters the production process. In this model production system we will use a production plan (the sequence of orders) consisting of 60 production batches ranging from 1 to 6 pieces (4.4 pieces on average). This is 264 pieces in total. The volume reflects the capacity of one truck. The sequence is illustrated in Tab. 2.

Tab. 2: The sequence and volume of customer orders

Order Sequence	Type of Product	Number of Product
1	Product3	6
2	Product3	6
3	Product4	3
4	Product1	3
5	Product2	4
6	Product3	3
7	Product3	5
8	Product2	4
9	Product1	4
10	Product2	5
11	Product2	5
…	…	…
60	Product1	3

In line with the manufacturing operation for each product there is production time for the machine ranging from 20 to 120 seconds. There is also a set-up time for each station. For example, Product 1 has a set-up time of 10 seconds and a set-up occurs after 5 components are manufactured.

3. DESIGNING A DIGITAL MODEL AND CARRYING OUT SIMULATION

Based on data in Chapter 1 we have designed a digital model of the production system (Fig. 2) using the Tecnomatix Plant Simulation software produced by Siemens Product Lifecycle Management Software Inc. [7,8]. This is object-oriented software for discreet simulation of production and logistics systems that is used, apart from production, in non-production areas such as transportation, banking, healthcare etc. The digital model arises from a set of basic, parameterized objects that represent, for example, a production process, a conveyor, a pallet truck, a buffer, etc. For simpler models, it suffices to interconnect the individual objects, whereas for more complex models programming of a varying degree of complexity is needed. With the final model, we can carry out analyses of the current state of affairs, the bottlenecks, the workload of the stations and transportation routes, what-if analyses, etc. Using simulation, we can also test various optimisation solutions or conduct optimisation directly using a genetic algorithm in line with set criteria (cost minimisation, production lead time minimisation, ...).

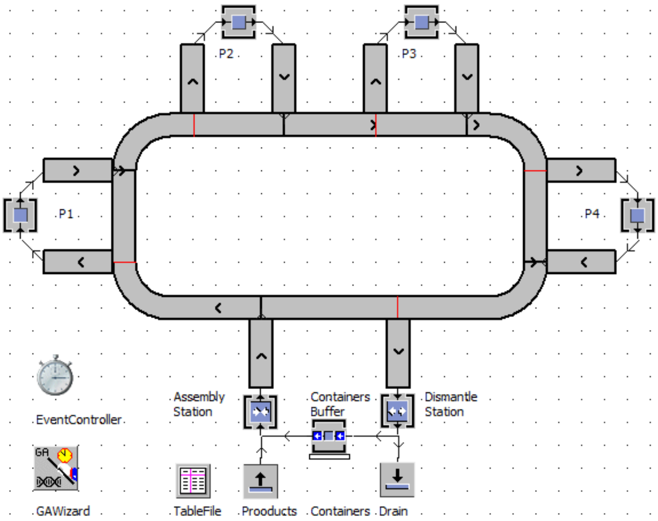

Fig. 2: Digital model of production system

The model consists of 4 objects that represent production processes (P1 to P4). Furthermore, there is an Assembly Station and a Dismantle Station and between them there is a Buffer for pallets. The stations are linked by conveyors. At the point where the linking conveyors are connected at a right angle to the direction of the main conveyor a red line marks the placement of the sensors that route the pallets, in line with the manufacturing process, to individual stations.

Another object is the "Source Products" that generates the production batches according to the sequence of orders (Tab. 2) entered into the TableFile object. In the Drain object the finished products cease to exist. Individual Products 1 to 4, described in the software as objects of the moving units type, are marked in various colours for better visualisation (Tab. 3).

Tab. 3: Colours assigned to individual products

Product1	Product2	Product3	Product4
Green	Light blue	Red	White

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There are two remaining objects in Figure 2. GA Wizard is used to conduct optimisation via a genetic algorithm. Its utilisation is described in Chapter 3. The purpose of the Event Controller object is to launch or stop optimisation, to reset it etc.

After simulating production of the planned 60 batches (264 pieces in total) we found out that the total production lead time for all batches is 6 hours 37 minutes and 20 seconds. There are at least two reasons why the total lead time is relatively long. Firstly, and most importantly, if the pallet cannot enter the linking conveyor heading to the station due to full capacity, it stops on the main conveyor and entirely blocks the operation (Fig. 3). The second reason, which goes hand in hand with the first one, is a small capacity of the linking conveyers. Alternatively, there may be a problem of a lack of pallets for the transport of the products.

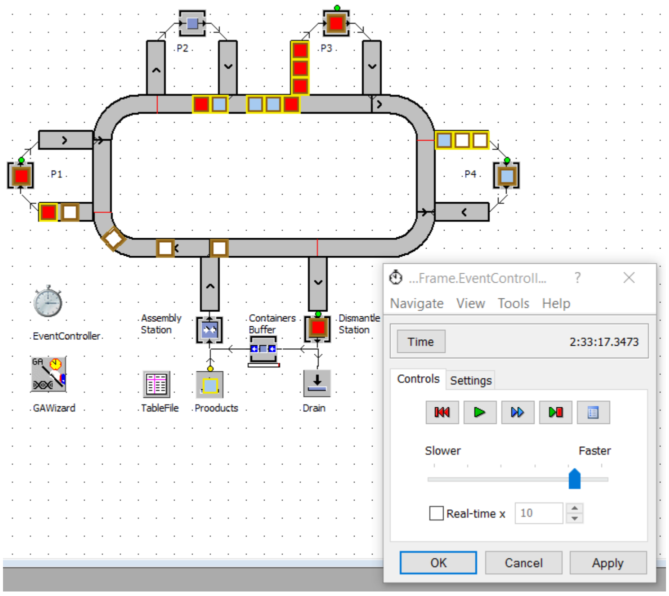

Fig. 3: Simulation of the current state of affairs

4. OPTIMISATION OF THE SEQUENCE OF PRODUCTION ORDERS USING A GENETIC ALGORITHM

The production lead time of 6 hours and 37 minutes is not ideal. Understandably, we would like to produce the same volume (number of products) in less time. Therefore we conduct optimisation of the sequence of the orders in order to minimise the total lead time. For this purpose, we use GAWizard that works with genetic algorithms.

4.1 Genetic algorithm

Genetic algorithms constitute an effective tool for finding an optimal (best) or sub-optimal (next best) solution when searching for so-called constraint extremes. This means that we seek an extreme (minimum or maximum) of the objective function containing a number of variables $F(x_1, x_2, \ldots x_n)$. We must define the values of the unknown quantities x_1, x_2 to x_n so that the objective function reaches, for example, the minimum. At the same time, various limiting conditions are set for the variables sought. For example, x_1, x_2 to x_n must be integral numbers, or they may only be 0 or 1, or $x_1 + x_2 = 50$ etc.

GAs may be viewed as a special area of heuristic methods that solve a problem by means of seeking an extreme while working with randomness (random search) [10]. GAs have been known since the 1960s or longer [10] and a number of types and modifications for various tasks concerned with constraint extremes have been developed. GAs strive to simulate evolution in seeking the best (optimal) solution and, starting from the initial allowable solution, to achieve an optimal solution through controlled selection of the best individuals and breeding, where the initial solution is continuously improving. The improvement is discernible from the value of the solution. For example, if a problem is concerned where variables representing scheduling of production operations are sought, the objective function may be the total production lead time - and its minimisation is requested. In this case each allowable combination (every allowable solution) corresponds to the value of the objective function (total lead time), and if the algorithm is heading in the right direction, other solutions are found where the total lead time is increasingly shorter. The algorithm continues working until a pre-defined number of interactions is carried out, or until the length of the total lead time drops to the defined value. One disadvantage of this approach, and of genetic algorithms in general, is the fact that we do not know whether the lowest possible value (a global minimum) has actually been found. On the other hand, genetic algorithms are capable of finding solutions relatively quickly (through a relatively small number of steps) where the function relationships and the limiting conditions are defined in a complex manner. This means in cases where there is a number of local extremes that should be avoided (not to get stuck in them) and where the point is to find, or to get as close as possible to a global extreme. In these cases genetic algorithms are effective and efficient.

The basic principle of genetic algorithms, or optimisation calculations inspired by genetic processes, consist in the following steps:

1. Creating the initial population either through random selection of allowable solutions, intuitively, or by means of an approximate calculation.
2. Selecting the best individuals in the population. Each solution has the value of the fitness function that points to how good the solution is. The selection is normally made so that the quality of the solution is directly proportional to the probability that the solution will be selected to generate new individuals - solutions. This means that a bad solution may be involved in the generation of new individuals, but the probability is not high.
3. A new population (set of solutions) is generated from selected suitable individuals with the expectation that it will be better than the previous population. Two techniques are used for the selected individuals to create a new population: crossover (Fig. 4) and mutation. In crossover the individual is created by combining two parts of information from two former individuals - solutions (Figure 4). Mutation is carried out in a tiny portion of the new population and it consists in a random change of a small part of the information of the new individual. The reason for conducting mutation is to increase the diversity of the population, which brings about new solutions. In this way it is possible to prevent the algorithm getting stuck in the local extreme, which would result in a failure to find the global extreme.
4. The best solutions are selected from the new population where, again, the better the solution, the higher the probability of its selection. In this way the process is reiterated.

Through this process a solution is found showing a large improvement compared to the initial population [3].

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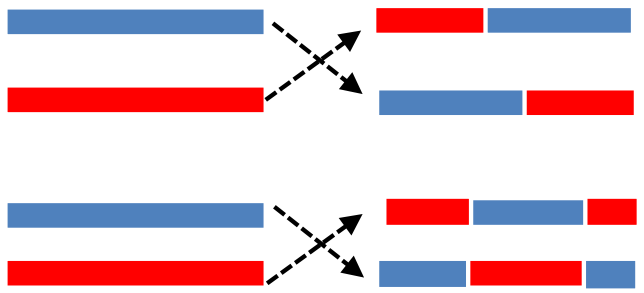

Fig. 4: Examples of crossover (exchange of information) and generation of new solutions

During crossover and mutation processes it is essential to ensure that the new solution is also allowable. The procedure is as follows:

- Solution 1 can be as follows: 1 2 3 4 5 6 7 8 9
- Solution 2 can be as follows: 4 5 2 1 8 7 6 9 3

Crossover produces a new individual:

- 1 2 3 // 1 8 7 6 // 8 9
- 4 5 2 // 4 5 6 7 // 9 3

More specifically, it produces an individual and an inverse individual. However, if crossover was carried out in this simple manner, the solutions would not be allowable (value 1 occurs twice, etc.). The procedure must therefore be modified.

Exchange of information occurred in the middle part:

- x x x // 1 8 7 6 // x x
- x x x // 4 5 6 7 // x x
- 1-4; 8-5; 7-6

We copy the remaining information, but only partially so that the solution falls within the admissible solution.

- x 2 3 // 1 8 7 6 // x 9
- x x 2 // 4 5 6 7 // 9 3

Now missing figures are added so that two inverse solutions (individuals) are created.

In the first parent the first figure was 1, which changes in line with the 1-4 procedure, and the same goes for the inverse solution. Then:

- 4 2 3 // 1 8 7 6 // x 9 the figure that is still missing is 5
- 1 x 2 // 4 5 6 7 // 9 3 the figure that is still missing is 8

The resulting solutions are as follows:

- 4 2 3 // 1 8 7 6 // 5 9
- 1 8 2 // 4 5 6 7 // 9 3

These are admissible solutions. This is one of the ways to proceed when carrying out crossover so that admissible solutions are generated.

Mutation is used very rarely - for example, in one individual out of a thousand. The individual is selected randomly and the changed information will again change randomly. [5]

Example:

- Individual: 1 **8** 2 4 5 6 7 9 **3** randomly selected positions of values that will change.
- Mutated individual: 1 **3** 2 4 5 6 7 9 **8**

As mentioned earlier, mutation is carried out in order to increase the diversity in the population and to avoid getting stuck in a local extreme. On the other hand, if mutation is implemented too frequently, this slows down progress towards the optimal solution.

It is apparent from what was mentioned above that this is about probabilities and randomness created by means of random, or pseudo-random figures. This means that randomness plays a partial role in seeking the optimal solution. On the other hand, as the populations are continuously improving, there is convergence towards the optimal solution which is both attained or significant approach to it can be managed.

4.2 Carrying out optimisation by means of GA

Before use the GAWizard (Genetic Algorithm) tool must be set up (Fig. 5). Applying GAWizard a set of steps must be performed [8,9]:

1. First we must assign that we will seek an extreme in the form of a minimum.
2. Then we set up the number of generations (11) and the size of the generations (11).
3. Following this we will determine what we want to optimise - the sequence of orders.
4. And we identify the objective of the optimisation - the total production lead time (simulation time).

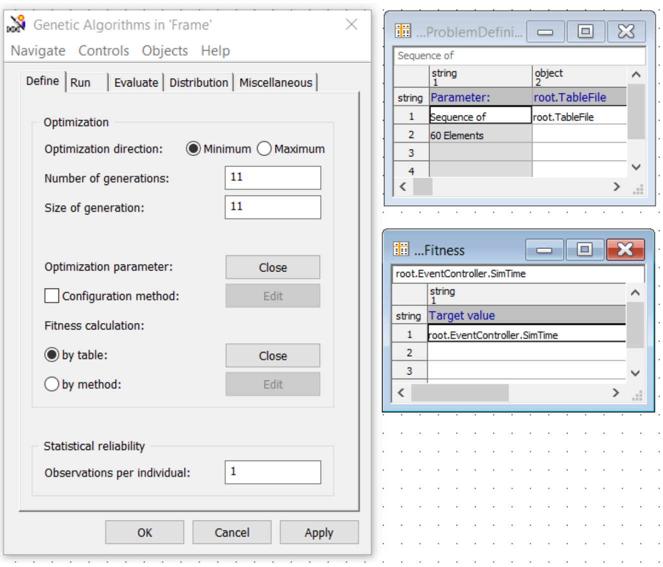

Fig. 5: Set-up of GAWizard

After setting up all parameters we launch the process. After some 8 seconds the optimisation process is completed. GAWizard has found a new sequence of production orders (Fig. 6) that is not in line with the FIFO principle, but allows for achieving the total production lead time of 5 hours 21 minutes and 34 seconds.

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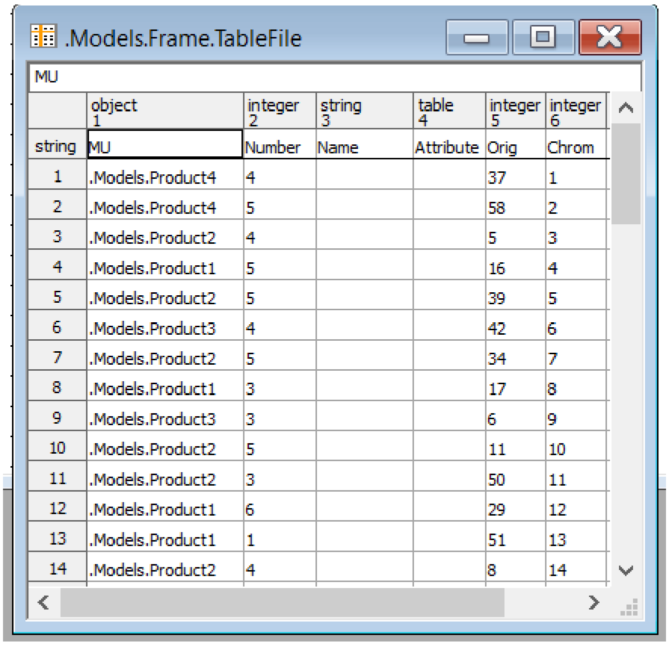
.Models.Frame.TableFile

MU

	object 1	integer 2	string 3	table 4	integer 5	integer 6
string	MU	Number	Name	Attribute	Orig	Chrom
1	.Models.Product4	4			37	1
2	.Models.Product4	5			58	2
3	.Models.Product2	4			5	3
4	.Models.Product1	5			16	4
5	.Models.Product2	5			39	5
6	.Models.Product3	4			42	6
7	.Models.Product2	5			34	7
8	.Models.Product1	3			17	8
9	.Models.Product3	3			6	9
10	.Models.Product2	5			11	10
11	.Models.Product2	3			50	11
12	.Models.Product1	6			29	12
13	.Models.Product1	1			51	13
14	.Models.Product2	4			8	14

Fig. 6: New sequence of orders (compare with Tab. 2)

In Fig. 7 we can see the values of the total lead time for various generations (best solution, average and worst solution).

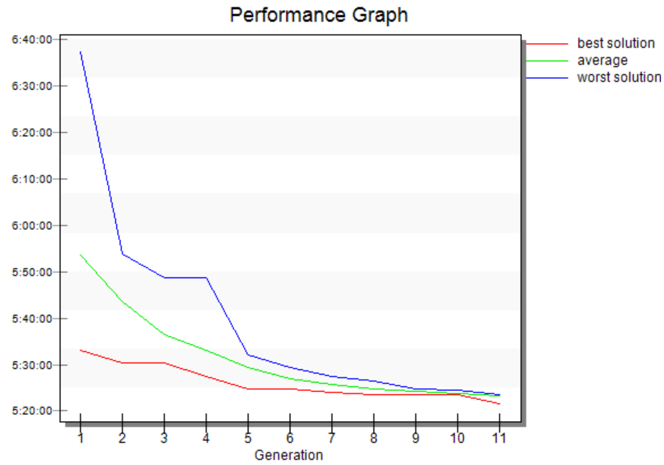

Fig. 7: Diagram of values of total lead time for various generations

5. POTENTIAL BENEFITS OF PRODUCTION SCHEDULING SYSTEMS

The growing complexity and intensity of the impact the constantly increasing number of external and internal factors have on the businesses have resulted in an enormous increase in the range and complexity of problems production is forced to face. This is particularly apparent in customised production that is driven by demand and where orders differ in terms of the sequences of manufacturing operations involved as well as in terms of the inputs and time necessary for their implementation [2,6].

The need to respond to low – to medium – volume orders requires an ability to produce a wide variety of outputs at adequate costs. For this it is necessary to have flexible production equipment capable of performing a range of operations needed to produce various types of products. Efficiency is not achieved due to the economies of scale, but due to a wide variety of a large number of products or a large number of small product batches.

Along with the growing complexity of production there is an increasing need for appropriate management tools to support production management systems. In case of manufacturing process in which small batches of a variety of custom products are made Advanced Planning and Scheduling (APS) systems are efficiently used on an increasingly larger scale. APS are very sophisticated and elaborate systems that work with a great amount of data and variables and, in spite of this, are capable of delivering the required outputs very quickly. These systems, which are designed for planning and scheduling manufacturing operations, allow for continuous rescheduling of production schedules in line with arriving orders or changes in demand.

Detailed and accurate scheduling is increasingly important particularly in situations where demand changes over time and it is hard to foresee future customer orders, and also in situations where management of a large number of products and operations is required. Moreover, such scheduling is important where there is a wide variety of products that "compete" for the production capacity and, last but not least, in situations where frequent changes in production scheduling are required for reasons that are difficult to predict [2,6].

6. THE KEY IMPACT OF PRODUCTION ON BUSINESS ORGANISATIONS' COMPETITIVENESS AND STRATEGIC POSITION

In a competitive environment responsiveness becomes a critical factor of competitiveness. This capability involves factors such as customisation, quality, innovativeness and response time. The importance of these order winning factors [4] varies depends on the market and the business strategy. The most successful producers seek the best possible compliance of these factors with customer requirements and the highest possible balance in their levels.

It gives a competitive edge to business organisations if they are responsive to market changes, and if the level of their product customisation corresponds to customer demands. It is apparent that achieving the necessary level of responsiveness is significantly influenced by production management, more specifically by the use of production planning and scheduling systems.

One important element of responsiveness to new needs and customer requirements is shortening the lead time. The ability of the business organisation to produce as fast as possible allows for achieving higher and faster revenues, better relationships with customers, minimisation of WIP and finished products inventory, bottlenecks elimination, smoother material flows and unit cost reduction due to economies of scope. Another benefit of reduced lead time is reduction in unit costs which makes it possible to lower the price. The customer gets greater value due to both faster response and lower price. Better responsiveness to customer demands as compared to that of competitors also makes it possible to increase the market share and decrease the risk of the product obsolesce or similar products being introduced by competitors [2,4].

One of the key benefits of a quick response to demand is that it reduces the number of processes that add no value. Activities that do not add value are typical particularly in customised production [1]. This is due to the layout projection, long set-up time, difficult synchronisation of material flows, waiting times, and planning systems inefficiency. These latent inefficiencies interrupt and lengthen the production process. It is important to strive to reduce the time between operations and the set-up times, as this makes it possible to produce economically even single units or single small batches of a variety of custom products.

7. CONCLUSION

Customer satisfaction is a strategic factor determining business success. Key to success is to identify what customers want and to produce and deliver this to them in the shortest possible time without compromising on costs, quality, maintenance and reliability.

The Advanced Planning and Scheduling systems considerably contribute to ensuring a smooth and optimal management of orders and, as a result, to increasing customer satisfaction. They make it possible for the business organisation to respond quickly to changes in customer orders, to reduce lead and set-up times, to eliminate delays and to set a reliable delivery time immediately upon receiving the customer order. Besides better customer service the systems allow for reduction of WIP and finished goods inventory, elimination of bottlenecks, better use of capacity, increase in throughput, synchronisation of production orders and material flows with capacity, and direct linking of production orders with demand.

Of the range of possible uses of APS the article describes optimisation of the sequencing of production orders by means of a genetic algorithm and shows it on a model production system. The results of the APS application in this case study clearly illustrate and quantify the relevant reduction in total lead time needed to produce a set of production orders.

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