

Chapter 2

Manufacturing System Planning and Scheduling

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Abstract This case study concerns support for customised solving of a production planning and scheduling problem in the piece-part medium-sized manufacturing company. To make the best use of an advanced scheduling tool and to find an optimal configuration of its rules and parameters, modular simulation models of the entire business/production process and production anodising stage are developed. Planning scenarios intended for optimising business processes in the company and different sequencing rules to improve processing of production orders are analysed. The improved approach and its benefits in practice are described.

2.1 Introduction

Modern production scheduling tools are very powerful and offer a vast range of options and parameters for adapting the tool's behaviour to the requirements of the real process. However, the more options exist, the more difficult it becomes to find the best configuration of the tool in practice. Even experts cannot often predict the effects of many possibilities. Testing out even a small number of possible configurations in reality and studying their effects on the real production process might take months and might severely reduce the overall performance. Hence, such tests are not feasible in practice. It is much faster, easier, safer and cheaper to test

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and optimise a production scheduler using a simulation model than using the real process [1].

In order to make the best use of an advanced and sophisticated scheduling tool in the piece-part medium-sized manufacturing company and to find an optimal configuration of its rules and parameters, modular simulation models of the entire business/manufacturing system and production process anodising stage are built in order to test out the effects of various scheduler configurations [2]. Testing and optimisation of the scheduling tool configuration is carried out off-line by using simulation models. The real production process is not disturbed, and the optimal configuration can be found very quickly and at low cost.

2.2 Problem Formulation

Decorpart, a UK-based medium-sized manufacturer, produces a wide range of different small pressed aluminium parts in large quantities to a range of other consumer-focused businesses. Typical applications include spray assemblies for perfumes and dispenser units for asthma sufferers. The business lies in a highly competitive sector, and success depends on achieving high efficiency and low cost of manufacturing. Production scheduling is therefore very critical.

In the past, the company had already installed software tools supporting the scheduling of individual areas of the production process. To improve the overall company performance, increase its output and reduce the product lead time, they have planned to implement an automatic Preactor supply chain planning server – an overall scheduling system coordinating all local business and production areas. In order to deliver the best possible solution, the supplier of the scheduling tool, Preactor International (<http://www.preactor.com>) decided to use simulation for finding the optimal configuration of the scheduling tool.

The problem is to build a simulation tool, which will embrace the arrival of customer orders and sequencing of production orders to meet these demands. An important aspect is to model the production process itself in order to ensure that its main stages are optimally loaded at all times. The anodising stage is known to be particularly important for the overall production. Thus it has to be modelled in great detail and used in order to test to what extent the overall lead time of the orders can be reduced by optimisation of the anodising process stage.

The following key objectives are stated in this case study: (1) to model inter-related business and production processes at the company and to determine the overall lead time of orders, (2) to analyse and optimise business processes at the planning department dealing with processing of incoming enquiries and planning production orders, (3) to test the sensitivity of the overall production lead time to improvements, in particular, to determine whether introducing specific sequencing rules of production orders will decrease their total processing time at the anodising process stage.

Moreover, a simulation tool is aimed to be used for testing the configuration of the scheduling tool and for iterative optimising its performance off-line prior to its

implementation and integration at the customer's site. The envisaged scheme is designed to complement and link together localised advisory systems previously installed on individual areas of the production process.

The main impact of simulation is expected to be a higher system throughput with lower product unit costs.

2.3 Modelling Approach

A custom-built business/manufacturing system model is created that simulates the arrival of orders, their queuing and their flow through all steps of the production process. For the overall coordination and schedule optimisation, each process stage is modelled as a group of machines with an overall capacity per day or per week. The model is built in a modular style so that each production stage could be further modelled to a greater level of detail. As mentioned above, the anodising process stage is known to be particularly important for the overall production. Thus this production stage is modelled in a greater level of detail following successful validation of the initial model.

Therefore the model of the anodising process is refined and the individual anodising tanks are described in detail, so that colour changeover and set-up operations could be studied more precisely. In this way, order queue ranking rules that minimise colour changes are introduced and tested as to what extent the overall lead time of orders can be reduced by optimisation of these rules at the anodising process stage.

Next, the Preactor scheduling tool is coupled with: (1) a high-level business/manufacturing system model, and (2) a detailed representation of the anodising process stage, both of which were developed using production simulation system ProModel [3] and used for finding the optimal configuration of the scheduling tool.

2.3.1 *A High-Level Business/Manufacturing System Model*

In this section we will provide the conceptualisation and input data analysis for a high-level business/manufacturing system model. It is aimed at modelling inter-related business and production processes at the company in order to analyse and optimise business processes at the planning department. These processes relate to the processing of incoming enquiries and planning of production orders confirmed by customers. The model is used to compare two alternative planning scenarios (see Sect. 2.5) and analyse the benefits of introducing an advanced production scheduling and capacity optimisation tool at the company with the maximal response time of 0.1 hour per enquiry.

Model conceptualisation. The custom-built entire business/manufacturing system conceptual model is given in Fig. 2.1. The model simulates the arrivals of

enquiries and their processing time; generates orders becoming confirmed by customers and their planning time, and shows the queuing of the production orders for processing. There are two types of incoming enquiries – pharmaceutical enquiries and personal care enquiries, which are denoted as *PH_Enquiries* or *PC_Enquiries*, respectively.

Production itself consists of the following processing stages: pressing, degreasing, jigging, anodising and packing. In this model the production of orders does not need to be modelled in detail. So, in each production stage the individual machines are modelled as a group with an overall capacity per week. No queues are defined for locations used to simulate different production stages in the system model.

The following parameters could be controlled in the system: the number of planners that process enquires from customers as well as respond to customers and plan confirmed orders for production; the response time for enquiries, and planning time for confirmed orders. These system parameters define the controllable variables in the simulation model.

Parameters such as time between arrivals of enquiries, customer response time to confirm or cancel enquiries, the probability of an enquiry becoming confirmed or becoming an order, and order processing time for different production stages could not be controlled in the system. These parameters are regarded as environmental variables in the model.

The system key performance indicators such as total revenue, an average lead time, the percentage of cancelled enquiries and utilisation of planners define the model performance measures.

Data collection and analysis. Based on the analysis of the historical data and taking accounts, their stochastic nature probability distributions given in Table 2.1 are derived. For example, the time between arrivals of *PC_Enquiries* is exponentially

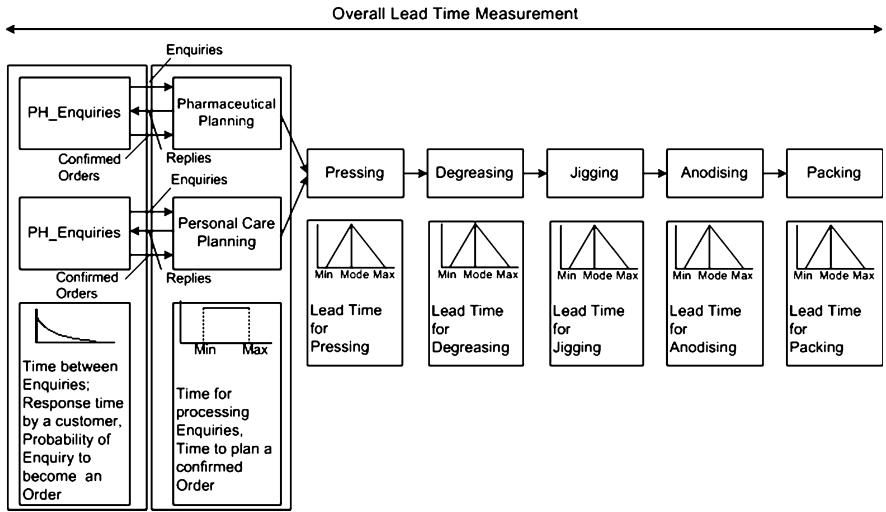


Fig. 2.1 The high-level business/manufacturing system

distributed with the mean equal to 20, and processing time of the enquiries is uniformly distributed with the mean and half range equal to 35 and 5, respectively (see ProModel distribution functions in [3]). These distributions are used in the model to generate the time between arrivals of enquiries, processing times of the enquiries, an average response time from a customer and actual planning time of confirmed orders. About 33% of all incoming enquiries are *PH_Enquiries*. The probability of enquiries becoming an order decreases as a function of the planning department response time including enquiries queuing time and is given in Table 2.2. On the other hand, the value of confirmed orders received by the company increases as a function of the planning response time. In the case study, the average order value is defined.

An average order lead time in each production stage is defined by the triangular distribution with the following parameters: min = 1,080, mode = 1,440 and max = 1,800.

Currently *PH_Enquiries* are processed by one planner, and *PC_Enquiries* are processed by another three planners that spend about 70% of their working time on planning operations. The working day is eight hours long starting from 9.00 a.m. Planning staff employment costs per year are fixed.

Model building. The entire business/manufacturing system simulation model is built using the ProModel basic modelling elements such as locations, entities, arrivals and processing. A number of variables are defined as well. Some of these variables are counters which record statistics about cancelled enquiries, orders in process, completed orders, etc. So-called processing variables are introduced to make it easier to change processing times in the model.

Visualisation of the model is presented in Fig. 2.2. On-line and off-line statistics are provided. Simulation outputs reflecting the model dynamics (i.e. *Waiting enquiries*

Table 2.1 Probability distributions (all values are given in minutes)

Data	Distribution type	Distribution
Time between arrivals of enquiries		
<i>PH_Enquiries</i>	Exponential	E(60)
<i>PC_Enquiries</i>	Exponential	E(20)
Processing time of enquiries	Uniform	U(35, 5)
Response time from a customer	Constant	24 * 60
Actual planning time of confirmed orders	Uniform	U(55, 5)

Table 2.2 Probability of enquiries becoming an order

Enquiries becoming confirmed (%)	Planning response time
50	< 1 hour
20	1–8 hours
10	24–48 hours

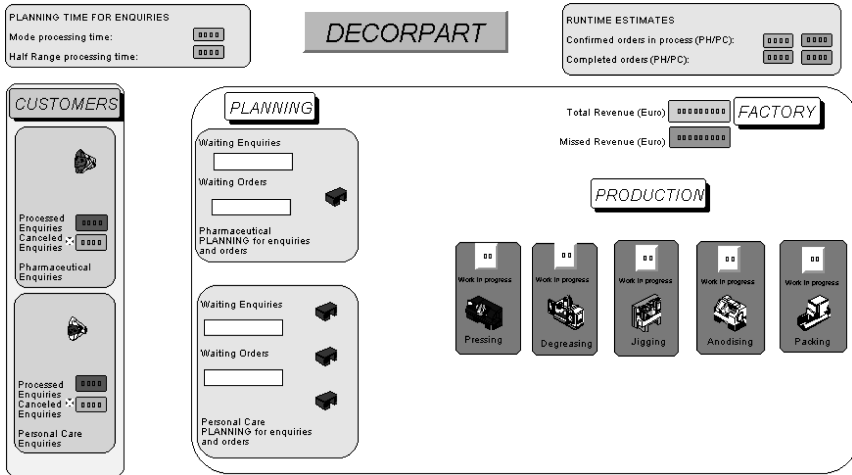


Fig. 2.2 A high-level business/manufacturing system model screenshot

ries, Completed orders, Total revenue) can be followed on the model main screen. Results of conducted experiments are automatically saved in the model database and presented in Excel spreadsheets.

In order to check if the model reflects the real process adequately, a set of historical data was compared with the data produced by the simulation model. It was found that the model and the real process produced more or less identical results.

2.3.2 A Low-Level Anodising Process Stage Sub-Model

Model conceptualisation. The low-level anodising process stage sub-model [4] is aimed at testing whether the implementation of specific sequencing rules of incoming production orders will decrease their total processing time at a batch anodising plant.

Batch anodising refers to anodising of series of small parts produced in batches. The anodising process contains the following steps. First, the metal parts are batched on racks. After batching the metal parts are degreased and cleaned. Then batches of cleaned metal parts are put in a bath of acid where the oxide film around the aluminium is created. After that the aluminium parts are rinsed with cold water. Then the oxide film around the aluminium is coloured with a spray. This spray, which is also called as a dye, is typically a kind of paint, mixed with water. Dying can be done in several steps in order to provide the right colour. Changing the colour of the dying process is a bottleneck in a real system. Coloured parts are rinsed first with cold water and then with hot water.

The model itself simulates the individual anodising tanks so that colour change-over, set-up operations and processing times can be modelled. Based on the his-

torical data about order processing, the most probable list of incoming orders to be weekly processed is generated in the model. Specific sequencing rules of incoming orders are simulated and tested in order to decrease the total processing at the anodising stage. Production rate, which is defined as an average number of flight bars processed per hour, and the frames utilisation coefficient are used to measure the effectiveness of the anodising plant itself.

The anodising sub-model black-box diagram is presented in Fig. 2.3. The sequence numbers of incoming orders that have to be processed in a week is controlled in the model. The order quantity, part colour and used frame type for incoming orders are regarded as environmental or independent variables. If these properties are given, the other properties of orders in the order list can be determined. Other environmental variables are the number of frames in stock, the time it takes to load and unload flight bars, the time it takes to set-up flight bars between the processing of different colours and the processing time necessary to anodise one batch of components.

The most important performance indicator is defined as the total processing time of all orders in the order list. Among other performance indicators that could be used to control an anodising process in the real system, the following performance measures can be mentioned: average production rate, frame loading efficiency, flight bars utilisation and plant productivity.

Data collection and analysis. First, based on the analysis of historical data about the orders that were planned and processed at the plant in a certain period the general order list is created. It includes the following input data: week number, order number, order quantity, colour, frame type and frame capacity, the number of frames in stock, number of batches and sequence number (Table 2.3).

The last four digits of the order number, *Order no.*, refer to the code of the colour which the components should get. Each frame type has a different number of components that can be placed upon it, which is called as *Frame capacity*. The number of frames of a specific type available is called as *Frame in stock*. Only three frames can be loaded on each flight bar.

Processing time of one batch of the components in a flight bar depends on the program that is used in the anodising process is defined by a sequence number *Seq. no.* in Table 2.3. Based on the input data analysis, processing times are described by the triangular distribution and generated in the simulation model. For example, for sequence 8, which is used by orders with colour code 0001 the triangular distribution with endpoints (54, 72) and mode at 58 is used in the model.

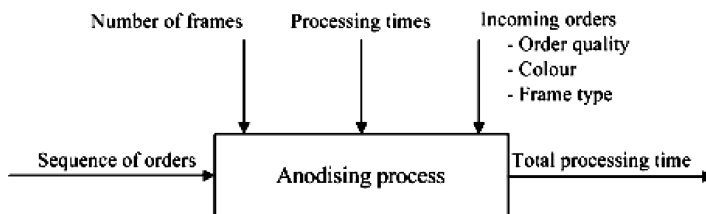


Fig. 2.3 Anodising sub-model black-box diagram

Table 2.3 A fragment of the general order list

No.	Week	Order no.	Order qty (× 1,000)	Colour	Frame Type	Frame capacity	Frames in stock	Number of batches	Seq. no.
1	1	1135	1	Bright	Silver	1292	15	26	8
2	1	1135	1	Bright	Gold	1292	15	26	6
3	1	1407	0	Bright	Gold	2400	11	1	6
4	1	1135	1	Bright	Gold	1292	15	15	6
5	1	0803	0	Bright	Gold	2400	11	4	8
6	1	1210	1	Bright	Silver	2500	18	40	8

Table 2.5 A fragment of the input order list

No.	Colour code	Qty (× 1,000)	Frame type	Frame capacity	Processing time (min)	Process- ing time (mode)	Processing time (max)	Batch no.	Frames no.	Frames left
1	0058	28	7	3456	54	58	72	3	9	0
2	0003	225	2	1900	64	87	92	45	135	0
3	0001	224	6	3456	54	58	72	22	65	2
4	0001	711	3	2400	54	58	72	99	297	0
5	0058	139	6	3456	54	58	72	14	41	2
6	0001	93	4	2500	54	58	72	13	38	2

Table 2.4 Empirical probability distribution for order quantity (colour number 0001)

From	To	Probability
0	100	0.407
100	200	0.507
200	300	0.759
300	500	0.815
500	600	0.928
600	700	0.963
700	800	0.981
800	1000	1

Second, based on the general order list the most probable list of incoming orders to be weekly processed in the model is generated. The number of orders in this order list is fixed equal to the average number of orders in a week. Frequencies of order colour and order quantity as well as of the frame type to be used are derived from the general order list data and defined by empirical distributions (see an example in Table 2.4). For simplification it is assumed that order quantity and frame type depends on the product colour to be anodised. Fitted probability distributions are used to generate the most probable list of orders or so-called input order list. A fragment of the completed input order list is given in Table 2.5.

Note that parameters of the probability distribution that fit processing times (such as minimum, maximum and most likely value), the number of batches that an order should be split up in, the number of frames necessary to process all batches and the number of frames left are also included in the Input order list. The Input order list is generated in Excel spreadsheets that allow automated retrieval data from it within the simulation experiments.

Model building. The anodising process stage sub-model is built using the Pro-Model basic elements and includes three types of locations: a location where entities that are batches in the model arrive, another location where processed entities move to and the number of locations where entities are being processed.

Figure 2.4 shows a screenshot of the model visualisation that is created by animation of pictures that simulates order arrivals and storage as well as colour change-over, set-up and order-processing operations. The user can follow the flow of batches from the arrival location and analyse the current stage of the anodising process for each order. Different colours are used for incoming and processed entities. Entities that are processed move on to the storage location.

On-line statistics are provided by three counters on the right-hand side of a screenshot that display the following performance characteristics of the anodising plant: the number of orders that are left to process, the number of batches left to process and the average number of processed batches per hour. Two additional counters along with the flight bars indicate the current number and the colour of the order that is currently being processed. Total processing time of all incoming

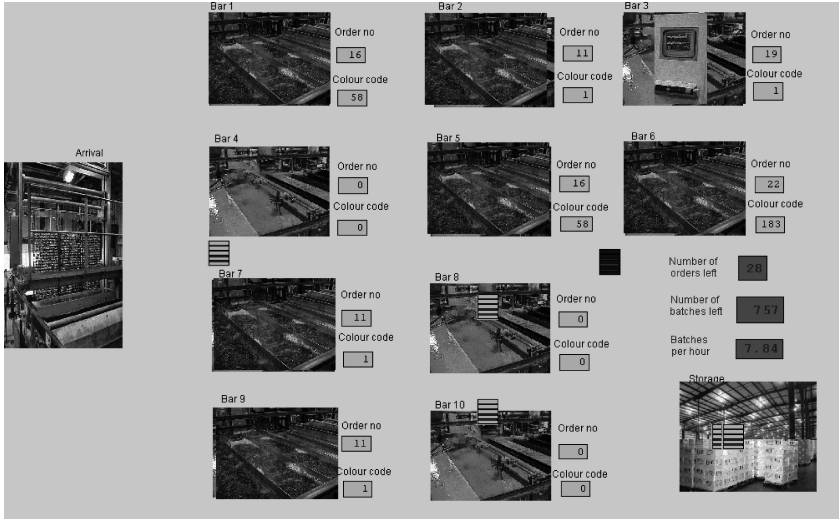


Fig. 2.4 The anodising process stage sub-model screenshot

orders, frames loading efficiency and plant utilisation can be found in the general simulation output report.

In the case study, validation of the anodising process stage sub-model is not described in detail. Note that similar to the entire business/manufacturing system model, in order to validate this model a set of historical data was compared with the data produced by the simulation model.

2.4 Experimentation

To identify the warm-up period, to select the replication length and the number of replications, and set these options in simulation experiments, we refer the reader to statistical methods of simulation output analysis and simulation options provided by ProModel simulation software [3].

2.4.1 Planning Scenarios for Business Process Optimisation

To understand the entire business/manufacturing model behaviour and define which input factors have important impacts on the model outputs, regression-type simulation metamodels were built in the case study. For example, the following regression equation was received, which shows the effects of input factors to *PC* order lead time in the system:

$$\text{Lead time (PC)} = 9277.03 - 21.05 * \text{Enq} + 4.83 * \text{Ord} + 0.62 * \text{Enq}^2 + 0.41 * \text{Enq} * \text{Ord},$$

where *Enq* and *Ord* denote *PC_Enquiry* processing time and order planning time, respectively. As the result we conclude that the model outputs are more sensitive to enquiries processing time rather than to orders planning time.

Then to investigate how sensitive the model outputs are to the changes in the important inputs, these inputs were systematically changed and simulation outputs were observed. It was stated that if the response time for customer enquiries could be reduced by 5%, the total revenue of the company would grow by about 10%.

For business process optimisation within available system resources two optimal designs of the system using the ProModel SimRunner® Optimiser were generated. They define the optimal combination of enquiry processing time and order planning time that maximises the total revenue and minimises the lead time indicator, respectively. The results (see Table 2.6) show that the maximum revenue could be achieved if enquiry processing time does not exceed 6 minutes. This could be achieved by introducing the automatic Preactor supply chain planning server with a maximal response time of 0.1 hour, or 6 minutes per enquiry.

To improve the planning process at the company, two alternative scenarios were compared:

- *Scenario 1* in which the scheduling of individual areas of the production process is provided – the current situation with the maximal response time equal to 1 hour per enquiry, not including queuing time
- *Scenario 2* in which an overall scheduling system coordinates all local business and production processes – introducing the automatic Preactor supply chain planning server

The results of simulation experiments (Table 2.7) show that the number of cancelled orders in Scenario 2 can be decreased by 14–18%, which would cause the total revenue or the total value of confirmed orders to increase at least twice. This can be explained by a shorter enquiry processing time that provides a faster response to the customer and leads to a higher probability for enquiries to become an order.

Table 2.6 Comparison of two optimal designs

	Enquiry processing time (min, max)	Order planning time (min, max)	Revenue €	Leadtime, PH (min)	Leadtime, PC (min)
Maximised revenue	(4, 6)	(2, 8)	49,900,000	9,218.2	9,261.1
Minimised lead time	(1, 11)	(3, 7)	48,210,000	9,244.4	9,134.7

Table 2.7 Comparison of alternative planning scenarios

	Lead time (min)		Total revenue (€)	Cancelled enquiries (%)	
	<i>PH</i>	<i>PC</i>		<i>PH</i>	<i>PC</i>
Scenario 1	10,805	10,414	17,170,588.24	57	57
Scenario 2	9,793	9,617	41,758,823.53	43	39

Moreover, instead of four planners, only three would be needed if the new scheduling tool were introduced. Thus, employment cost can be saved as well.

Notice that the total revenue value was estimated based only on observations on the steady-state behaviour of the model. The counters for completed orders are stated for the replications including the model warm-up period. The last one is estimated almost by three weeks. The replication length is defined as twice as the warm-up period. While the planning department works only on weekdays, the production process continues 24 hours a day, seven days a week. After ten replications the variance in the output variable such as average lead time is small enough to get a half range of 5% average.

**2.4.2 *Testing Sequencing Rules
for Processing Production Orders***

The scheduling of order processing at a batch anodising stage is to be interpreted as a finite capacity scheduling problem. This is defined as the process of creating an operation schedule for a set of jobs that are to be produced on a limited set of resources. In the problem, the number of frames in a stock available for a specific frame type and the number of flight bars that the frames are loaded on are limited.

Since this frame type is limited, it could cause queues of orders waiting for free frames, while the flight bars could be empty. On the other hand, processing of production orders with different colours could lead to multiple set-up operations, while decreasing the number of necessary set-up operations will result in reducing the total lead time at the plant.

For testing different order sequencing rules four simulation scenarios were introduced in this case study (see Table 2.8). In Scenarios A0 and A1, single queue sequencing rules are applied. Scenario A0 represents the initial situation, in which the incoming orders are processed according to their arrival mode. In Scenario A1, the orders with the largest quantity of components are processed first. But in Scenario A2, the orders wait in separate queues determined by order colour and single sequencing rules are applied to orders within each queue. In Scenario A3, an order sequencing rule combination is used in which the colours that appear less frequently in the list are processed first, while within the group of the same colour, the orders with the largest number of components are processed first.

Table 2.8 Simulation scenarios

Scenario	Sequencing rules
A0	First-come, first-served
A1	Largest order quantity first
A2	Queuing by colour
A3	Less frequent colour first–largest order quantity combination

To implement sequencing rules for processing production orders in the simulation model, the input order list described in Sect. 2.3.2 was rescheduled in the way the scenarios describe. The difference between mean values of the total processing time of all incoming orders was estimated from simulation experiments for scenarios with specific sequencing rules and the initial scenario. The length of the simulation run was defined to be equal to the time between the start of the week, which represents the initial situation in the real system, and the time that all the week’s orders had been processed. For each replication, the common random numbers were used to simulate both scenarios, leading to a lower variance of the mean estimate.

The results of simulation experiments with the detailed model of the anodising stage have demonstrated that introducing new specific sequencing rules for incoming orders could provide significant improvements. While comparing Scenario A0 and A1, 20 replications were performed for each scenario and the difference of two means $\mu_{A0}-\mu_{A1}$ was estimated as 11.51 hours with 95% confidence interval equal to (3.82, 19.9) hours (see Fig. 2.5, a). This led to the conclusion that the A1 sequencing rule for incoming orders in a week could reduce the total lead time of this stage by at least 4 hours, in some cases even by 19 hours. As a result, the production rate of the anodising stage will go up by 10%, and a significant increase in equipment utilisation and reduction of unit manufacturing cost can be achieved.

At the same time, the confidence interval for two other cases (see Fig. 2.5, b and c) contains zero. These results show that there is no significant difference between the mean total processing times produced by Scenario A0 and Scenarios A2 and/or A3, respectively, and there is no sufficient evidence to pick one alternative scenario over another one.

Then what-if analysis was performed to test whether the implementation of Scenario A1 is still an improvement if the number of frames in stock will be increased. In this case frames are not considered as limited resources in the real system. The results of comparison of sequencing rules with unlimited frames showed that Scenario A1 will not make a significant improvement compared to Scenario A0 (see Table 2.9).

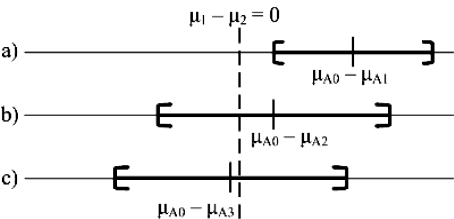


Fig. 2.5a–c Positions of the confidence intervals relative to zero

Table 2.9 Comparison of alternative sequencing rules with unlimited number of frames

Scenarios		Mean difference (hours)	95% confidence Interval	Significant
A0	A1	0.01	(−0.55, 0.58)	No
A0	A2	6.27	(5.85, 6.89)	Yes
A0	A3	6.23	(5.59, 6.86)	Yes

On the other hand, the orders queuing by colour in Scenario A2 will decrease the total processing time at least by 5.85 hours. At the same time, there will be no significant difference between Scenarios A2 and A3.

2.5 Conclusions

This case study demonstrates that the modular simulation models provide an inexpensive tool for an overall guidance and testing of advanced scheduling middle-scale software packages prior to their implementation at the customer's site.

The modelling approach used in the case study – to test and optimise advanced planning and control tools off-line by using simulation models rather than using the real process – can be applied to many other software tools, to higher-level (MRP; ERP tools) as well as to lower-level control tools (MES, warehouse control systems). On the other hand, the development of such relatively simple simulation tools in different industrial sectors could also provide an inexpensive approach to an overall guidance of small and medium-sized manufacturing towards the optimal conditions without resource to high-cost integration of expensive ERP systems and downstream control systems.

2.6 Questions

1. How can simulation help test and find the best configuration of the scheduling tool in a real system?
2. What is the range of scenarios for which simulation is used in planning and scheduling of the manufacturing system?
3. What is the main feature of the modelling approach applied in this case study?
4. What are the most significant differences between simulation models built within this approach?
5. What are the characteristics of the simulation model used for business process optimisation?
6. What are the characteristics of the simulation sub-model that is used for sequencing of the production orders at the anodising stage?
7. What does the confidence interval express about the order sequencing rules at the anodising stage?
8. Which techniques are used to validate the simulation models?
9. Define the main operational and financial benefits of this study.

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