Production Control System to Visualize Future Effects by Production Trouble

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OVERVIEW: When unexpected problems or accidents occur at the production and logistics sites that have spread throughout the world in conjunction with the globalization of business, it is essential that the supply chain be able to minimize the effects of such events in ways that are as flexible and resilient as possible. Using a statistical model of unexpected component shipment delays and manufacturing equipment failures, Hitachi has developed a production control system that predicts future variations in production volumes resulting from such incidents with high accuracy. This system uses prediction to select appropriate loss recovery strategies and is able to minimize production volume dips and delivery delays. Using this system, Hitachi intends to extend its application to applicable processes, and to develop it for sale by a production control consulting business.

INTRODUCTION

IN recent years, along with the globalization of business, the supply chains of various manufacturers' production sites have expanded worldwide. However, there have been times when these supply chains have been disrupted by unexpected events, such as during the natural disasters that occurred around the world in 2011, including the Great East Japan Earthquake and flooding in the Kingdom of Thailand. These and other events have resulted in service disruptions to a steadily increasing number of customers. Thus, there is a clear need for production control methods that can minimize the influence of such problems while also providing flexible and resilient support to supply chains.

In conventional production control, the estimated number of available components and production volumes are set for each production process. When unexpected problems occur in an upstream process, such as an unexpected component shortage or manufacturing equipment failure, these can affect downstream processes as well. They cause shortages in component deliveries and place excessive demands on manufacturing capacity in downstream processes, thus delaying progress and ultimately causing delivery delays. In response, Hitachi has developed a production control system, based on a statistical model, that is capable of making highly accurate predictions of the future production volume variations resulting from the flow-on effects to downstream processes of problems in an upstream process. This article describes the production control, which uses a statistical model for the highly accurate control of the variations that occur in production volume after an unexpected problem.

STATISTICAL-MODEL-BASED PRODUCTION CONTROL

Fig. 1 shows a diagram of the statistical-model-based production control developed in this project. The first task is to gather, in realtime, actual data for each component from the manufacturing shop floor, such as when it completes each process. Next, the statistical model is applied to this collected data to

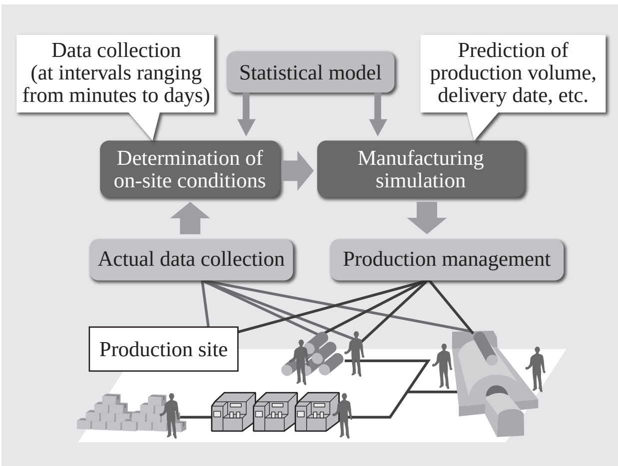


Fig. 1—Statistical-model-based Production Control.
The future production volume is predicted by a manufacturing simulation that uses a production model generated from actual data by a statistical model.

generate input data for a manufacturing simulation. This provides a model of the current production situation. The manufacturing simulation is then run using the generated model to predict future production volumes and delivery times.

If the predictions indicate that upstream problems will propagate to downstream processes, potentially reducing production volumes, delaying deliveries, or causing other issues, the system triggers an investigation of loss recovery strategies. Manufacturing simulations are then performed to examine each loss recovery strategy and assess its effectiveness. The strategy found to be the most effective is adopted to resolve the problem.

This production control scheme involves two tasks: modeling and visualization. “Modeling” means that a high-precision production model is generated from the gathered actual data. “Visualization” means providing a visual representation of the conditions that result as the effects of problems in upstream processes propagate to downstream processes. A variability modeling technique was then developed to aid in creating production models, and a technique for predicting how problems propagate was developed to aid in visualizing the influence that problems have on downstream processes.

Variability Modeling Technique

This section uses an example of a mass-produced product to describe the issues associated with the generation of input data for a manufacturing simulation from the collected actual data (see Fig. 2). For a mass-produced product with a production volume that exceeds several million units annually, the volume of actual data collected from the plant will total several million data points each day. Using hypothetical lots A, B, and C, consider an example in which lot A is handled in four sub-processes, lot B, in two sub-processes, and lot C, in three sub-processes. Data on the start and completion times for the overall process are collected separately for lots A, B, and C. However, the period between the start and completion times also includes the time needed for transportation between processing equipment, the time spent waiting for loading into a new sub-process, and the time needed for removal from each process. In other words, collecting only the start and completion times fails to provide any information about the times required for each sub-process.

A variability modeling technique based on statistical work was developed to address this issue. This technique considers the number of sub-processes

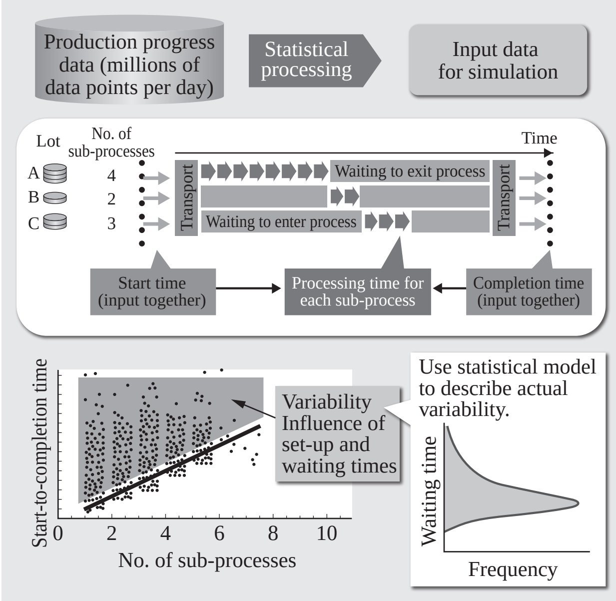


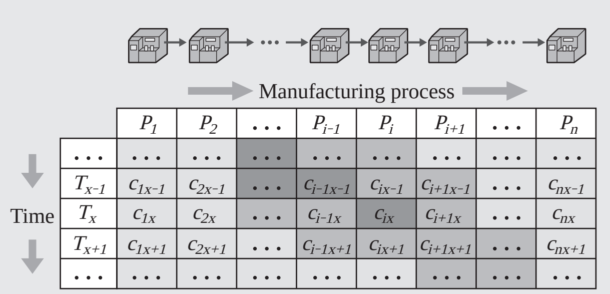
Fig. 2—Variability Modeling Technique.
A statistical model was used to describe the distribution of the variability of actual results in the form of an equation, and the equation was then used as the input to a simulation.

included in each lot and the time required from start to completion. The graph at the bottom-left of Fig. 2 shows a scatter plot with the number of sub-processes on the horizontal axis and the start-to-completion times on the vertical axis. Each point represents an actual product. The slope of the line visible along the bottom border of the scatter plot is related to the processing time for a single sub-process. Meanwhile, the variabilities in the upper portion of the scatter plot are influenced by set-up and waiting times. These variabilities can be expressed with the statistical model shown at the bottom-right of the figure.

Propagation Prediction Technique

Next, a manufacturing simulation is created based on the variability modeling technique and incorporating information such as machine times and production volumes (see Fig. 1). This simulation is used to predict the influence that unexpected problems in upstream supply chain processes have on downstream processes.

Essentially, an unexpected problem in an upstream process will always cause some variations in the production volume downstream, and while some of these variations in the supply chain will be damped, others will be amplified, ultimately resulting in delivery delays. Therefore, in order to examine ways of responding to problems, it is essential to be able to visualize just how variations arising in upstream processes will propagate to downstream processes.



Type	Class	Color	Assumed production conditions
A	c_{ix} < Threshold 1	☐ (light)	Steady production (variation can be ignored)
B	Threshold 1 ≤ c_{ix} < Threshold 2	☐ (medium)	Some variation in production
C	Threshold 2 ≤ c_{ix}	☐ (dark)	Significant variation in production

Fig. 3—Propagation Prediction Technique.
A map is used to provide a visual representation of how variations in the productivity index propagate.

In response, Hitachi has developed a propagation prediction technique for intuitively visualizing how variations occurring in upstream processes propagate to downstream processes (see Fig. 3). In this approach, the coefficient of variation (CV), which quantifies the variability, is extended and replaced by a new index called the "visualization coefficient"(1). The visualization coefficient is defined as the value of the variance to the productivity index during the current process, divided by the moving average. As shown in the figure, the propagation prediction technique employs a map to help users visualize the propagation of variations from upstream to downstream. In this map, the horizontal axis represents production processes while the vertical axis represents time. Each square represents the state of progress in a process at a given time. The visualization coefficient associated with the productivity index for each square is calculated from the prediction data, which are generated using actual data and the manufacturing simulation.

Calculated visualization coefficient values that are less than or equal to threshold 1 indicate that production will be steady, with negligible variations, while values between thresholds 1 and 2 indicate that some production variation will occur. Values greater than or equal to threshold 2 indicate that variations will be ongoing. These are shown with different colors. Thus, by visualizing production variations at each process, this method can be used to visualize variations at any time and in any production process, and can show the extent of their propagation to downstream processes with the passage of time(2), (3).

APPLICATION EXAMPLE

Production Control of Mass-produced Goods

The production control based on the statistical model described above was implemented at a Hitachi facility and the results were observed. This section describes how the system handled problems in this test(4) (see Fig. 4). The horizontal axis of Fig. 4 represents the production schedule, and the vertical axis represents the cumulative production volume.

In this example, a piece of manufacturing equipment failed on the fourth day. The production volume through to the end of the month was then predicted using the manufacturing simulation based on the input data generated with the variability modeling technique. The results indicated that cumulative production would be 60% lower than the monthly goal.

The propagation of variations resulting from manufacturing equipment failures was visualized with the propagation prediction technique, and countermeasures were investigated (see Fig. 5). The horizontal axis represents production processes from the input of components through to product shipment, while the vertical axis represents time. The gray horizontal line in the figure represents the present time. The region above the horizontal line visualizes the actual result, while the region below visualizes the propagation of production variations, as predicted by the manufacturing simulation using current production conditions as initial values. The figure shows how manufacturing equipment failures occurring in upstream processes cause variations in production volumes, which then propagate to

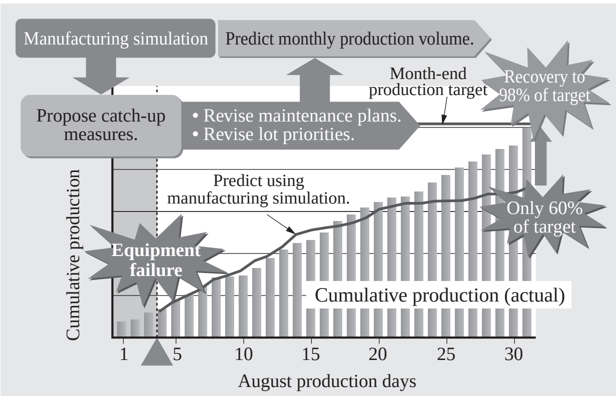


Fig. 4—Example of Response to Problems Using Developed Production Control.
Measures such as changes to manufacturing equipment maintenance schedules and lot priorities are made in order to catch up with the target for month-end production.

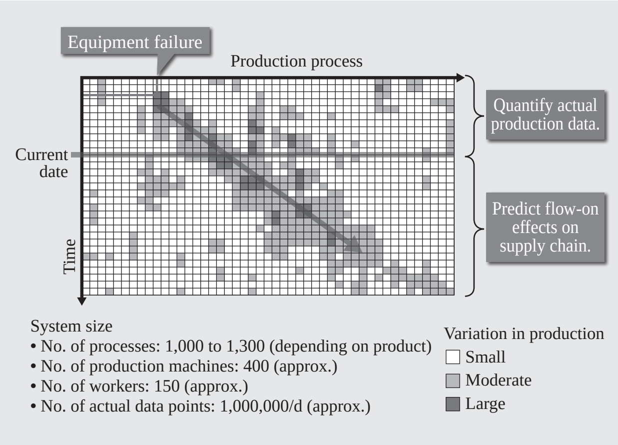


Fig. 5—Example Application of Propagation Prediction to Mass-produced Goods.
The technique predicts the flow-on effects (variations in production volume) after a manufacturing equipment failure occurs.

downstream processes over time. Based on this figure, we could predict that delivery delays would occur in the light gray and gray regions, which were affected by the variations.

The prediction was then used as a basis for drawing up countermeasures, including revisions to manufacturing equipment operation times and front-loading the production of products with little flexibility in their delivery dates. A new manufacturing simulation that took these changes into account was then generated and run to produce revised predictions for cumulative production by the end of the month. The simulation results indicated that the countermeasures would restore production to 98% of the monthly goal (see Fig. 4).

Production Control of Non-mass-produced Goods

With the addition of multivariate analysis, which can be used to generate production models on the basis of design data and other characteristics, this statistical model-based production control is also applicable to non-mass-produced goods produced in volumes of between one and several tens of thousands, such as components for manufacturing plant. Multivariate analysis is a procedure used in statistical theory for analyzing the correlations within a group of variables using data related to the variables. In the context of this study, multivariate analysis can be employed to estimate the machine time for each component and task (see Fig. 6) by modeling the relation between the gathered machine times and design data, such

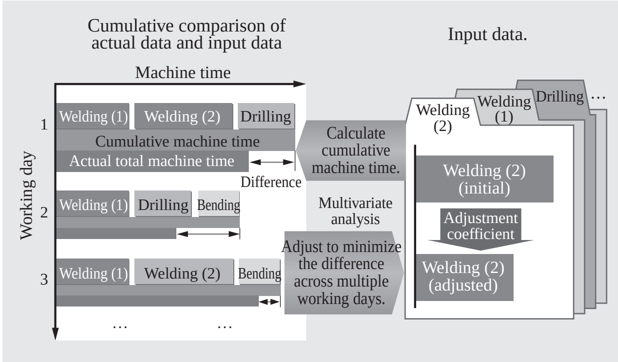


Fig. 6—Machine Time Estimation Using Total Machine Time.
The estimated machine time was adjusted to minimize the difference between the cumulative machine time for tasks performed on working days and the actual total machine time.

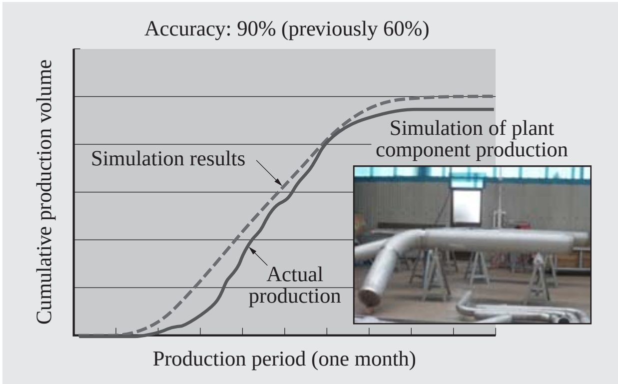


Fig. 7—Production Volume Prediction for Manufacturing Plant Components.
When compared against actual production, the machine times estimated using multivariate analysis had a simulation accuracy of 90%.

as the component size after a task or the number of processes.

When applied to manufacturing plant components, the method was able to predict production volume one month ahead with an accuracy of 90% (see Fig. 7).

CONCLUSIONS

This article has described a highly accurate statistical-model-based production control system capable of predicting variations in the future production volumes of production processes when unexpected problems occur, such as component shipment shortages or manufacturing equipment failures. The system is currently used for production control of manufacturing plant components at a Hitachi facility, and the intention is to extend its use to more processes in the future. Hitachi also plans to introduce a production control consulting service for external customers based on this technology.

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