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PAINT LINE COLOR CHANGE REDUCTION IN AUTOMOBILE ASSEMBLY THROUGH SIMULATION

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ABSTRACT

The painting process is an important part of the entire automobile manufacturing system. Changing color in the painting process is expensive because of the wasted paint and solvent during color change. By intelligently selecting cars toward downstream operations at the places where conveyors converge or diverge, we can reduce the number of such color changes without additional hardware investment. Discrete Event Simulation is a tool of choice in analyzing these issues in order to develop an effective and efficient selection algorithm to ensure the system throughput. The concepts and methods presented here are also applicable to other discrete event manufacturing processes where setup reduction is pursued.

1 INTRODUCTION

Automotive manufacturing is a complex task involving several steps of machining and assembly. Typically, large components of an automobile such as the body, engine etc. are assembled over multiple systems. The three main stages of an assembly line in the automotive industry are: the body shop, the paint shop, and the trim and chassis shop. Cars flow through the assembly line from stage to stage in sequence (see Figure 1).

Figure 1: Stages of the Automobile Assembly Process

An automotive company will typically sequence cars based on several objectives, most dealing with line balancing and material management. In the first and last stages (the body shop and the trim and chassis shop), different cars might require the installation of different components. Such imbalance of the workload at the automotive assembly line can be due to 1) different options of the same car model (e.g. one car might have an automatic transmission and sunroof, while another car might have a manual transmission, but no sunroof), 2) different types of the same model (e.g. sedan vs. wagon), or 3) different models assembled in the same line. To balance the workload, an automobile manufacturer will sequence cars so that even over small sets of consecutive cars, the frequency of each installation is approximately equal to its overall frequency. For example, if 10% of all cars have a sunroof, then one out of every 10 consecutive cars in an ideal sequence would have a sunroof. If this were the case, a worker at the sunroof installation station would have a fairly constant workload. By balancing workloads, the plant can avoid bottlenecks that may slow down the line.

Since workload balancing and other principles is considered so important, the creation of color blocks (or paint blocks, i.e. consecutively-sequenced cars with the same required color) at the painting station of the assembly line is considered less important. As a result, the average color block size of the incoming car to the paint shop is usually very low. However, because the plant must cleanse the painting apparatus of one paint color before painting a car a new color, it can sacrifice efficiency and money when the average color block size is small.

The data collected from a major automobile assembly plant in US (with which we are conducting a research project now) show that we can save a lot just by increasing color block size (i.e. the number of cars coming together with the same color). We note that the cost associated with implementing such color block size increase is a one-time expenditure and is expected to be relatively small compared to the possible saving amount (thanks to the fact that all we need to do is just to change the control logic of conveyors). We also expect this savings amount to be increased further since we found several other candidates where the same approach can be applied for further increases in average color block size (i.e. reducing the number of purges).

Reducing the number of paint purges can also reduce environmental impact, as the cleaning solvents often contain environmental pollutants such as volatile organic compounds (VOCs).

The remainder of this paper is organized as follows. Section 2 describes the problem, section 3 make brief explanation on our analytical model for the problem, and section 4 explains why discrete event simulation model is needed for our problem. Section 5 presents the simulation model for this problem and section 6 makes conclusion. Screen captures from our simulation model implementation are presented in Appendix.

2 PROBLEM DESCRIPTION

Changing color in the painting process is expensive because of the wasted paint and solvent during color change. That fact justifies our effort to reduce the number of color changes in the painting process. Besides its original function of transporting cars to downstream operations, the conveyor/transfer systems can be used for buffering and can be also used to re-sequence to maximize average color block size, which is equivalent to minimizing the total number of color changes.

Let us describe the problem we want to solve using a very simple example. This example with two white cars and one black car illustrates our novel method of increasing color block size (see Figure 2 through 4).

In Figure 2, there are two options available for sending cars from two incoming conveyors (conveyor A and B) to one outgoing conveyor. Instead of painting the black car between the two white cars (Figure 3), we would like to paint the black car first, and then paint two white cars (Figure 4). In this way, we have reduced the number of paint color changes from two to one.

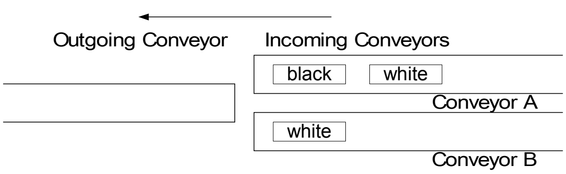

Figure 2: Example (Two Incoming Conveyor and One Outgoing Conveyor)

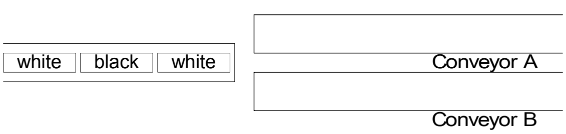

Figure 3: 1st Option (if the Car in Conveyor B is Picked Up First)

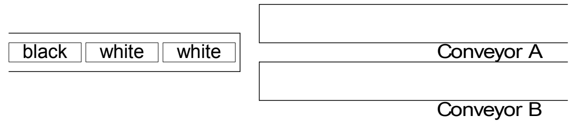

Figure 4: 2nd Option (if the Car in Conveyor B is Picked Up Later)

We can think of a reverse example with one incoming conveyor and multiple outgoing conveyors (see Figures 5 through 7). While in the previous example we had to decide which car to choose from incoming conveyors, in this example we have to determine to which outgoing conveyor we will send the car. In Figure 5, there are several options available for sending cars from one incoming conveyor to two outgoing conveyors (conveyor A and B). Instead of randomly choosing the destination conveyor (with Figure 6 as a possible result), we would like to use smart logic in which conveyor A gets black cars only while conveyor B gets white cars only (Figure 7). In this way, we have reduced the number of paint color changes from two to zero.

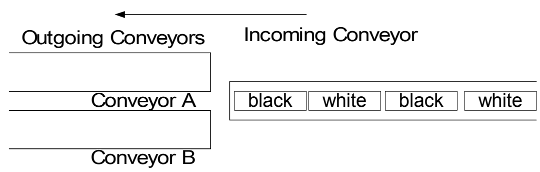

Figure 5: Example (One Incoming Conveyor and Two Outgoing Conveyors)

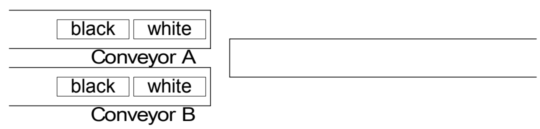

Figure 6: 1st Option (Possible Case if Cars are Randomly Selected)

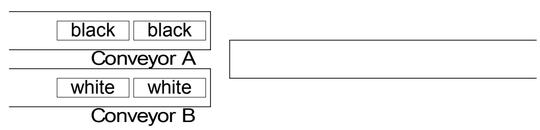

Figure 7: 2nd Option (Black Cars Go to Conveyor A and White Cars Go to Conveyor B)

While for both of the above samples it is easy to find the optimal solution to decrease color changes, finding the optimal solution is no longer intuitive when the number of incoming cars increases (e.g. 30 cars for each conveyor).

3 ANALYTICAL MODEL

The optimization problem induced by this situation is to minimize the total number of color changes (or, equivalently, maximizing the size of the average color block) given the initial ordering of automobiles, the colors they are to be painted, and the way conveyors are connected.

The above problem can be generalized as follows. It is the problem of resequencing a pre-arranged set of jobs on a moving assembly line with the objective of minimizing changeover costs. A changeover cost is incurred whenever two consecutive jobs do not share the same attribute. Attributes are assigned from a set of job-specific feasible attributes. Re-sequencing is limited by the availability of the conveyor connection points and offline buffers.

We developed a finite-horizon analytical model for this optimization problem. This integer programming model is flexible in that if given minor assumptions are satisfied, it can handle all cases with different initial ordering of automobiles, color sequence to be painted, and number of incoming and outgoing conveyors. In addition, this model has been extended to handle the more general case where an offline buffer is used. A typical example is given in Figure 8.

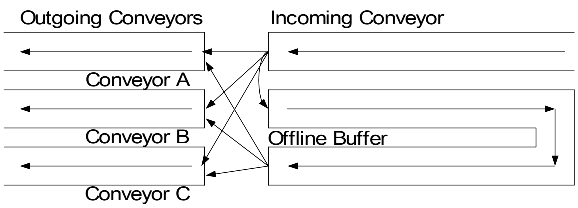

Figure 8: Diagram for Prime Storage Area in Atlanta Assembly Plant

In this example, for the car at the end of one incoming conveyor, we have an additional option to send this car to the offline buffer (as well as sending it to three outgoing conveyors). Since the car entering the offline buffer will appear at the end of the offline buffer (which is right below of the end of incoming conveyor) and will be available for sending to downstream conveyors after some time, we can use offline buffer for further reducing color changes.

4 WHY SIMULATION?

There are many reasons why we need simulation model in our case. In summary, discrete event simulation is a tool of choice in analyzing the issues discussed below in order to develop an effective and efficient selection algorithm.

4.1 Limitations of the Analytical Model

The mathematically optimal solution we can get from the analytical model may not be an optimal solution for our real system. Our analytical model cannot address all aspects of the real system. For example, cycle time is one of the top concerns of the plant managers but our analytical model is unable to handle any time-related constraint.

In addition, from our problem viewpoint, the entire painting processes can be thought of as a collection of conveyors connected in various ways. While our analytical model yields the optimal solution for each connection configuration subsystem, the collection of these local optimal solutions may not be the global optimal solution of the whole system. So we need to validate the solutions we get from analytical model using a simulation model.

These limitations of the mathematical model make our simulation model indispensable for evaluating solutions including the solution from the mathematical model.

4.2 Expensive Real System Implementation

The conveyor system design change as well as control logic change is expensive. Simulation is also a less expensive option compared to actual controls programming and fine-tuning of the real system. Furthermore, simulation software available today provide programming constructs and abilities that allow intricate operating details of such complex systems to be modeled with relative ease and accuracy (Jayaraman 1997).

4.3 Ideal Tool for Evaluating Complex System

Simulation has been extensively used for simulating automotive production processes. Example of such successful applications can be found in Park et al. 1998 and Graehl 1992. More specifically, with its inherent ability for modeling randomness, simulation is an ideal tool for evaluating different rule sets and for predicting the throughput capability of a selectivity system. It provides an easier option for evaluating different scenarios without affecting the current operation of the actual system.

4.4 Additional Advantage of Simulation Model

In addition, plant managers can use our simulation model in doing what-if analysis or sensitivity analysis. For example, simply looking at the simulation animation can easily identify bottlenecks in the paint shop and managers can determine how fast the conveyor should move to get the desired throughput.

5 SIMULATON MODEL

5.1 Input Data Selection

Quality of simulation output heavily depends on the quality of the input data to the simulation model (garbage in, garbage out). If complete data is ready for use, usually it is best to use the available data without modification. However, if complete data is not readily available and to get complete data is either not available or available at a certain cost, decision on how detailed data the simulation model will use should be made in advance.

Two kinds of data are available for the input to our simulation model – time domain data and frequency domain data. Time domain data is the data with the time related information. In our case, it is the data on incoming car sequence to the paint shop with the specific color of each incoming car and its time stamp data. Frequency domain data is the data containing frequency information (not time information). In our case, it is the historical data on the distribution of colors on incoming cars as well as the average arrival rate to the paint shop. Time domain data can be converted to frequency domain data while frequency domain data cannot be converted to time domain data.

The property of the system we measure (i.e. average color block size) makes time domain data more suitable for the input to our simulation model. That fact can be illustrated by the following example. Consider the following two different sequences of incoming cars.

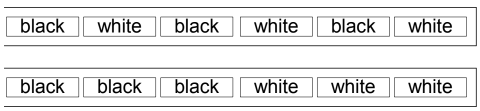

Figure 9: Two Different Sequences of Incoming Cars

From frequency domain data perspective (3 black cars and 3 white cars), both of the above sequences are identical. While such abstraction (time domain data → frequency domain data) has no effect on some performance measures of the system, e.g. throughput, other performance measures, e.g. average color block size, are heavily affected by that abstraction. Please note that it took negligible time to change color in painting process we observed. Since we are mainly concerned with average color block size, which is heavily affected by such abstraction, it is evident that we should use time domain data in our simulation model.

However, the automobile assembly plant we were working for does not collect time domain data while they collect frequency domain data only. So we had to collect time domain data manually for a limited amount of time, and to compare our collected time domain data with the existing frequency domain data for verifying that there is no big discrepancy between our collected data and existing frequency domain data.

We note that time domain data derived from frequency domain data (infinite number of different time domain data can be generated from one frequency domain data by changing time-related parameter arbitrarily) is not useful as an input data to the simulation model for predicting real system behavior, while they are useful for evaluating robustness of the control policy of the conveyor control point.

Our simulation results show that average color block size was bigger when manually collected time domain data were used (compared to the "derived" time domain data). We suspect that such increase is due to the fact that actual incoming car sequence is not randomized while the derived data is completely randomized (the color of each car is randomly decided according to the historical distribution of incoming car color).

5.2 Control Logic Evaluation

The main purpose of our simulation model is to evaluate various solutions for increasing the desired property (average color block size) of the system. Each solution is implemented on the system by changing the control logic for each place where conveyors diverge and/or converge (we call it a *conveyor control point* hereafter). Ideally, best decision at each control point can be made when complete information of the whole system is given (complete information in our case means data from all sensors installed on the paint shop). However, in our case each Programming Logic Controllers (PLCs) governing each conveyor control point could "see" only a few sensors nearby and PLCs couldn't communicate with each other. Furthermore, decision at each conveyor control point should be made on real-time basis (in our case within 1 minute) because of the dynamically changing environment. In addition, because the logic in the PLC is implemented by the ladder diagram (that is a low-level language like Assembly and therefore hard to program and debug), the logic itself should not be too complex.

Because of the above practical difficulties, in addition to the analytical model discussed in section 3, we also developed a few heuristics for each conveyor control point and evaluated these heuristics using the simulation model to choose the best one. Since we had 6 control points and we developed two heuristics for each control point, we chose the best from $2^6 = 64$ possible combinations. For evaluating the robustness of the heuristics (discussed in section 5.1.), additional runs using the derived time domain data were performed.

6 CONCLUSIONS

In this paper, we explained why the color change reduction problem in the paint shop of automobile assembly plant is important. We also justified why simulation model should be used in our problem and how it can be modeled (analytically as well as by simulation model). We also discussed the detailed simulation implementation issues such as input data selection and control logic evaluation.

The concepts and methods presented here are also applicable to other discrete event manufacturing processes where setup reduction is pursued.

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APPENDIX: SCREEN CAPTURES

2 screen captures from our simulation model implementation are given in Figure 10 and 11.

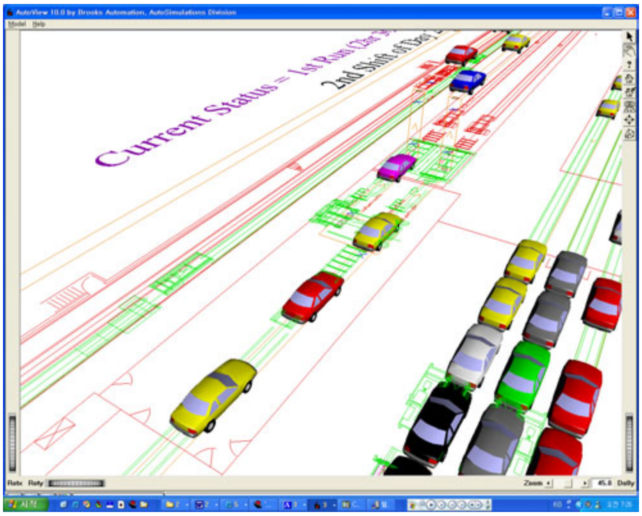

Figure 10: Prime Spray Area → Prime Oven Area (Left), Prime Storage Area (Right)

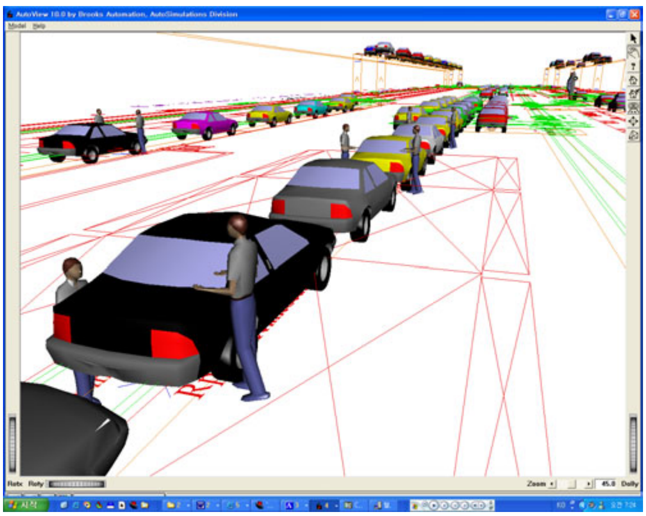

Figure 11: Prime Scuff Area

REFERENCES

Bras, B., S. Duncan, M. Franz, T. Graver, Y. Han, L. McGinnis, S. Velasquez, B. Wilgenbusch, and C. Zhou. 2001. Real-Time Integrated Economic and Environmental Performance Monitoring of a Production Facility. *Society of Automotive Engineers*, Paper No. 2000-ES-23.

Graehl, D. 1992. Insights into Carrier Control: A Simulation of a Power and Free Conveyor through an Automotive Paint Shop. In *Proceedings of the 1992 Winter Simulation Conference*, eds. J. Swain, D. Goldsman, R. Crain, and J. Wilson, IEEE, Picataway, N.J., 925-932.

Jayaraman, A., R. Narayanaswamy, and A. Gunal. 1997. A Sortation System Model. In *Proceedings of the 1997 Winter Simulation Conference*, eds. S. Andradottir, K. Healy, D. Withers, and B. Nelson, IEEE, Picataway, N.J., 866-871.

Magnanti, T. and J. Sokol. 2002. Modeling Automobile Paint Blocking: A Time Window Traveling Salesman Problem. Ph. D. Thesis, Massachusetts Institute of Technology, Cambridge, MA..

Park, Y., J. Matson, and D. Miller. 1998. Simulation and Analysis of the Mercedes-Benz All Activity Vehicle (AAV) Production Facility. In *Proceedings of the 1998 Winter Simulation Conference*, eds. D. Medeiros, E. Watson, J. Carson, and M. Manivannan, IEEE, Picataway, N.J.

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