Using Simulation-Generated Operating Characteristics Curves for Manufacturing Improvement

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Abstract. Improving manufacturing operations is an initiative that all manufacturing firms need to engage in to stay competitive. The needs and ways to improve differ between companies. A thorough understanding of the operating characteristics is required for successful improvement of manufacturing operations. By modeling the plant or manufacturing system in a simulation model and create operating characteristics curves, it is possible to investigate trade-offs and improvement potentials that otherwise would be impossible to quantify by other means of analysis. This paper describes how to manage such an approach by using a simulation model of a manufacturing plant to derive operating characteristic curves. The paper also describes how these operating characteristic curves can be used to improve plant performance.

1 Introduction

In order to stay competitive any manufacturing firm needs to continuously improve their manufacturing operations. The operating characteristics, that describe how different variables such as lead times, lot sizes, capacities etc are interrelated, differ between companies with respect to specific manufacturing conditions. However, a thorough understanding of these is required for successful improvement of manufacturing operations. By introducing simulation modelling, it is possible to create operating characteristics curves that otherwise would be impossible to quantify by other means of analysis. This task is increasingly more difficult with the number of products, the number of resources, the number of routings, and capacity constraints. Different parameters interact and may have direct and indirect effects, which are difficult to predict. For example, multiple products create different queuing situations at resources with constrained capacity, with respect to the routings, setup times, processing times, order quantities, etc. Knowledge concerning these interactions is important for understanding how to best improve manufacturing operations towards a specific goal. In order to illustrate these interactions, a simulation model of a production system in a manufacturing plant can be developed. The construction of operating characteristics (OC) curves or performance curves can then be used for decision support concerning improvement initiatives in the manufacturing system. Han and McGinnis (1989) use OC curves to analyze the effect of buffer space, flow control rules, and processing time variation on the relationship between throughput and flow time. Nazzal et al. (2006) use a simulation model to create dependency curves between cycle time and production volume for certain technology choices.

This paper describes how to manage such an approach by using a simulation model of a manufacturing plant to derive different types of OC curves. The paper also describes how these operating characteristic curves can be used to improve the performance of the plant.

2 Operating Characteristics Curves

Operating characteristics (OC) curves are curves displaying the relationship between two or more variables. The factors of interest can be related to market factors such as demand volume and variability, system factors such as setup and processing times, control parameters such as lot size and planned lead times, and output variables such as capacity utilization, queuing times, and costs of various kinds. The relationships illustrated through OC curves are such that the specific shape most typically will differ between different manufacturing systems, wherefore it is important to establish the specific relationships for each system, for example as a basis for improving the manufacturing operations. Another characteristic of OC curves is that the relationship is not fundamentally mathematical, i.e. that one of the variables can be calculated from the other. Of course, the OC curve can be displayed in such cases, but it would most likely be more useful to use the mathematical relationship, when analyzing manufacturing improvement initiatives.

Figure 1 displays a basic form of an OC curve. This figure illustrates the relationships among two variables; in this case capacity utilization and lead time. The specific curve will depend upon the distribution of orders arriving to the system and the distribution of the processing times. For simple systems queuing theory formulas can be developed for this relationship. However, for more complex systems, these relationships are non-trivial and specific to the manufacturing system. So if a firm wants to have an illustration of the relationships for a specific plant, simulation offers a way to derive the specific OC curve.

In Figure 2 variability is added as a third variable. Variability can be induced by market demand or by internal system imbalances. If three variables are to be included in one graph, one of these needs to be treated as a factor leading to different curves. This means that the third variable is treated as a discrete (non-continuous) variable.

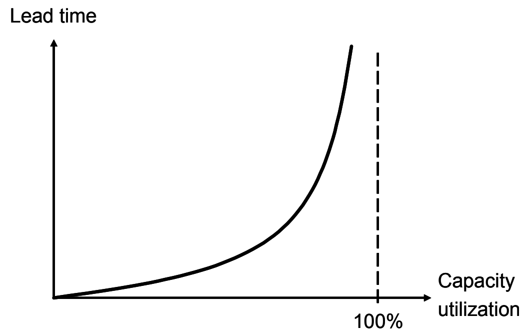

Fig. 1. An operating characteristics curve displaying the relationship between two variables; lead time and capacity utilization

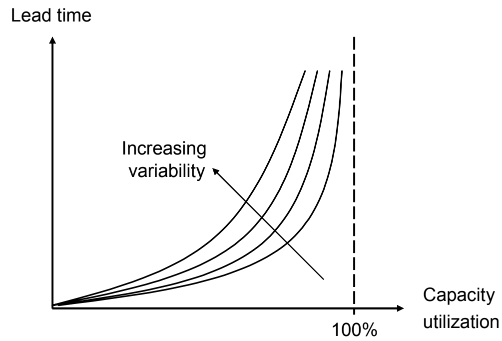

Fig. 2. An operating characteristics curve displaying the relationship among three variables; lead time and capacity utilization for different levels of variability

The shape of the curve illustrating the relationship between the two (or three) variables is of interest. For example, if the relationship is linear or non-linear, convex or concave, or if other shapes are present. Especially, many relationships between variables change when moving from a slack capacity situation to one with tight capacity.

3 Simulation Model

Simulation can be used as a technique for analyzing manufacturing systems that are too difficult or too costly to analyze in any other way. Simulation modeling offers a highly flexible tool that provides assistance in solving a variety of different problems and to find 'cause and effect' relationships. Simulation modeling can also be used in order to find relationships between two or more variables in a manufacturing system.

This paper uses the term simulation in a rather narrow sense. What is really meant is discrete event – continuous time simulation, where time is treated as a continuous variable and events occur at discrete instances in time. These kinds of models are stochastic, dynamic, and discrete in nature depicting the modelled system (Persson, 2003). Discrete event simulation has found an application in the field of operations research as a tool to improve, analyse, and visualise different characteristics of manufacturing systems and supply networks. The simulation results are often used as predictions or for what-if questions (Law and Kelton, 1991).

When generating operating characteristic curves to analyze manufacturing or supply chain systems, the parameters can be divided into three groups; (i) input factors, describing the market environment and the system characteristics, (ii) control parameters, describing the active choices for planning and control of the system given the input parameters, and (iii) output variables, describing the performance outcomes and statistics concerned with the status of the system. In the simulation model used here, input factors, control parameters, and output variables are concerned with the characteristics of a production and inventory control system. The simulation software used in most parts of this paper is PICSIM (Production and Inventory Control Simulator); initially developed by Jönsson (1983), and most recently used and described in Olhager and Persson (2006).

3.1 Input Factors

Input factors are external and internal factors that define the manufacturing environment, such as product mix, demand distributions, bills of material, capacities, processing times, setup times and routings. These can be changed or affected by decisions of the company. The change process is however typically associated with time and cost.

3.2 Control Parameters

The parameters that define the control system in the simulation model are called control parameters and are used as inputs to each simulation run together with the input factors. Each item must be given an order quantity (or lot sizing technique in combination with setup ordering and inventory holding costs), a lead time (potentially including safety lead time), and a safety stock. Safety stocks or safety lead times can be used to cover for uncertainties in demand or lead time. The simulator allows for using a reorder point system, material requirements planning (MRP), and cyclic production scheduling.

3.3 Output Variables

Outputs of the simulation model include performance measures as well as production statistics. The basic performance measures include customer service and total inventory levels (raw materials, work in process and finished goods inventory). These are traditionally assumed to be conflicting since low inventory is typically associated with poor customer service, and high customer service requires large inventory. In the simulation model, customer service is calculated as the fill rate for finished goods inventory; a fill rate of 100 % is equal to no shortages. Costs for handling backorders, and setup and ordering costs can be added to the inventory holding costs to provide for the cost performance. The production statistics include actual lead times per item, average queue times and capacity utilisation rates per work centre, and inventory turnover rates for raw materials, work-in-process, and finished goods.

4 Generating Operating Characteristic Curves

Operating characteristics curves can be generated through simulation results or from data collected in a manufacturing system. However, simulation offers many advantages over observing and collecting data from a system. OC curves can be generated that are difficult, or even impossible, to get from a real system. Simulation offers the opportunity to extend the analysis beyond what is currently done or is realisable in the physical system, as well as simulating scenarios related to different improvement initiatives. Even though simulation typically is performed as discrete-event systems with discrete variables, OC curves illustrate a continuous relationship such that the curve has to be fitted to the simulation output data.

4.1 Types of Operating Characteristic Curves

In general, there are three basic types of OC curves: (i) an input factor vs. an output variable, (ii) a control parameter vs. an output variable, and (iii) an output variable vs. another output variable. Thus, the y-axis is always related to an output variable. If the analysis is expanded to three variables (cf. Figure 2), the third variable (not on the x- or y-axis) has to be an input factor or a control parameter, since this one has to have discrete choices, and cannot thus be an output variable which cannot be controlled to have discrete steps.

Input factors and control parameters are inputs to the simulation model and can thus be changed in a controlled manner. Thus, it is possible to create equidistant steps along the x-axis. Also, it is possible to perform multiple simulation runs with different seed numbers to the random number generator at each x-value, whereupon confidence bounds can be calculated. Although the OC curve typically is a single curve, it is valuable to know if the curve is exhibits a strong relationship with little variance or if the relationship is heavily influenced by any stochastic behaviour of the system. Thus, when generating the first and second OC curve type, the x-axis factor or parameter can be controlled and upper and lower bounds with respect to confidence levels can be generated. In the third type two output variables are analysed. These cannot be controlled in terms of equidistant steps with multiple seeds for creating confidence levels. The type of chart for this case is a scatter diagram plotting the two output variables relative one another, with subsequent curve fitting. Here, joint confidence regions can be established. If the shape of the OC curve is non-linear, the curve can be segmented and approximated as piece-wise linear, around which confidence regions can be calculated.

In figure 3, 4 and 5, the three types of OC curves with respect to the type of variable are illustrated.

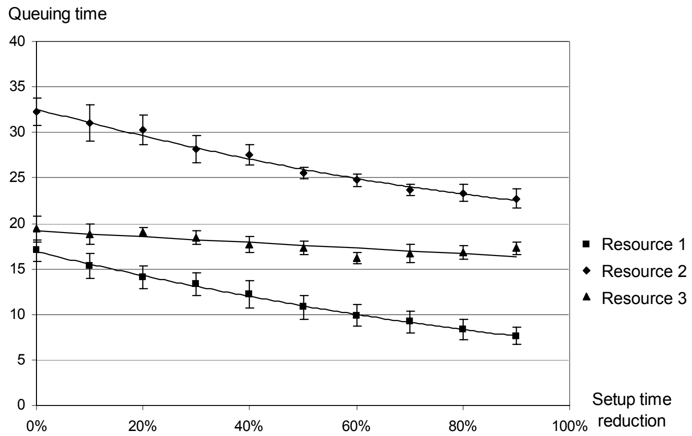

Fig. 3. Operating characteristics curve, type 1, illustrating the impact of setup time reduction (input factor) on queuing times (output variable) at three different manufacturing resources

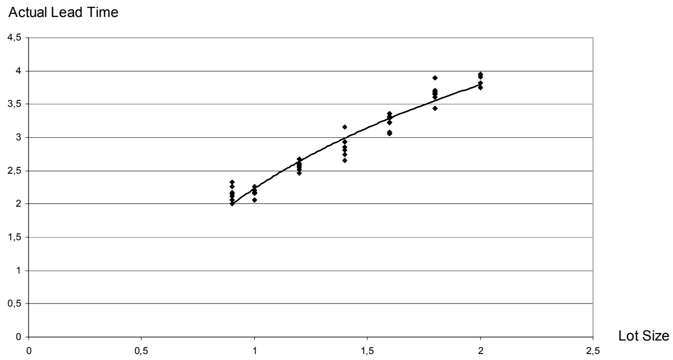

Fig. 4. Operating characteristics curve, type 2, illustrating the impact of lot size (control parameter) on actual lead times (output variable)

These curves show that input factors and control parameters can be controlled in a simulation setting, whereas output variables cannot. The three examples above are taken from three different simulation projects wherefore they differ somewhat in terms of result presentation design.

4.2 Simulation Procedure to Generate Operating Characteristic Curves

The simulation procedure to create operating characteristic curves is to first identify the variables that are of interest to study, secondly to determine the experimental plan to set the boundaries of the variable values. First, the input factors, control parameters and output variables must be determined. The improvement initiatives are typically related to input factors such as setup times, quality factors and bottleneck capacity or to control parameters such as lot size, planned lead time and planned buffer sizes. The output variables are typically the performance indicators of the system behavior.

Fig. 5. Operating characteristics curve, type 3, illustrating the relationship between actual finished goods inventory (output variable) and customer service (output variable).

The controllable variable must be sampled for values that span the area of interest for the output variables and the number of observations in that area must allow for a resolution in the operating characteristic curve that includes all interesting aspects of the relationship between variables. For each observation of the influence of the controllable variable value on the other variables, a number of replications are simulated. This will allow for analysis of variances and not only mean values. The number of observations and replications can only be determined by studying the simulation model and running a few test experiments.

For the first two types of OC curves, the input factor or control parameter are controllable and are subject to the experimental design procedure described above. The third type of OC curves, however, do not need dedicated simulation runs but can be based on output data from the other simulation runs. The tighter the scatter diagrams between two output variables irrespective of the changes in input factors or control parameters, the stronger the relationship between these two output variables. If the scatter diagram seem to display two or more curves, then backtracking is necessary to identify the source of this diversity.

There are two approaches for using OC curves when analyzing specific improvement initiatives. One approach is to study the direct impact of a change in an input factor or a control parameter on a performance indicator (output variable), such that the factor that is to be improved is depicted on the x-axis or as a curve indicator. The other approach is to define different scenarios involving improvements in one or more areas. Based on these scenarios the relationships among various variables are studied in OC curves. The first approach is used by Han and McGinnis (1989), and

Persson and Olhager (2002), and the scenario approach is used by Nazzal et al. (2006).

However, introducing simulation modeling in the process of generating operating characteristic curves will add uncertainty to the outcome and recommendation given by a decision maker. The process of generating these graphs is divided into three steps, (i) obtaining basic factor data from the real system, (ii) creating the simulation model and making sure it is a valid representation of the system, and (iii) running the simulation model to get output data so that the operating characteristic curves can be constructed. Each step can introduce errors into the final result and the data collection, simulation modeling, and simulation experimentation must be done in such a way that risk of introducing errors is minimized.

5 Using Operating Characteristic Curves for Improving Operations

Questions like "what if…" can easily be answered with a simulation analysis and providing decision makers with a set of operating characteristics curves is one way of shoving what would happen if some decisions were to be undertaken. Using simulation we can also extend the analysis beyond what is currently realisable in the system and allow the imagination of the decision maker to flow freely.

Simulation generated operating characteristics curves also introduces the possibility to test extreme scenarios, to test the boundaries of the system. How far is it possible to stress a certain parameter or factor? When will the system start behaving poorly? How can the system cope with extreme circumstances?

Operating characteristics curves also allow for the analysis of how control parameters and input factors affect output variables in terms of the sign (decreasing or increasing behaviours), the magnitude (amplifications of relationships), and the shape (linear or non-linear, convex or concave).

The use of OC curves is at least twofold; there is a learning aspect (which indirectly can lead to the improvement of manufacturing operations) and a decision support aspect.

5.1 Learning

Learning about a certain system and how the system behaves under different scenarios can indirectly lead to manufacturing improvements. Curves that map relationships between input factors and control parameters can be used to increase the understanding of system behavior both concerning a specific system and in more general terms. This understanding will implicitly lead to better informed decisions on how to improve the system.

5.2 Decision Support

Operating characteristics curves can be used as a decision support system. It is a simple task to choose the best or most suitable system from a set of scenarios using the operating characteristics curves as decision variable. Both the magnitude and the robustness of a solution can be studied and based on such an analysis, a decision can be made.

Operating characteristics curves can also be constructed with a certain aim with the analysis; cf. e.g. Nazzal et al. (2006). In this case it is important to have a fairly good idea about the relationships between studied parameters and variables. It is easy to miss the interesting part of a relationship if the analysis does not allow the parameters and variables to take on their extreme values.

As part of a decision support system, operating characteristics curves can be used to study the potential effects of a change initiative. What are the benefits of reducing setup times? Is it worth pursuing a setup time reduction and what is the cost limit for that? Operating characteristics curves can also be used to investigate how e.g. the demand variability influences the rest of the system. In this case, operating characteristics curves can be used to capture the effects of increasing (or decreasing) demand variability, or as a support tool to tweak the system so that it can counteract any increase in variability.

Improving planning and control is another issue within the decision support. The planning and control system can be optimised so that the best setting among control parameters such as lot sizes, lead times and safety mechanisms are found. The operating characteristics curves are developed for this certain manufacturing and supply chain system environment and the results can be implemented directly.

One example of an OC curve involving one input factor (quality), one control parameter (lead time), and one output variable (total cost) can be found in Persson and Olhager (2002). In figure 6, the relationship between quality levels, lead times and total operating cost is depicted. Persson and Olhager (2002) modelled a real supply chain and used the simulation model to generate a set of graphs to capture the relationships among variables. Different lead times were introduced as different scenarios where the supply chain configuration was altered. The quality levels were introduced as different levels in a set of quality control functions. This input factor (lead time, related to a specific supply chain design) and control parameter (quality level) provided observations on the output variable of total operating cost.

As part of the study by Persson and Olhager (2002), the relationships between lead times, quality levels, and total cost could be quantified. It also permitted an analysis of the behaviour of the relationships as being non-linear. As lead times increase and quality levels get worse, the total cost increases in a non-linear way.

6 Concluding Remarks

In this paper we have demonstrated how to derive operating characteristics curves using simulation, and how these can be used to gain knowledge about a particular manufacturing system to guide the choice of improvement initiatives. OC curves can be used for learning about the system behavior, as well as for decision support concerning specific situations. An important aspect of using simulation for the construction of OC curves is that the analysis can be extended beyond what is currently realisable in the physical system; thus testing for more far-reaching improvement initiatives.

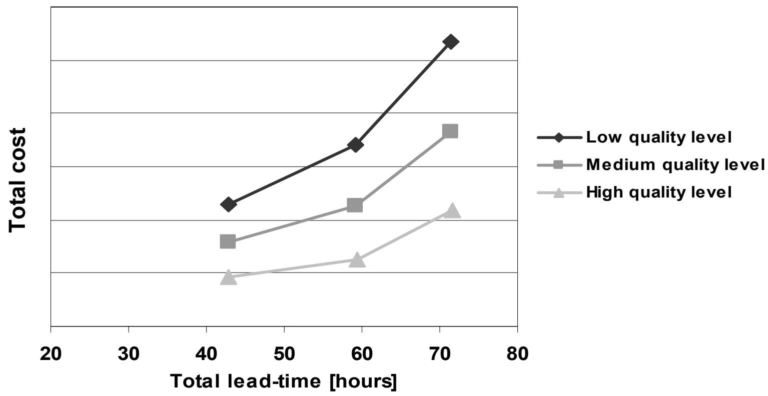

Fig. 6. The relationship between quality levels, lead times and total operating cost (Persson and Olhager, 2002)

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