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Inventory simulation and optimization using system dynamics, structural modeling equations and genetic algorithms in the drivetrain division of an automotive manufacturer

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INVENTORY SIMULATION AND OPTIMIZATION USING SYSTEM DYNAMICS, STRUCTURAL MODELING EQUATIONS AND GENETIC ALGORITHMS IN THE DRIVETRAIN DIVISION OF AN AUTOMOTIVE MANUFACTURER

A Dissertation

Submitted

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Industrial Technology

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ABSTRACT

Strategic planning and control are among the most critical activities that modern enterprises require to succeed in the global economy. This research is an original study that investigated the combination of tools and methodologies in order to apply them to a midwestern tractor manufacturer. The current study identified the constraints applicable to a polishing line in the Drivetrain Division of a major tractor manufacturer interested in exploring alternative techniques to improve its worldwide manufacturing operations.

The specific questions that this project tried to respond are stated as follows:

1. What were the most important variables that affected inventory levels of an assembly line of an automotive manufacturer?
2. What were the significant effects of the causal relationships identified in order to determine an initial model structure?
3. What constrains restrict the behavior and improvement of the selected variables?
4. What levels of the selected variables could be used in order to improve production levels?

The current research explored the impact of a series of variables (work-in process, process utilization, cycle time, queue size, utilization of work centers, capacity, and others) in order to examine their impact in the overall performance of the polishing line. Two main models were developed based on two algorithms created for each of the

selected part families (PTO and Covers), and in combination determined material flow, resource utilization, and sequencing within and outside the automatic polishing line. The two computer models combined both dynamic and discrete simulation to establish a reference to be used for improvement of similar processes within the company using structural equations modeling, path analysis, scatter plot diagrams, and eigen value plot.

Besides, the results of this research indicated that: (a) cycle time can be improved with the addition of a new transporter in order to reduce the moving time within and between work centers; (b) the queue sizes of the polishing line were not improved significantly using either genetic algorithms (GA) and full factorial designs because of the low initial variability of the system; (c) the structural modeling equations model allowed to identify possible material flow errors based on its relationships, in this way it is possible to have a benchmark to compare both the results of the current study and the outcomes of similar studies developed by the company. In summary, a new methodology has been developed in order to study and optimize manufacturing systems, and avoid cost reductions without any statistical significance that might affect the strategic position of the company in the long run. The current study did not give a simple answer to the complexity of the discussed problem, but an alternative to many of the current academic and industrial solutions that can have more than one correct answer.

DEDICATION

To God, my family, and friends

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The author would like also to express his appreciation to all people and managers from Deere & Company for their technical support, as well as their valuable comments in order to develop this work. It is important to consider that all the information presented in the current project has been changed from its original results in order to avoid any damage to Deere & Company Worldwide Operations.

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CHAPTER I

INTRODUCTION

The improvement and development of manufacturing systems is a challenge by itself and requires both empirical and scientific approaches. It is simple to determine that a process performs or does not perform to specifications, but it is more difficult to actually replicate that process in order to simulate those behaviors that were undesirable.

The purpose of the current research was to propose an alternative and high-level methodology for improvement of manufacturing processes. For that reason, the combination of three areas of study: genetic algorithms, discrete and dynamic simulation were used in order to propose an alternative solution for a highly complex problem.

The researcher was interested in proposing several alternative models to improve rather than "optimize" the performance of a polishing line of an automotive manufacturer. The term optimization itself is well understood in industry and academia, but still creates confusion between managers and engineers because of the diverse availability of tools and techniques to accomplish a similar objective. Byrne (1998) mentioned that the term optimization is considered to be a relative improvement of the current performance without necessary achieving the real optima of the system, which was considered to be the case for the current research.

For that reason, the term optimization and improvement were considered to be synonymous for the present study. Thus, the analysis of results was cited as "optimization" but for the researcher means only improvement based on the current process constraints that might change if further information is available after the completion of the study. In reality, what the present study showed was a sub optimum value, which could be an intermediate result between the current performance and the real optimum.

The project concluded with improved levels of several performance variables that were key for the objectives of the Drivetrain Division of the automotive manufacturer. The study was an introduction of advanced planning techniques into a Fortune 500 company, meeting the company's constraints and interests.

In summary, the final models replicated accurately the general constraints of the system, but required further research in order to develop a single simulation model that integrates the total production system for the selected automotive manufacturer.

Problem to Investigate

The problem of this research was to develop a simulation model for an automotive polishing line that allows the optimization of the inventory levels.

Purpose of the Investigation

Simulate and demonstrate how inventory levels of a polishing line of an automotive company can be improved using system dynamics, structural modeling equations and genetic algorithms.

Type of Research

This investigation was directed to develop a computer simulation model using both qualitative and quantitative approaches to develop causal and inferential relationships of variables that supported managerial decision-making. The computer software used for the research in order to develop the different algorithms and simulation models were: Promodel, Powersim, Statistica and EQS.

According to Fraenkel (2003), qualitative research studies investigate and infer relationships of a phenomenon, and quantitative studies, specifically causal-comparative, analyze cause and effect relationships within dependent and independent variables. Both characteristics can be combined according to Byrne (1998) using quasi-experimental exploratory research, because random assignment, independent and experimental data was not always feasible, and for this particular case the researcher had to develop assumptions based on managerial insight due to unavailability of information.

Byrne (1998) refers to this strategy as the "modus operandi approach" or the same strategy used by "a detective trying to solve a crime", since the researcher was the one who lead the investigation and there were no initial theories, rather than managerial knowledge, to support the conclusions and findings of this applied research project. Besides, this approach maintains the qualitative orientation of the research since quasi-experimental studies, according to the same author, creates an approximation to experimental designs and provides causal inferences of relationships between variables. However, as mentioned by Fraenkel (2003) this type of research study has two main weaknesses: "lack of randomization and instability to manipulate an independent variable." Fraenkel mentions that the random assignment is not possible since the groups were already formed and the manipulation of the independent variables is not possible because the groups have been already exposed to them and the information has already affected the response variable.

For this reason, the application of system dynamics (SD), structural modeling equations (SEM) and genetic algorithms (GA) into the study considered these elements into consideration while dealing with non-experimental (also referred to as historical or observational) and non-independent data collected during a long period of time.

A selected number of key variables chosen by a management team of the selected company provided the initial population of variables to investigate; the research determined their operational impact of the selected process. These variables were strategic, explicit and meaningful in order to be measured and included during the investigation and the development of the simulation model.

Kaplan (1996) mentioned that this kind of simulation models require that these relationships (hypotheses) among objectives (and measures) be explicit enough so that they can represent an approximation of the real managerial problem.

Justification of the Study

The justification of the study depends on the need of Drivetrain Management to explore a more scientific approach to manufacturing improvement using advanced six sigma tools such as discrete simulation and structural equation modeling. The basic need of management is to explore new ways that the assembly and polishing operations could be improved with a more scientific approach, and in order to guarantee that the changes made over the manufacturing lines, will have positive impact in the future improving production levels and reducing work in process.

For this reason, the development of a mathematical computer based model to test future changes in the polishing line will have a significant effect in the organization and planning of future production plans. It is required by Management, that the final output of the study be a computer-simulated model that allows adding, removing, and modifying the production rules for a polishing line. In this way, it is possible to reuse the simulation model in order to build similar representations of other manufacturing lines with just small changes in the basic algorithm.

The methodology developed during this study was oriented to be a standard procedure to scientifically analyze and improve different sets of values for a given production system. The scope of the project will limit not only its complexity but also the final results obtained from using the suggested procedure of this research. The procedure used in this project could be equally applied to simulate the total manufacturing plant or simply just one small line but the results cannot be same because of differences of scope.

In addition, the increasing amount of information available to managers makes it more difficult to provide, in a short period of time, a valid insight regarding the impact of their decisions over the Supply Chain or the financial performance of the company. Roberts (1999) points out that business leaders are influenced by an "image of the future" that is vague and have a strong impact on the long-term decisions of the company.

According to Roberts (1999), it is a major breakthrough in understanding how an industrial company success depends on the interaction between the flows of information, materials, money, manpower, and capital equipment. In this way, the manager's role can be more visualized and simulated as any other measurable process.

Manufacturing processes were an important part of the success of high technology enterprises and, according to Skinner (1985), is the formidable competitive weapon, since most of the decisions related to manufacturing and product development influenced directly the company's long-term success in the marketplace, and the product life cycle directly.

For that reason, the current project provided a simplified approach to deal with top managerial problems with an integrated approach using system dynamics modeling (SD), structural modeling equations (SEM), and genetic algorithms (GA). The first two techniques have been applied extensively in the social sciences and were becoming more applicable to ease the problems to manufacturing companies in areas of decision and policy development, time compression, demand amplification, supply chain design and integration, international company integration and many other applications according to the Massachusetts Institute of Technology (MIT) System Dynamics Group (2002).

The same research institute at MIT concludes that current simulation and managerial practices were directed to discrete simulation and were reluctant to incorporate managers as active players in the model building and enterprise design process. The techniques to be used in this study incorporated managers into the simulation process from beginning to end, using their insights as the "backbone" to develop an algorithm that can be understood by both managers and engineers in order to identify optimized inventory levels. A research developed at Arizona State University (1998), supports the development of SD models using management insights as a way to provide early predictions and enable planners to see the potential impact of various project control decisions.

The development of nonlinear models based on approximated linear models comes as a response to the great instability and oscillation of real-world variables. Craig Kirwood (1998), from Arizona State University, mentions that models that assume a process is linear have been extensively studied because the mathematics for such models is relatively easier in comparison with the development of non-linear models.

In this way, SD, SEM, and GA, can be perceived as useful combination not yet explored to solve the managerial complexity and give statistical support to the decision-making activities and reduce uncertainty.

Research Questions

The following statements determined and establish which elements were tested in order to show the effect of nonlinear relationships over decision-making of a manufacturing activity. However, it is important to point out that due to the nature of the study causal inference and correlational analysis were expected to have nonrandomized, non-independent, non-experimental and biased samples that have been already exposed to different treatments for a long period of time, and as previously discussed by Fraenkel (2003), their effect can only be reduced but not eliminated from the data.

Bill Shipley (2002) and Bollen (1989) presented several statistical methods that can test and discover cause-effect relationships between variables in situations where it is difficult to conduct randomized or experimental studies that also supported this research.

Based on these issues the research questions helped to initiate the exploratory analysis towards the development of a simulation model that behaves similarly to the real system. According to Byrne (1998) the term quasi-statistics is quite appropriate to the study of real processes, since statistical analysis was used in order to validate qualitative data and support the researcher findings along the project.

The current research addresses the following questions. The findings were reported in Chapter IV.

1. What were the most important variables that affect inventory levels of an assembly line of an automotive manufacturer?
2. What were the significant effects of the causal relationships identified in order to determine an initial model structure?
3. What constraints restrict the behavior and improvement of the selected variables?
4. What levels of the selected variables could be used in order to improve production levels?

These statements were the basis for the current research using biased and nonlinear data that was tested using descriptive and inferential statistics to guarantee that the findings were supported by reliable techniques and experience.

Assumptions

The development of any research activity required that the researcher defined a basic set of general assumptions in order to guarantee validity of his/hers results. The following assumptions were the starting point for development of a simulation model and different conclusions with the decision makers. The way that variables were monitored, managed and controlled depended directly on the relationships identified initially as well as the level of details required by top management.

These assumptions directed how the managerial variables were analyzed in combination with causation and inference theory that it is suggested that the reader consult Byrne (1998), Glymour (1999), Bollen (1989), and Shipley (2002) before questioning any of the following statements.

The fundamental assumptions for the study were:

1. Correlation can be used to infer causation in combination with Bayesian Networks.
2. The observed (historical) data is biased, dependent, and nonrandom.
3. The initial population of variables is nonlinear and managerial insight is a good source to validate intermediate and final results in combination with quasi-statistics.
4. Key variables that influence the inventory levels in the Drivetrain Division were measurable.
5. The manufacturing and assembly operations can be graphically represented and simulated using computerized software.
6. The allocated resources to the manufacturing and assembly processes that cause fluctuation of the inventory levels were limited and must be optimized.

Limitations

The researcher is concerned about the importance of statistical techniques and their application to the observational data; in addition, it is important to consider that there were several new changes in the processes of the Drivetrain Division, and many of the final conclusions might not be applicable to the new processes.

The limitations of this study were stated as follows:

1. Development of the simulation model was oriented to the 20 most important variables in the selected processes.
2. Due to the type of variables available to analyze and study, experimental research is not possible due to the amount of resources required as well as the time needed to evaluate them.
3. The application of correlational analysis determined a basic causal inferential relationship between selected variables.
4. The solutions provided by the simulation model were limited to specific scenarios determined by the company's interest.
5. Due to the nature of this study the development of the simulation model was biased and non-random.
6. The allocated resources to the study were limited.
7. The application of the decisions and policies generated from this study were limited to the company resources and ability to implement them.
8. The historical values provided by the company are considered to be valid and representative for simulation purposes.

Definition of Terms

The following terms describe the most important definitions that are required to clarify the analysis to be performed during this investigation. Each of them has close relationships either with system dynamics, genetic algorithms or structural modeling equations.

1. Bayesian Networks or Path Diagram: "a directed acyclic graph in which nodes represent variables and arcs represent probabilistic dependence."(Glymour, 1999).
2. Delay: "delay is an interruption between an action and its consequences." (Senge, 2000)
3. Feedback: "information coming from outside of a system and that influences its behavior." (Sterman, 2000)
4. Flow: "elements that represent decisions." (Sterman, 2000)
5. Genetic Algorithm (GA): "stochastic search technique based on natural selection and natural genetics." (Gonzalez, 2003).
6. Model: "a model is an abstraction, a simplified representation of the real world."(Sterman, 2000)
7. Levels: "blocks that accumulate flows."(Sterman, 2000)
8. Operations Research: "the study of allocation of limited resources" (Lieberman, 1990)
9. Optimization: "the improvement of a mathematical model meeting predefined constraints." (Lieberman, 1990)

10. Simulation: "a broad collection of methods and applications to mimic the behavior of real systems, usually on a computer with appropriate software." (Kelton, 1998)

11. Structural Modeling Equations: "is a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the multivariate analysis of a structural theory bearing on some phenomenon." (Byrne, 1998)

12. System Dynamics: "is a methodology for studying and managing complex feedback systems, such as one finds in business and other social systems. In fact it has been used to address practically every sort of feedback system." (MIT System Dynamics Group, 2002)

13. System: "A system is a set of organized, interacting parts which, when complete, exhibits properties or capabilities of the set as a whole which were not attributable exclusively to any of the parts." (Senge, 2000)

Procedure of the Investigation

The following procedure is a standard procedure for the development of system dynamic activities used in academia and in the different consulting firms. The procedure to be used is suggested by the MIT System Dynamics Group, Powersim Consulting, Ventana Systems and also it is similarly applied in other doctoral theses at the same institution (Ahn, 1999).

The following procedure reflects a standard model development process tested and applied by MIT System Dynamics Group:

1. Identify the problem.
2. Isolate the factors that appear to interact to create the observed symptoms.
3. Trace and create cause-effect information-feedback loops.
4. Identify relationships inside the selected polishing line.
5. Construct a mathematical model of the decision policies, information sources, and interactions of the system components.
6. Generate the behavior through time of the system.
7. Compare results against available information of the real system.
8. Generate recommendations to modify the real system.

CHAPTER II

REVIEW OF LITERATURE

Today, optimization has become one of the most discussed topics in engineering and applied research (Zeaman, 2003). The fact that optimization is commonly associated with simulation and advanced statistical techniques makes it a complex topic and overwhelms managers and engineers with a lot of information and data that are difficult to generate and analyze, and which is relative to the subjective perception of optimization itself.

The creation of "virtual worlds" or computer simulated models that can support decision makers to improve their managerial skills, explain causality, conduct experiments, and "play", is part of a scientific and non-empirical way of planning (Schon, 1983). Simulation, a word that comes from the Latin "simulare", which means "imitate" is not universally accepted within academia and industry as a useful resource to improve engineering and managerial processes.

According to Davidsen (2002), simulation models, in particular, can be used to investigate the intimate relationship that exists between the structure and behavior of dynamic systems. This chapter provides a review and analysis of the literature related to manufacturing simulation and how it can be complemented with genetic algorithms (GA), structural modeling equations (SEM) and system dynamics (SD).

Genetic Algorithms (GA)

History

According to Golberg (1989), genetic algorithms originated from the studies of cellular automata, conducted by John Holland and his colleagues in the Department of Psychology at the University of Michigan. Holland's book, published in 1975, is generally acknowledged as the beginning of the research of genetic algorithms. Until the early 1980s, the research in genetic algorithms was mostly theoretical with few real applications (Davidor, 1989).

This period was characterized by work with fixed length binary representation in the domain of function optimization, such as those developed by De Jong and Hollstien. Hollstien's work provides a careful and detailed analysis of the effect that different selection and mating strategies have on the performance of a genetic algorithm.

From the early 1980s genetic algorithms experienced an abundance of applications in many disciplines. Each additional area of study gave a new perspective to the theory and contributed on its development, robustness and applicability (Golberg, 1989). Effort was deviated in order to create improved algorithms for science, engineering, and business towards optimization, scheduling, data fitting, trend spotting, clustering and path finding in the following years, with the result that genetic algorithms were classified as a new area of Artificial Intelligence (AI).

Functionality

According to Holland (1975), a genetic algorithm is a probabilistically guided search method "developed originally in the 1970's as a computer science tool to improve programming structures and performance." From another perspective Golberg (1989) defines a genetic algorithm (GA) as "a model of machine learning which derives its behavior from a metaphor of the processes of evolution in nature."

These changes are made by the creation within a machine of a population of individuals represented by chromosomes, in essence a set of character strings that are analogous to the base-4 chromosomes that can be found in the DNA of many organisms. The individuals in the population then go through a process of evolution using the Darwinian theory of "survival of the fittest" based on the principles of mutation, selection, crossover and isolation (Davidor, 1989).

Basically, genetic algorithms are intended to interchange elements or groups of elements between individuals as if by sexual combination and reproduction (crossover) took place. In other cases, changes take place at random or via mutation that happens when the process cannot generate children that can outperform their parents.

New generations appear from clones of the current population, in proportion to their fitness: a single objective function of the parameters that returns a numerical value, to distinguish between good and bad solutions. Fitness is then used to apply selection pressure to the population in a 'Darwin' fashion (survival of the fittest; Golberg, 1989).

Davidor (1989) mentions four features that are widely accepted in relation to coding and encoding processes that are presented as follows:

1. Evolution is a process that operates on chromosomes rather than on the living beings they encode.

2. Natural selection is the link between chromosomes and the performance of their decoded structures. Processes of natural selection cause those chromosomes that encode successful structures to reproduce more often than those that do not.

3. The process of reproduction is the point at which evolution takes place. Mutations may cause the chromosomes of biological children to be different from those of their biological parents, and recombination processes may create quite different chromosomes in the children by combining material from the chromosomes of the two parents.

4. Biological evolution has no memory. Whatever it knows about producing individuals that will function well in their environment is continued in the gene pool- the set of information carried by the current individuals-and in the structure of the chromosome decoders (p. 2-3).

All these elements make genetic algorithms (GA) an easier optimization tool compared to alternative processes such as differential calculus, Lagrange multiplier, or design of experiments. Cavalca (2003) mentions that genetic algorithms are robust methods because they are not influenced by local maximums and minimums, discontinuity or noise in the objective function. For these reasons, Cavalca (2003) suggests that GA can work not only with one point in a search space but also with a cluster of points simultaneously that helps to reduce the amount of time required to find an optimum point.

Structural Equations Modeling (SEM)

History

According to Bollen (1989), most researchers applying statistics think in terms of modeling individual observations. In multiple regression or ANOVA (analysis of variance), for instance, Bollen mentions that the regression coefficients or the error variance estimates are derived from the minimization of the sum of squared differences of the predicted and observed dependent variable for each case. These discrepancies have misled researchers towards minimization functions of observed and predicted individual values rather than mathematical equations that reduce the difference between the sample covariances and the ones predicted by the model (Bollen, 1989).

The origins of structural modeling equations (SEM) are difficult to determine since it is mostly a combination of methods (path analysis, conceptual synthesis and measurement models, and general estimation procedures) that continue being developed and refined. The first one, path analysis, was invented by Sewall Wright in the 1900's as a diagram that represents correlations or covariances of parameters, and the decomposition of their effects using simultaneous equations and Bayesian networks (Bollen, 1989).

A simplified version of the theory developed by Wright is shown in Figure 1. Here two independent variables, X1 and X2, are part of a latent variable ε (an unknown variable that is affecting the process) that together influence directly the dependent variable Y.

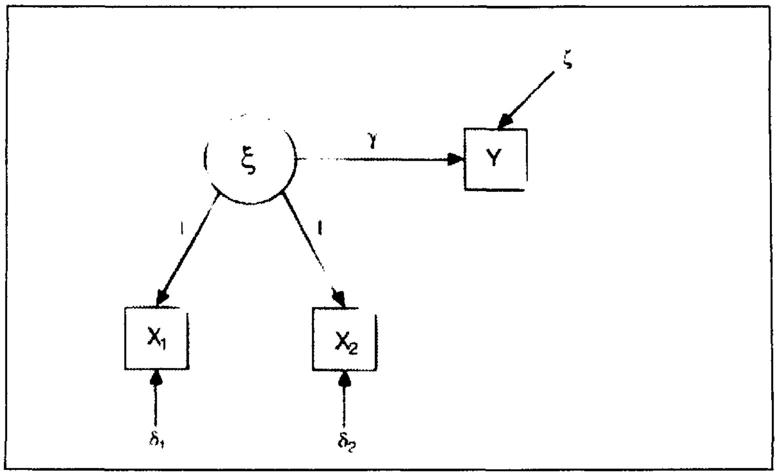

Figure 1. Example of a simple path diagram (Bollen, 1989)

From Figure 1, the error variables ς, δ_1, and δ_2 are uncorrelated with each other and latent variable ε. Single-headed variable arrows represent one-way causal influences from the variable at the arrow base to the variable to which the arrow points. The implicit coefficients of one for the effects of ε on x1 and x2 are made explicit in the diagram (Bollen, 1989).

Based on this diagram, Wright proposed a set of rules that relate correlations or covariances with the model variables in order to obtain parameter estimates of direct and indirect causal effects. However, the scientific community did not recognize his accomplishments until many years later.

The path analysis equations for Figure 1 used by Bollen (1989) based on the Wright's research are shown as follows:

$$y = \gamma\varepsilon + \varsigma \qquad (1)$$

$$x_1 = \varepsilon + \delta_1 \qquad (2)$$

$$x_2 = \varepsilon + \delta_2 \qquad (3)$$

During the 60's and early 70's, path analysis theory was the starting point for the development of conceptual synthesis. These models were more complex than those proposed by Wright's and linked latent variables based on the covariance of the observed indicators. It was not until Joreskog (1979) that these models reached a practical approach in order to apply the technique into real world problems.

Joreskog and other collaborators finally derived the two most popular procedures in structural modeling equations: generalized least squares (GLS) and maximum likelihood estimator (ML). Both of them are still being used as the best alternatives to solve structural modeling equations, although their applications have been largely limited to the social sciences.

Functionality

The terms of causality and inference are two important parts of the development of a structural equation model using observational data. Glymour (1999) suggests that observational data cannot be manipulated or controlled in comparison with the results obtained from experimental studies. The traditional thinking of correlation does not imply causation, fails when analyzing observational (historical) data since it has already being exposed to the treatments, and random assignments are not possible in order to study it (Fraenkel, 2003).

Sterman (2000) and Glymour (1999) mention that causal relationships and correlations differ in the sense that the second one does not represent the causal structure of the system. Both authors agree that correlations only reflect past behavior but the fact that could suggest an initial structure of the system is an issue not yet explored. Sterman shows in his work that if new policies or changes are added to the causal structures the model needs to behave accordingly and correlations within the system will emerge when it is simulated.

However, structural modeling equations using correlations or covariances could be used to infer initial causal structures from data that was not experimental. Glymour (1999) explores this issue using sensitivity analysis and associations without any substantial knowledge in order to solve this problem.

Despite the fact that many of the elements previously mentioned still puzzle researchers in science, engineering, mathematics, psychology and many other areas, it has not discouraged the development of these techniques in order to approximate real-world causal structures. Some of the applications according to Statsoft Corporation (2004) for which SEM could be applied are:

1. Causal modeling, or path analysis, which hypothesizes causal relationships among variables and tests the causal models with a linear equation system. Causal models can involve either manifest variables, latent variables, or both;
2. Confirmatory factor analysis, an extension of factor analysis in which specific hypotheses about the structure of the factor loadings and intercorrelations are tested;
3. Second order factor analysis, a variation of factor analysis in which the correlation matrix of the common factors is itself factor analyzed to provide second order factors;
4. Regression models, an extension of linear regression analysis in which regression weights may be constrained to be equal to each other, or to specified numerical values;
5. Covariance structure models, which hypothesize that a covariance matrix has a particular form. For example, a hypothesis can be tested with a set of variables that have equal variances with this procedure;
6. Correlation structure models, which hypothesize that a correlation matrix has a particular form (p. 1-2).

From the previous list of applications this research will focus on causal modeling using inferred relationships from observational data. Thus, Bayesian networks will be used as a way to represent causality based on the three components of a cause: isolation, association, and direction of influenced (Bollen, 1989).

Goldstein (2003) suggests the use of structural modeling equations when measurements are difficult to be defined precisely so that the investigator can assume the existence of an underlying structure evaluating a number of relevant indicators. Goldstein suggests that structural modeling equations were specifically designed to develop and measure individual's behavior, attitudes or mental performance over time and for the purposes of the current study can provide a basic view of causal structures.

For example, if variable y1 is isolated from all other variables except x1, a change in x1 alters the values of y1, then it can be said that a modification of x1 is associated with a change y1. Under these circumstances a causal relationship can be constructed based on the relationship discovered with x1 and y1. However, it is important to first isolate the variables and then make their association based on the well-known statement; correlation does not imply causation, in order to guarantee their relationship and direction of influence. Thus, in the previous example the arrow that represents the causal path that x1 causes y1, not the opposite, needs to be reflected in the Bayesian network.

Once the network diagram has been constructed, using the collected data identified the correlations or covariances calculated for each variable in order to input them into the causal model. However, the usage of nonrandom or observational data will create problems of internal validity and bias that need to be solved using nontraditional statistical procedures.

Box (1978) proposed an alternative approach to resolve such problems when performing statistical analysis over nonrandomized data. Box mentions that random sampling is considered in statistical writing as a law of nature, but when dealing with real data this property cannot be considered to be true. To solve this issue, Box developed a procedure called "external reference distribution" based on real data coming from a chemical production process in order to compare the performance of two alternative production methods using historical and not independent observations.

Here the dependency of the data and the effects of the previously applied treatments were eliminated using an equal moving average value. Applying the central limit theorem, the effects of any disturbances will be reduced by the moving average value and the resulting data will have a normal distribution (Box, 1978).

Using this approach solves part of the complications of using real data, but again the development of causal structures will need to identify another major issue. While working with statistics, it is important to understand that two structures could be equally valid but with different mathematical values (Box, 1978).

For that reason, structural modeling equations can provide different causal structures after analyzing covariances or correlations and all of them can be equally valid. In Figure 2 such a case is shown using ten statistically identical models coming from the same covariance matrix that provide different causal networks (Bollen, 1989).

At this point the only way to determine which structure is closer to the real system will require managerial and engineering knowledge. The causal structure selected will constrain any optimization strategies to develop and will give an initial shape of the decision-making processes study with the Bayesian networks.

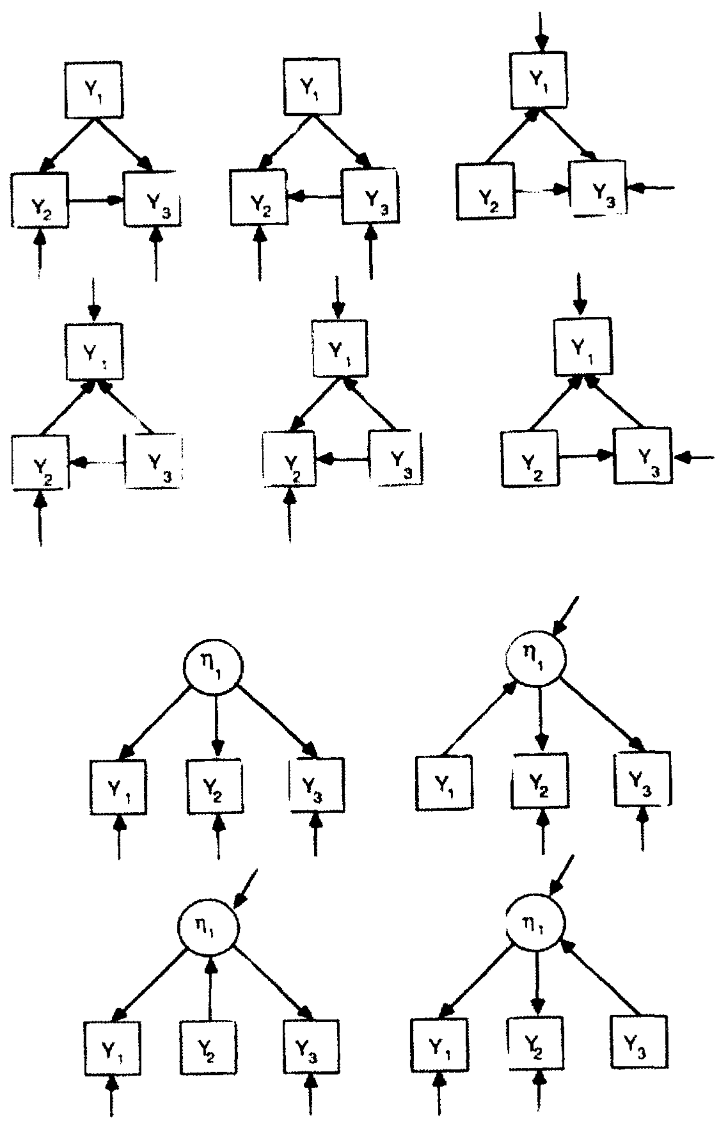

Figure 2. Ten models for three observed variables that have "perfect" fit with the same covariance matrix (Bollen,1989)

System Dynamics (SD)

History

System dynamics is the application of feedback control systems principles and techniques to managerial, organizational, and socioeconomic problems. For managerial usage, system dynamics advocates seek to integrate several functional areas of an organization into a conceptual and meaningful whole, and to provide an organized and quantitative basis for designing more effective organization policies (Roberts, 1999).

The beginning of system dynamics was originated during the 1940's and 1960's because of its initial applications to the military. The high technology created during and after World War II on feedback systems design and analysis, computer simulation techniques, and the increasing experience in decision-making modeling, required a field that could integrate knowledge of several disciplines in order to improve the utilization of limited resources.

Professor Jay W. Forrester, from the Sloan School of Management, pioneered in each of the engineering-related areas mentioned, and developed system dynamics as a formal discipline and created the Industrial Dynamics Group at MIT. The initial philosophy rests on a belief that the behavior (or time history) of an organization is principally caused by the organization's structure. This structure includes not only the physical aspects of plant and production processes but, more importantly, the policies and traditions, both tangible and intangible that dominate decision-making (Roberts, 1999).

Analysis and control of nonlinear systems is a major challenge to even the most experienced control system engineers, and an effective and reliable decision is even more difficult. For example, Figure 3 shows a general perspective on how system dynamics visualizes an advertising and consumer market integrating into the same model: production, inventory, distribution, retailing and other decision making processes and the way they interact with each other.

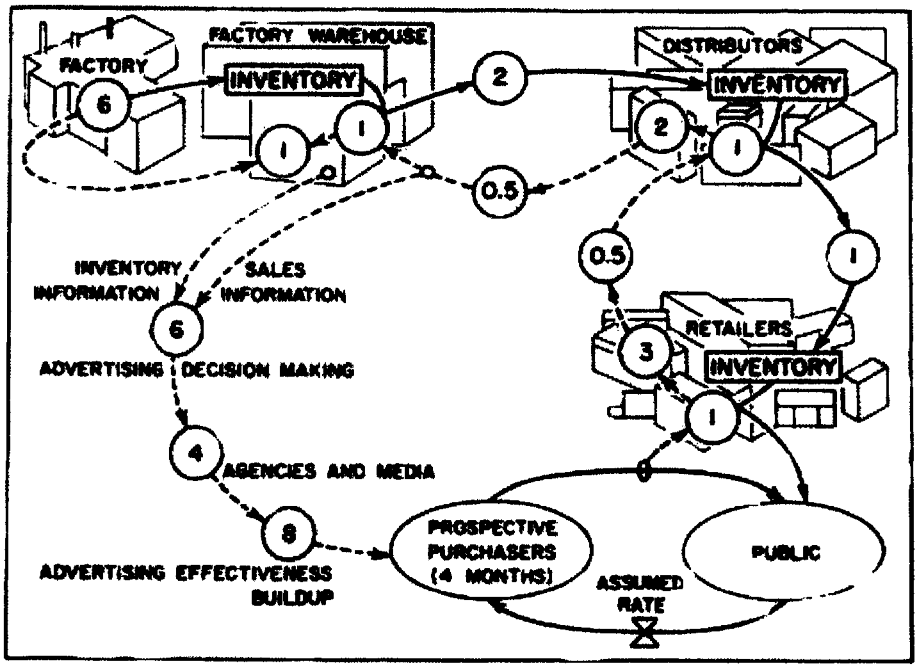

Figure 3. Advertising and consumer market model (Roberts, 1999)

In order to perform such analysis, system dynamics needed to apply tools coming from many technical disciplines. For example, signal-flow graphs of electrical engineering, and cause-and-effect arrow diagramming that were invented to support sequential process analysis. From this effort and with the support of MIT sponsors, the Industrial Dynamics Group, directed by J. Forrester, developed DYNAMO the first system dynamic software capable of handling linear, nonlinear, algebraic and differential equations with several thousand variables and later on tested on several industries.

Currently system dynamics is an active area of research at MIT and many other universities, and several computer packages have been developed to enhance the interface capabilities unavailable previously with DYNAMO (Roberts, 1999).

Functionality

According to Powersim Corporation (2004), system dynamics is a methodology to analyze complex systems, and has been widely spread in academia and industry. The word "dynamic" implies continuous change over time, as well as patterns of behavior.

Figure 4 describes the system dynamics process suggested by Powersim Corporation (2004), in which simulation of a business system is just part of the overall effort of development and improvement of organization's policies and strategies.

In order to start the model building of a system dynamics equation it is important to consider the basic flow notation used. Figure 5 shows an example of the notation utilized to construct a general system dynamics model.

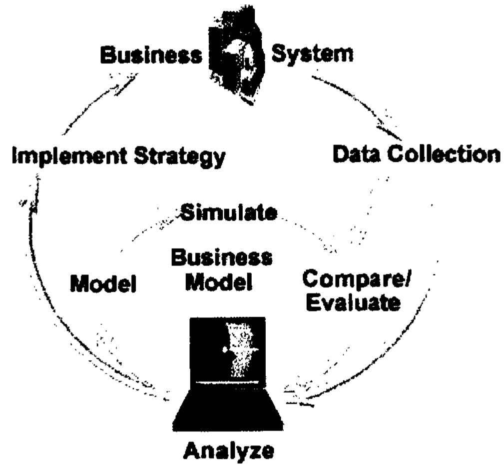

Figure 4. The system dynamics process (Powersim, 2004)

However, the identification of such patterns requires an organized process that collects, analyzes, and generates new information and adjusts the business models over time. The example presented in Figure 5 represents a model of a firm's inventory where a stock accumulates the inflow of production and is reduced by the outflow of shipments.

In Figure 5, the cloud symbols indicate that the stock of raw materials never starves the production rate and the stock of product is shipped to the clients, and never grows so high that it blocks the shipment rate.

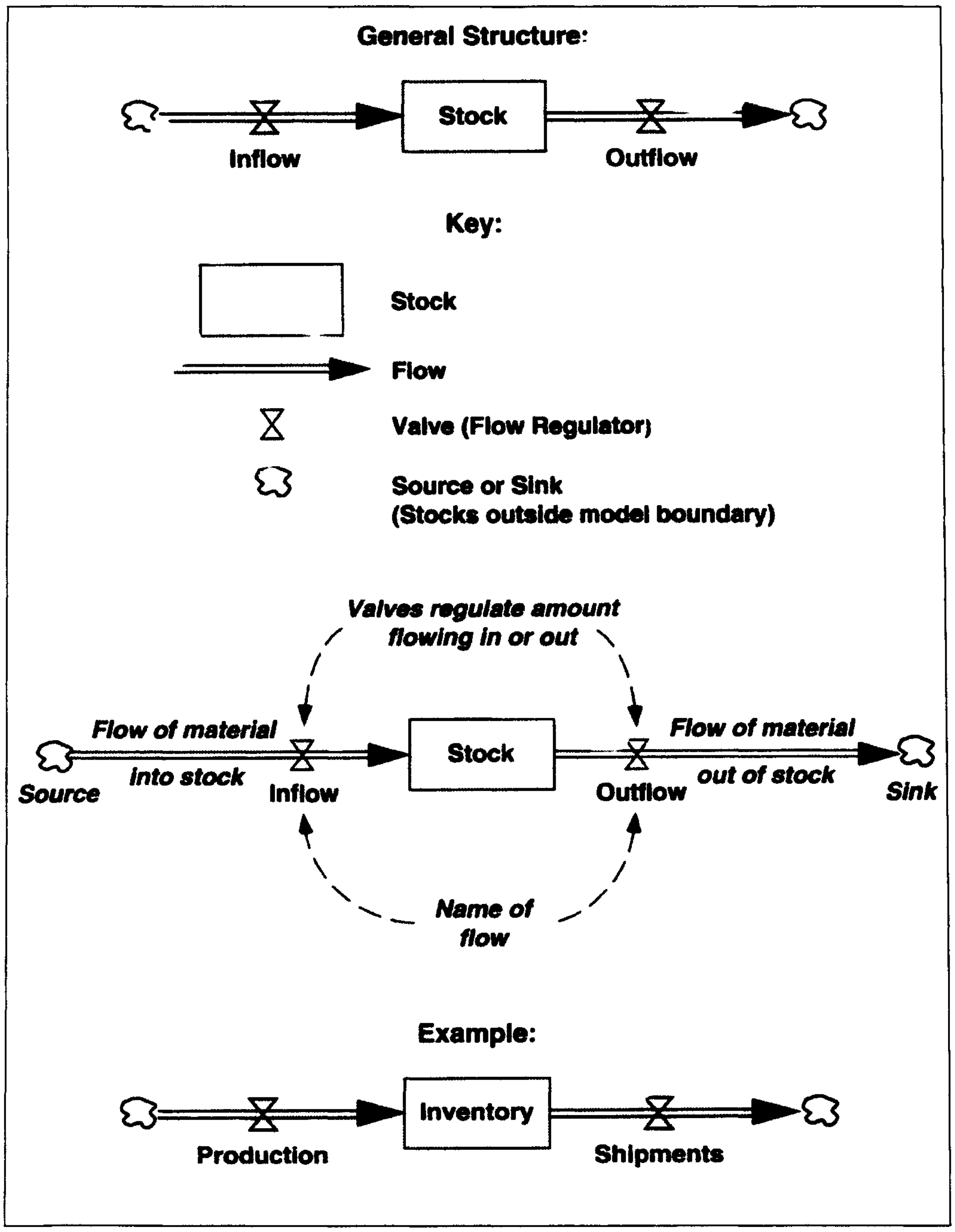

Figure 5. Stock and flow diagramming notation (Sterman, 2000)

These are the only flows considered in the model and any additional information would have a value of zero. According to Sterman (2000), system dynamics is based on stocks and flows using the following logic:

1. Stocks are represented by rectangles (suggesting a container holding the contents of the stock.
2. Inflows (adding) pointing into the "stock" are represented by pipes. Outflows (subtracting) pointing out of "stock" are also represented by pipes.
3. Valves control the flows.
4. Clouds represent the sources and sinks for the flows. A source represents the stock from which a flow originating outside the boundary of the model arises; sinks represent the stocks into which flows leaving the model boundary drain. Sources and sinks are assumed to have infinite capacity and can never constrain the flows they support (p.192).

The overall logic is based on the research presented by Sterman (2000) as a hydraulic metaphor the flow of water into and out of reservoirs. In addition to stocks and flows, another important element that is part of system dynamics is delays.

Delays are a critical part of the theory of developing complex systems, since they can not only cause instability and oscillation but also help to filter unwanted variability helping managers to separate signals from noise (Sterman, 2000).

Under such circumstances another problem arises, nonlinear behavior that is the common nature of real-world systems affects the stability of the model and can seriously damage the final results of the study (Sterman, 2000). For this circumstance, the mathematical equations that relate inputs and outputs need to be carefully investigated to consider the nonlinearity factor and the accuracy of the model.

Current approaches of system dynamics overlook the issue of mathematical relationships, and concentrates mostly on causal structures created based on experience. The simulation models are constructed under these assumptions and in many cases can mislead the investigation and cause association of variables with the wrong cause paths.

This problem could be solved using structural modeling equations in order to guarantee at least that the relationships identified have some mathematical validity, and do not merely reflect insight and multiple adjustments which have been the standard so far. However, dealing with too many variables will also raise another issue: multicollinearity. According to Schofer (2002), this factor is caused by the inclusion of highly correlated variables into a single model, which creates an increase in variance and correlation that could mislead toward incorrect conclusions. This final argument might cause complications in the study, and will require a consideration by the researcher while constructing the SEM model.

Discrete Event Simulation and System Dynamics

According to Gourgand (2003), industrial systems are subject to random (stochastic) events, which may disturb their working conditions and an optimal solution developed without considering its lack of scientific validity. For that reason, to develop a simulation study without considering any variation will not provide any useful information to the company or to the researcher. Besides, when analyzing simulation, specifically manufacturing systems, this factor becomes quite important because of the multiple states and the variables that influence their performance.

For the purposes of this study, only discrete event simulation (DES) and system dynamics (SD) would be compared since a combination of both of their approaches would be utilized to develop the current research. In comparison, system dynamics and discrete event simulation differ mostly in two levels as Arsham (2004) mentions: the way that modelers represent systems is different; as well as the underlying algorithms are also different. Each technique is well tuned to the purpose it is intended but one may use a discrete event approach to do system dynamics and vice versa.

Zahir (2002) mentions that discrete event simulation (DES) can also be used in order to explore causality and generalization of relationships performing qualitative and quantitative research incorporating resources and constraints into the same simulation model. This characteristic has made DES more applicable to manufacturing leaving system dynamics limited to research and development in the social sciences with few applications in manufacturing.

The main reason for this segregation is that system dynamics is focused more on identification of relationships than on specific levels of variable such as machine utilization, number of employees, or number of parts in queue that DES has mastered with the support of Operations Research and other analytical tools.

As Arsham (2004) reports, the most important distinction of both of these areas of simulation is the modeling purpose. For example, Discrete event simulation is more oriented to find how many resources the decision maker needs such as how many trucks, and how to arrange the resources to avoid bottlenecks, excessive waiting lines, or inventories, whereas system dynamics is directed at decision making required to promptly respond to any timely and structural changes, e.g., physical shipping delay time, so that inventories, sales, and production are optimized.

Arsham (2004) concludes that a modeler must consider both system dynamics and discrete event modeling as complementary tools to each other. For example, system dynamics could be utilized to develop a high level problem and identify areas that need detailed analysis. Then, discrete event modeling can support the initial findings and improve specific areas of interest such as finite capacity planning, goal seeking and design of experiments.

For the purpose of this research the combination of both system dynamics and discrete event simulation will be directed to create several simulation models that replicate the behavior of a manufacturing system and a causal structure using structural modeling equations that infer causal relationships within those models.

A summary that combines the views of Arsham (2004) and Sterman (2000) regarding system dynamics and discrete event simulation is presented as follows:

1. System dynamics supports the simulation models on mental models, qualitative knowledge and numerical information, while discrete event simulation supports their views based on analysis of data.
2. System dynamics applies methods and insights from feedback control engineering and other scientific disciplines to assess and improve the quality of models. Discrete event simulation uses techniques developed in operations research, design of experiment and other statistical areas.
3. Both DES and SD seek improved ways to translate scientific results into achieved implemented improvement.
4. System dynamics approach looks at systems at a very high level so is more suited to strategic analysis. Discrete event approach may look at subsystems for a detailed analysis and is more suited, e.g., to process re-engineering problems.
5. System dynamics is indicative, i.e., helps us understand the direction and magnitude of effects (i.e., where in the system do we need to make the changes), whereas discrete event approach is predictive (i.e., how many resources are needed to achieve a certain goal of throughput).
6. System dynamics analysis is continuous in time and it uses mostly deterministic analysis, whereas discrete event process deals with analysis in a specific time horizon and uses stochastic analysis.

Optimization and Operations Research

History

According to Winston (1990) and Lieberman (1990) the roots of operations research can be traced back many decades, when early attempts to apply the scientific method to management of organizations during World War II because of the urgent need to allocate scarce resources to the various military operations and to the activities within each operation in an effective manner. For this reason, the British and American military combined a group of scientist and engineers in order to develop a group of techniques that will able to handle this type of strategic and tactical type of problems.

The correct term utilized was to do research on (military) operations, and these efforts allegedly were instrumental in winning the Air Battle of Britain, the Island Campaign in the Pacific, the Battle of the North Atlantic, and others. Because of its success in the military, industry gradually became interested in this new field in order to solve the greater complexity of organizations. With the development of computers, the new field was called Operations Research (OR) as well as the great interest during the 1960's on statistics, optimization, and experimental design provided a great background for its development in industry and academia.

The term Operations Research (OR) was later on associated with the phrase "Management Science" as a correct manner to identify those techniques that apply the scientific methods to managerial decisions. Many industries, including aircraft and missile, automobile, paper, communications, computer, electric power, electronics, food, metallurgy, automobile, petroleum, transportation, financial institutions, governmental agencies, and hospitals are currently increasingly using operations research (Lieberman, 1990).

Later on professional societies devoted to this field and related activities have been founded in a number of countries throughout the world. In the United States, Operations Research Society of America (ORSA), established in 1952, and the Institute of Management Sciences (TIMS), founded in 1953 have led the way of developing and improving its applications in industry.

Functionality

The applications of OR initially to military applications were extended later on to industry. For example, the initial problems were directed towards the tactical planning for requirements and use of weapon systems as well as consider the larger problems of the allocation and integration of effort.

The usage of OR is oriented in the formulation, solution, and implementation of mathematical models for analyzing complex real-world systems. For that purpose several techniques that allow an initial understanding of the system using: linear, integer, nonlinear, goal, dynamic, stochastic processes, and probabilistic programming. Part of the problem is that due to the complexity of the real-world many of these techniques will bring limited solution, simply a mere approximation and for that reason the combination of OR and more advanced techniques such as simulation and advanced statistics supports the constraint development process while studying a process.

These techniques allow the development of advanced models for inventory handling, queuing processes such as machine scheduling or repairs, game theory, mixtures analysis, transportation problems, leasing or selling company's resources, PERT/CPM (project management), forecasting, reliability, simulation, artificial intelligence, and many more.

However, one basic element that is part of these mathematical techniques is the issue of mathematical optimization. The combination of OR and other techniques will cause that optimization to become a relative term based on the types of tools available. For example, a transportation problem that is resolved using traditional OR techniques will differ from a similar model built using genetic or tabu search algorithms because their calculation methods differ.

This issue makes it more difficult to guarantee that a process is really optimized because if new constraints are added to any system, this one might react differently than initially expected and maybe the initial solution will be quite different from the new problem structure. Thus, for this project when the term optimization is used, it would be referring to an improvement of the system based on the current constraints and variables, and not as the only possible answer that guarantees the maximization or minimization of the final answer.

CHAPTER III

RESEARCH DESIGN AND METHODOLOGY

Research Design

This quasi-experimental research was designed to develop a simulation model that replicated the behavior of assembly lines of the Drivetrain Department of an automotive company. The four research questions stated in Chapter I were used for this study:

1. What were the most important variables that affect inventory levels of an assembly line of an automotive manufacturer?
2. What were the significant effects of the causal relationships identified in order to determine an initial model structure?
3. What constraints restrict the behavior and improvement of the selected variables?
4. What levels of the selected variables could be used in order to improve production levels?

Managerial Variables

The current study was oriented towards the development of a simulation model that allowed Drivetrain Operations to plan and improve its manufacturing operations. The main goal was to improve the final output or the Drivetrain Buffer (which constituted the total number of finished parts coming from the line into final assembly).

In addition, Drivetrain Management wanted to have a modern simulation tool that supported its current Six Sigma efforts, in order to build a virtual manufacturing plant. For this reason, Drivetrain Management was interested in improving the following set of variables using the developed simulation models: work in process and production for each of the parts processed inside the line, utilization times for each of the work stations and the operator, queue size in front of the line and in the Drivetrain Buffer.

Initial Information

The selected manufacturing process initiates with a limited number of parts in front of the line (between 4 and 5 depending of the type of product), that were picked up by an operator that loaded them in groups of either 1 for covers or 2 for PTO parts. The different parts were loaded into an automated line that put them into the computerized control work centers that performed the operations of polishing.

The operator altered the loading and unloading operations of the different parts based on the availability of automatic work centers that processed the parts twice, one for every side of the part, which required that the part be unloaded from the work center and redirected towards the available workstation based on priority, machine availability, and part type. For example, a PTO (Power Takeoff) part that required processing in any of the three available work centers needed to compete for capacity with other processed parts, since each part had to be polished on two sides before leaving the line towards final assembly. There are three PTO parts called PTO195, PTO196, PTO197, and two cover parts called Cover1 and Cover2, which competed for capacity in the Unload/Load Station and the other parts of the system.

Each PTO load required one part in order to be processed in the different work centers, except the cover parts that required two parts per load in order to be processed by the automatic transporter. Before loading the polished and the raw (without previous polishing) cover parts into the line, two raw parts (status=1) were loaded if there were no previously polished parts (status= 2).

The operator loaded and unloaded the parts one at a time from the loading/unloading station, and those parts were either sent back to the process after their sides have been polished and switched, or simply moved to the Gage Station when they are completely finished. No parts were allocated to the Unloading/Loading station if the operator was busy, or if there was at least one part available in the work center in order to redirect the next part to this station.

The automatic transporter was in constant communication with all work centers, using the FIFO rule (First in First Out), and each part was processed based on its type, workstation capacity, and work-in-process (WIP) sequence. The operator's capacity was allocated based on the number of scheduled and ready-to- process parts (status=2); in the case that none were available, raw parts were loaded (status=1).

Each of the part types was competing for load capacity at the Load/Unload Station that had a maximum of two per load for cover and one per load for PTO parts. Once the part was loaded into the Unload/Load Station, this initiated its work-in-process (WIP) status, and a counter was increased based on the number of parts that entered and exited the system.

The automatic transporter picked up the parts and took them to their designated workstations, based on their classification, and routing depending on the "status" variable, that was assigned for raw parts as one, and for reprocessed parts as two. Parts with status=2, had higher priority than status=1, because it meant that the part has previously entered the system, and required a second processing but in the opposite side of the part in order to complete its routing and be able to exit the process.

A part must enter the system twice in order to be considered finished, and has to be loaded and unloaded by the operator based on its availability, otherwise it was considered work-in-process, and waited in the workstation queue in order to be picked up based on the loading/unloading station availability.

If the operator was too busy to unload/load the parts, they waited until he was ready to move them into the next routing sequence based on their status. For example, if the status of a PTO196 arrived to the unload/load station after completing its first pass, the operator unloaded and loaded the part, representing the real life operation of taking the part into the station and switch it into the other side in order to complete its polishing.

A representation of the described algorithm for the automatic line is presented in Figure 8 using Promodel, shown later on, in which each part is differentiated by color.

The idea behind the model is to approximate the behavior of the polishing line using a simulation model in order to test several scenarios before the new changes are applied to the real manufacturing cell.

The production orders for the polishing line were broken down into daily fixed demands, considering setups or breakdowns as negligible, since all the machinery is automatic. The build schedule was generated and distributed on the automatic line for the next production day and assuming 8-hour days.

A state transition diagrams presented on Figure 6 and 7 based on the interviews with the supervisors in charge, operator, and other managers in the Operations Department, in order to provide the sequences, times, production levels, shutdowns, routings, and time studies of the automatic line. The basic data was presented previously in Tables 1 and 2, to understand initially the simulation model and to assign the sequences based on the number of states and decisions involved in the polishing line. This general description established the background under which the simulation was developed in order to find improved (optimized) scenarios and a genetic algorithm that can be utilized by management and linked to an enterprise resource planning system and has been divided in three regions: A, B, and C.

Region A displayed the logic followed by both PTO and Cover parts in order to load, initiate the queue in front of the line, and increment the work-in-process (WIP) inside the line. Once the part entered the polishing line, Region B described how this part was directed to a specific routing that considered the processing time for the specific work center, the type of part that was processed; the machining time, loading and unloading logic in each workstation; and the priority that each part had in order to be picked up by the automatic transporter. Finally, Region C described the sequences required by the part in order to exit the polishing line, to be unloaded and loaded depending on its sequence and priority, the reduction in the number of parts that were in work-in-process (WIP) for each part type, and the following sequence required for each part before it arrived the Drivetrain Buffer.

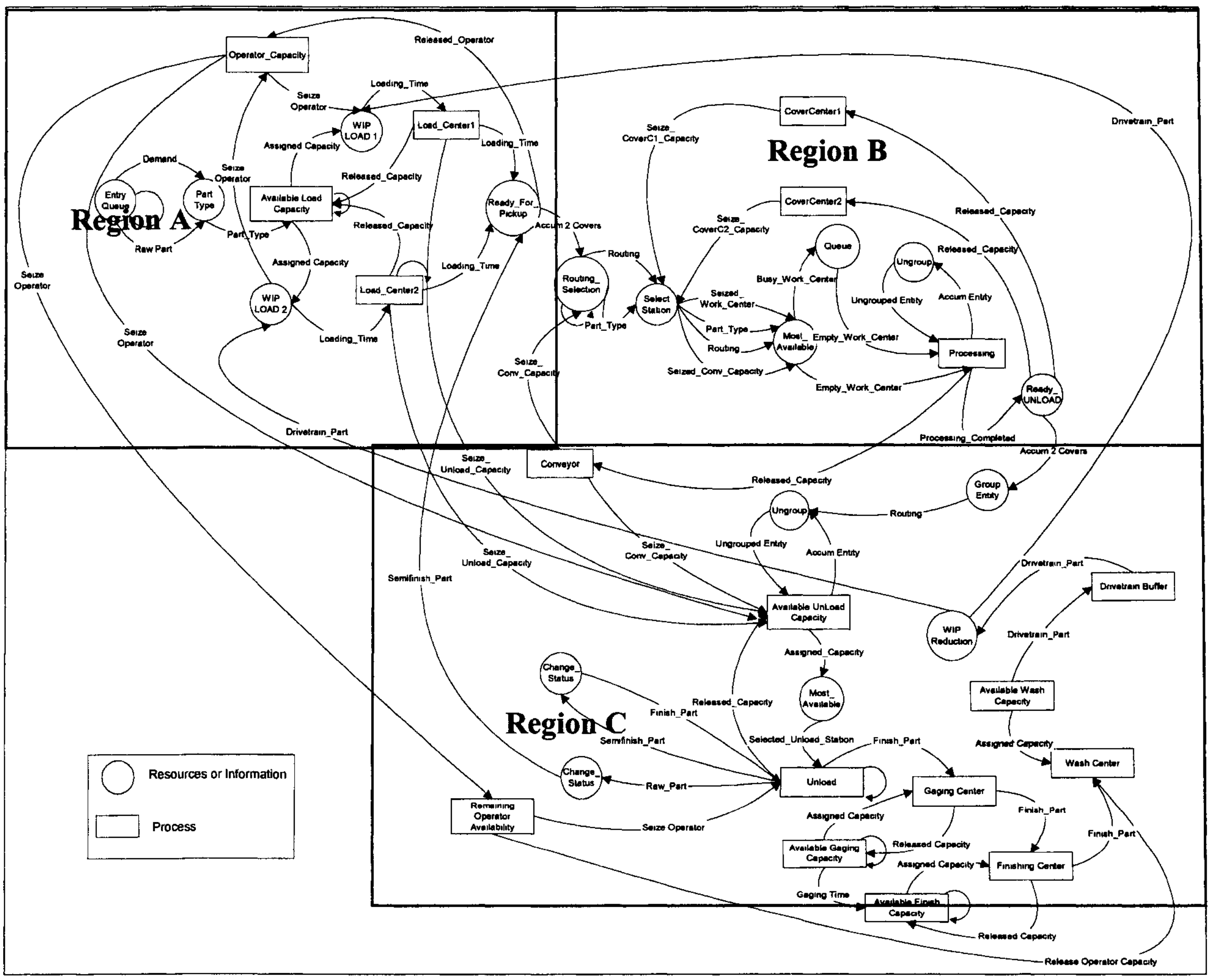

Figure 6. State transition diagram that represents the algorithm for the cover parts

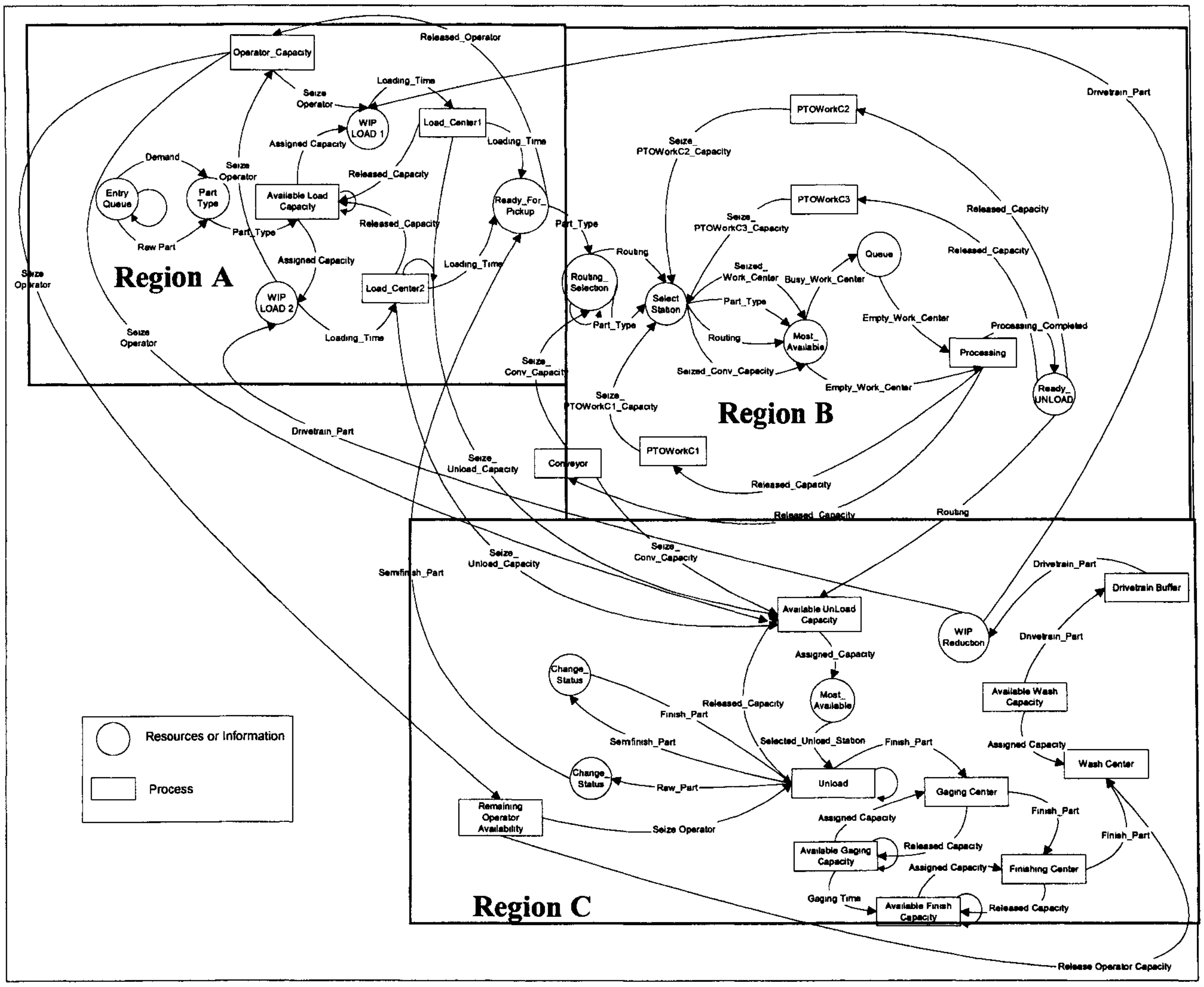

Figure 7. State transition diagram that represents the algorithm for the PTO parts

In Figure 6 and 7 the major algorithm of the study was represented using a state transition diagram. Here the boxes represented the resources and the circles represented the states or resources that the system had at any given time period. Initially, in Region A identified the area of the algorithm that controls the arrival of parts into the system. First, the PTO parts arrived at an entry queue and based on their classification WIP or Raw (initial state), were allocated to the available capacity from either Work Center 1 or Work Center 2.

The part changed into the WIP status and utilized the available capacity of the operator in order to load the part into the machine and once completed it was ready for pick up where it entered a queue FIFO that determined which part goes first to the unload/load station. Once there, the part maintained its status (WIP or Raw) at all times, and the WIP parts had the priority to use the available capacity of the conveyor, operator, selected work center, and change its state once it has been completed the task to WIP (status=2).

This value was used in the rest of the model in order to identify those parts that have passed through the line at least one work center and had the highest priority once they got back to the unload/load station to be rotated by the operator in order to apply the same process but in the other side of the part.

It is important to notice that in Region B, once the part has utilized the available resources, they were released in order to make them available to the next part in the routing and controlled the logic of the automatic robot that loaded and unloaded the parts inside the line. Region C controls the area of the line that assigned and released capacity to the unload/load station and the operator that performed the rotation of the part for both PTO and Cover parts. Once the conveyor arrived to the Unload/Load Station it released the capacity making it available to the operator to perform the rotation, however, if the station was busy the conveyor had to wait until the capacity for both the operator and the station become available.

In Region C once the operator performed the unload operation (if the part were polished in both sides) or the rotation (if the part were polished in only one side and required to go back to the line with high priority while queuing). If the part needed to go back into the line, its status was changed to the value of two, and had a higher priority in the next conveyor routing.

The next time that the part reaches the Unload/Load Station, the part would be unloaded and follow a similar procedure when moving from this station to Gaging, Finishing, and Wash Work Centers. It is important to notice that the queue line at the end of the polishing line is called Drivetrain Buffer, which is the WIP between this line and final assembly that included all the finished parts coming out of the polishing line. This variable is a key variable for management since improvement of the production levels of the line will improve the Drivetrain Buffer, allowing more parts to be delivered before final assembly and will help to improve the assembly rate of the main production line.

In Figure 7 the same algorithm performs the same operations for PTOs, but with the change that in the first one there are three work centers and for Cover parts there are only two work centers. In this way, the algorithms shown in Figures 6 and 7 will be working at the same for the same computer model, and will give priority to produce based on number of finished parts for each type in the Drivetrain Buffer. The processing times for each of the work centers depend on the time ranges previously defined for each resource, including the operator and each work center.

Experimental Groups

Several scenarios were run using the current operational values of the system that will be entered into a simulation model, in order to replicate the behavior of the automatic polishing line. The state transition diagrams presented in Figure 6 and 7 were coded into the simulation model including both production parts into the same system, which is presented in Figure 8.

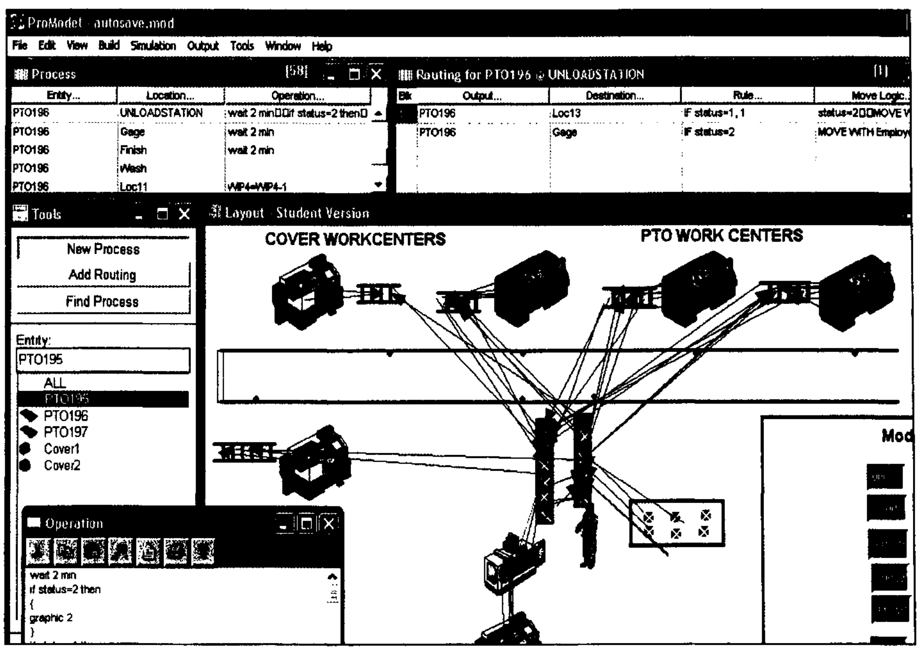

Figure 8. Discrete simulation model for the polishing automatic line

The first three machines on the right represent the workstations available to process PTO parts, and the other two are exclusively assigned to polish cover parts. The model is in design view, and shows the major components of the discrete simulation model used in order to construct the algorithms developed in Figure 6 and 7. This was the first approach towards the development of a dynamic simulation model that replicated the behavior of the automatic line. The management goals for developing this system lies in the prospect of simulating several production schedules and integrating them with a highly scalable Enterprise Resource Planning System called SAP.

The final outcome of this project must allow management to generate optimization strategies using full factorial designs and genetic algorithms in order to find variable levels that affected the production, the utilization, and the inventory levels inside and outside the polishing line. In this way, the company was able to generate a virtual manufacturing plant that replicated the behavior of the current manufacturing systems, and that had a higher level of complexity than the one presented in this project.

This research integrated available production time, production requirements, machinery and operator capacity, raw material, and other constraints into the same system. Figure 9 presented a block diagram that identified all the processes and inputs required for each phase of the project, in order to optimize the system based on using two approaches: full factorial designs and genetic algorithms.

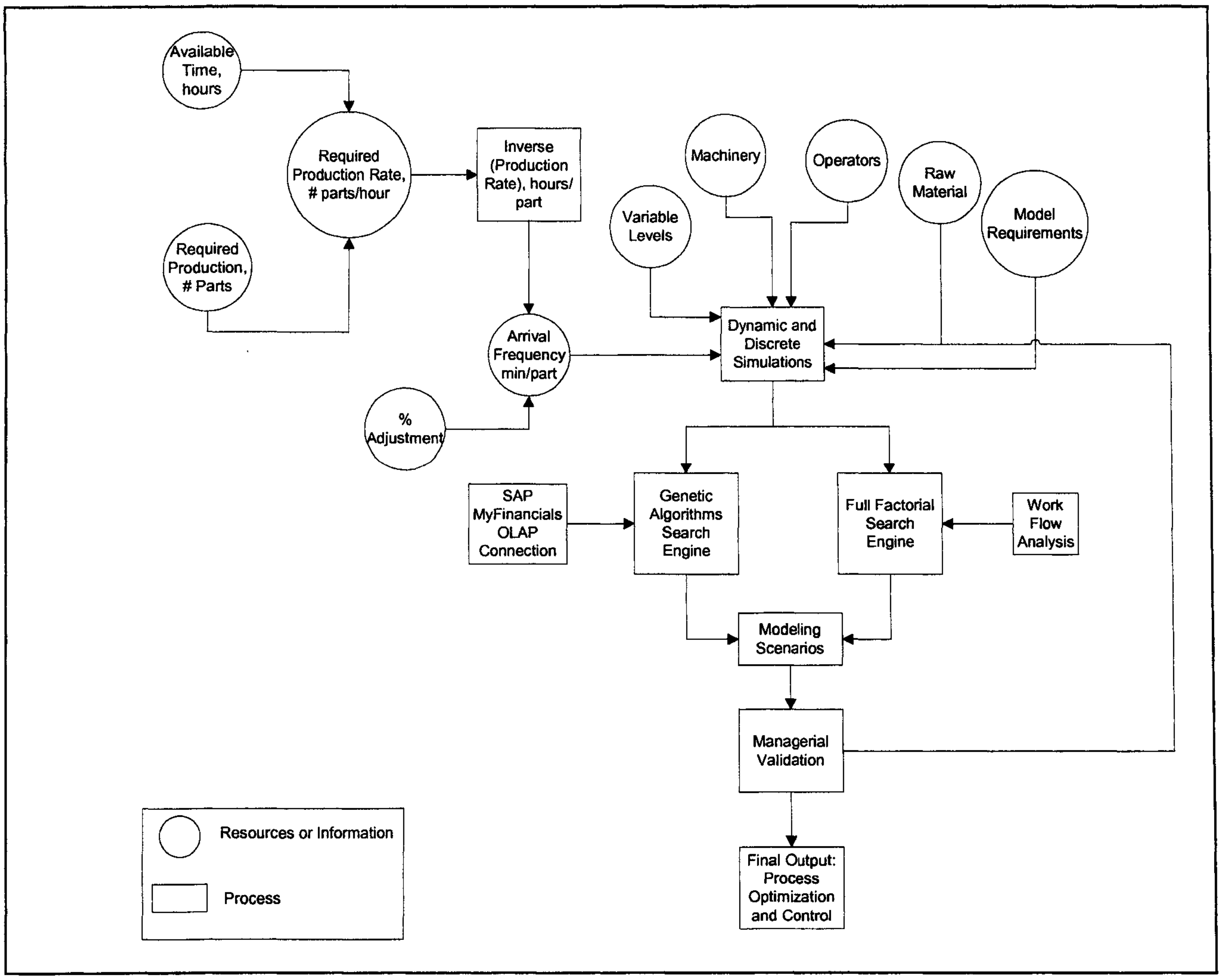

Figure 9. Block diagram representing the research methodology

Due to the limitation of resources in order to perform the present study by the company, this research was intended to be a pilot project to initiate a new development in the manufacturing facility of this automotive manufacturer towards simulation and optimization of the whole plant. Currently the company lacks instrumentation, training, experience, and software capabilities in this area to create such a project by themselves, and it is not in the interest of the researcher to expand the current study to other sectors of the plant.

The initial historical data used to create the first discrete manufacturing model using Table 1 and Table 2, considers system constraints, capacities, cycle times, and production outputs. These elements were coded and compared with the performance of the developed model versus the outputs of the real process.

Table 1. *Initial information of the real system*

	Part Type	Machine Cycletime Min	Load/ Unload Time Min	Gaging Time Min	Gaging Freq	Finish Time Min	Wash Time Min
RC	R163964	64.377	4.7304	5.524667	6	7.812	5.5
PTO	R183195A	66.996	4.8852	0	0	0.02	0
PTO	R183196A	54.936	4.8852	0	0	0.02	0
PTO	R183197A	68.508	4.8852	0	0	0.02	0
PTO	R183195B	23.526	4.0158	5.143	6	9.441	5.5
PTO	R183196B	18.675	4.0158	5.143	6	9.441	5.5
PTO	R183197B	20.961	4.0158	5.143	6	9.441	5.5

Table 2. *Maximum production per day*

Material	Pieces
COVER RAW	8
COVER FINISHED	8
PTO RAW	2
PTO FINISHED	6

In Tables 1 and 2 the time required to process each operation is established, and the simulation model must not have a statistical difference greater than 1 % (which includes the variation, shutdowns, and maintenance of the automatic machines included in the line and it is the standard value used by the company used for controllable variation) in order to be considered valid. In the same way, Table 2 provides the maximum number of raw and finished pieces that the current polished line is producing during a regular day. This information comes from measured results from the company and machine specifications from the CNC manufacturer.

Scheduling Scenarios

In order to find improved or optimized scenarios, a set of key variables would be selected based on the current managerial interests. Those variables were identified in the model using Figure 10, that were input into the system and others were displayed during the simulation run, their default status was Time Series, in order to collect information as their values change in time.

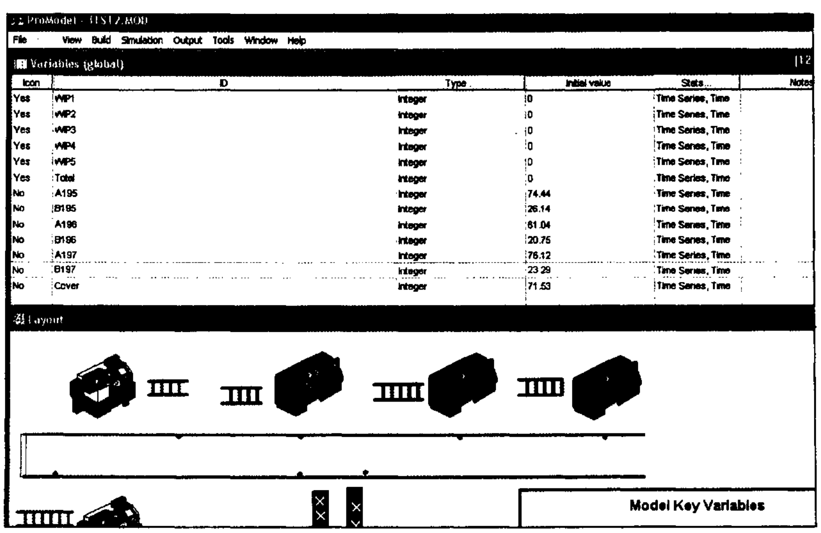

Figure 10. Variable definition for the discrete simulation model

The variable description is shown in Table 3 with its name, description, and initial value. Each variable will be input into the model, and with another default values that monitor the behavior of each of the workstations for example: utilization, time in transit, throughput, and many others to be discussed during the optimization phase.

Table 3. *Initialization values for the user-defined variables*

Variable	Description	Initial Value
WIP1	Work in Process (WIP) for Cover1, measured in units.	0
WIP2	Work in Process (WIP) Cover2, measured in units.	0
WIP3	Work in Process (WIP) for PTO195, measured in units.	0
WIP4	Work in Process (WIP) for PTO196, measured in units.	0
WIP5	Work in Process (WIP) for PTO197, measured in units.	0
Total	Total Production, measured in units.	0
A195	Processing time for PTO195 first pass (status=1), measured in minutes.	74.44
B195	Processing time for PTO195 second pass (status=2), measured in minutes.	26.14
A196	Processing time for PTO196 second pass (status=1), measured in minutes.	61.04
B196	Processing time for PTO196 second pass (status=2), measured in minutes.	20.75
A197	Processing time for PTO197 second pass (status=1), measured in minutes.	76.12
B197	Processing time for PTO197 second pass (status=2), measured in minutes.	23.29
Cover	Processing time for covers, measured in minutes.	71.33

These values were classified as counters and static values and derived from Table 1 and 2. The counters (initialized as zero in order to represent that there were no initial parts inside the system) and incremented as the number of parts enter and left the automatic line, representing the work-in- process, and they were measured as a discrete value in order to quantify the number of parts.

The variables' names are: WIP1, WIP2, WIP3, WIP4, WIP5, and Total, that represented the work in process for PTO195, PTO196, PTO197, Cover1, Cover2, and the total number of parts called Total. The other types of variables were those associated with the time required for each part to be processed in every work center depending on the type of part and its status. For example, A195 stands for the time in minutes that a PTO195 part requires to be processed in the first phase of polishing (status=1), and B195 is the time required in minutes that the part would need after it has been switched to the other side.

The same logic is used to code the other parts using the following code inside each workstation, using a normal distribution for the times inside the line, and a 10% variation as the standard deviation. The procedure shown in Figure 11 gives an example on the logic chosen to process the parts in each work center depending on the part status (either 1 or 2) as well as the routing logic. For example, if a part in the first time that goes into the work center will have to wait A195 minutes, the variable A195 is used to define the time for the first pass in the work center of PTO195, and B195 is the second pass defined in minutes as well.

```
IF status=1 THEN
{
WAIT N(A195, .1) min
}
ELSE
{
WAIT N(B195, .1) min
```

Figure 11. Processing code example for one of the PTO work centers.

The current planning systems of the company depend heavily on legacy systems, and offline systems do not allow developing either discrete simulation or dynamic simulation. Currently the company relies on an Excel based planning system called "@Risk" and "XLS" that are oriented towards analysis of data, and not towards analysis of flow and its integration with high level systems with the limited capabilities of any other Microsoft Office application. The integration with MSOffice is an extremely important capability for the company, and it is extremely reluctant to apply anything else out of this structure.

The importance of having great technological tools in this global economy depends on price, flexibility, and integration, but also of having people trained enough to use them and translate this knowledge into results for the company. In the case of the present research, the company has small amount of knowledge in the area of simulation, manufacturing optimization, and the current legacy systems do not address the management needs towards planning in the long run.

Currently the company is also moving towards a more advanced platform using Enterprise Resource Planning Systems (ERP) Technologies, with the software called SAP. However, the current resources are limited in order to purchase the complete application, and even given the considerable amount of money to be spent on the process, the final results did not address the current managerial need of planning and simulating their manufacturing processes because they are transactional oriented, and not simulation oriented.

The selection of two software products, Promodel and Powersim, relied on the need of providing an off-line approach to the project. Legacy systems do not allow developing detailed planning scenarios, since they record information based on transactions and data, and not on a long term planning view, or an extensive analysis of the behavior of the data in time.

For this reason, both software packages enhance the capabilities of the company to plan and connect to their future legacy systems. The initial model was created using Promodel and provided a first approach towards the development of an integrated algorithm using genetic algorithms (GA), and finishing with a causal structure using structural modeling equations.

The last part was developed using Powersim and Statistica in order to create a simulation model that replicated the real system, and that could be connected to the future Enterprise Resource Planning Software, SAP. Powersim was the base of the genetic algorithm optimization module, one of the most common techniques of optimization utilized in industry today, and the one requested by top management to be one of the final outputs of the present study.

Data Collection

The data supplied by the automotive company was reviewed in Table 1, allowing a 10% of variation for each of the data selected in order to increase the system variation. The model, using 8-hour days during 1-month period, and assuming normal distributions for each of the workstations, must match the selected data.

The final model must be easy to customize in order to increase the process variation as well as the instability during time reflecting stationary changes on demand. Currently management and middle management are reluctant to have a model that is too complex; however, their specifications are numerous and it will be difficult to accomplish such a goal with the scant resources available.

The main problem relied on the lack of experience in similar studies, and their applications are limited to the current technologies available to the company. Again the only known application currently developed that approaches the current model, has been developed using @Risk software. However, even though it implements a valuable model, it does not address the need of exploring several scheduling scenarios and monitoring their impact on the manufacturing floor in a simulated scenario.

With the combination of Promodel and Powersim, both needs were addressed and the development of online and offline planning system that supported the operation of the polishing line was an important factor. Changes on demand or changes in the characteristics of the line (such as increment in the number of machines, employees, demand, and reduction of the production cycle) must be easily modified in order to study their impact.

In the proposed models, the systems will perform both a full factorial and genetic algorithm optimizations using Promodel and Powersim. The model is intended to provide top management with a tool to perform what-if strategies before their assembly lines are changed due to new technology or variations on demand.

Statistical Analysis

After each simulation run using both optimization methods several statistical analysis (moving average, standard deviation, machine and operator utilization, work in process for each of the monitored, total production, blockage time, total of entries per work station, average contents per work station; percentage that each machine was in operation, idle, waiting, and blocked; average time per part that was in the system, waiting, in move logic, waiting for resource, and in operation; normal probability plot of residuals, path analysis, and others) would be performed inside the model, and the final results would be saved using a *.txt file. Please refer to the Appendix A for further details.

The three variables to compare and analyze are as follows:

1. Cycle time for each part (PTO195, PTO196, PTO197, Cover1, and Cover2) that enters the assembly line.
2. Queue size in front of assembly line.
3. Utilization of each of the work centers (three work stations to process PTOs and two to process Covers)

Using the current reference values, a causal-comparative model was constructed after the most important variables were identified, in order to explain the causal relationship inside the manufacturing line. This relationship was explained using statistical analysis to the strength of the relationship between the most important variables that affected the behavior of the process.

This causal-relationship diagram will help management to understand not only what variables affect the size of the Drivetrain Buffer, but also what variables have a causal relationship inside the process and its statistical behavior; and the consequences of changes will be evaluated using structural modeling equations (SEM) applying the computer software "Statistica."

Summary

The current research was designed to develop three computer models using discrete, dynamic, and causal comparative simulation grouping several parts with a common purpose in order to develop a system. The selected area for this research is a polishing line in an automotive manufacturer that is interested in exploring simulation techniques to create a virtual manufacturing plant before production strategies are implemented.

Several variables to analyze were selected by the Drivetrain Division Management in order to be improved (optimized) in order to replicate the real operations of a polishing line. The software selected for the project combines the utilization of Promodel, Powersim, EQS, and Statistica in order to develop the initial models and perform the optimization (improvement) algorithms. The first model takes a discrete simulation approach, and it is directed to an initial understanding of the variables, relationships, and flows that occur inside and outside the polishing line, and developing an initial optimization using full factorial design.

The second model was designed to create a dynamic simulation in order to integrate the initial state transition diagram and the relationships validated with the discrete simulation, in order to develop a model that allows integrating this process with ERP technology software called SAP. With this model another optimization strategy will be tested using genetic algorithms (GA) and compare with the solution obtained using full factorial designs.

The comparisons and analysis between the real system and two simulated models were done using statistical techniques (structural equation modeling, scatter plot diagram, eigen value plot, moving average and standard deviation), in order to compare their behavior and rank their performance versus the real system. However, due to the low variability of the system and its complexity to be simulated, does not provide a tool that can be easily used by any manager since it requires a high level of expertise and experience that currently the company does not have.

For this reason, all work of this research was concentrated on developing models that included the optimal (improved) variables with the correct relationships, rather than simply matching numbers. The third causal relationship model demonstrated how causality theory can be included into the developing of complex simulation models, and generates initial structures that explain the cause-effect relationships inside the polishing line.

CHAPTER IV

SIMULATION RESULTS AND DISCUSSION

The purpose of the present research was to develop and evaluate a model that generated an improved system for the polishing line of the Drivetrain Division of a tractor manufacturer considering the current constraints.

The simulations generated using the discrete and dynamic algorithms were run for 8 hour days during 30 days in order to represent a specific seasonal demand that the process must perform according to the historical data available in Tables 1 and 2.

Previously GPSS/H and PROOF simulation models were developed in the engine division (Choudry, 2000). However, their performance was still not close to the levels desired by the supervisor and management; moreover that interface is built using a low level system that interacted with Microsoft Excel called XLS, as well as another application called @Risk, which was very desirable for the common user but lacks the control to modify and customize changes in the polishing line for advanced discrete simulation applications and algorithms.

Also, the lack of expertise in the company directed towards manufacturing simulation also affects the study, since no previous project has been done in any other part of the process of the manufacturing plant. The generated model contains arrival cycles of the parts to the line, processing sequences, machine operation times, routings, logics, path networks, locations, and part types that maintain the current history and expectations of the supervisors in the line, however, there is no clear equipment that validates such results.

The combination of discrete and dynamic simulation in the study complemented the decisions drawn from each simulation model since its findings were similar. Besides that the two approaches had two different final users: discrete simulation was ideal for the supervisor and operations manager to visualize and control their levels of productions, cycle times, material flow, and related information.

In the other way, system dynamics was directly related to provide top management with a cost oriented approach to monitor their processes based on inflows and outflows of data, that can also be statistically analyzed, close to discrete simulation, but without the complexities of capacity planning that the first one required. Besides, since the system dynamic software was part of the current SAP Platform, advanced enterprise resource planning application, the genetic algorithm is quite oriented towards corporate policies of the usage of such technology for top-level decision-making.

It is important to consider that the two selected optimization strategies (genetic algorithms and full factorial designs) were chosen in order to compare which one provided the best information to achieve the same goal. Full factorial designs were selected as part of the discrete simulation model because of its flexibility to work in discrete simulation environments and because most of the processing times allowed this functionality to be easily integrated into the model.

The genetic algorithm search engine was used applied to the system dynamic models, because it was a specific managerial requirement and was tested against the results obtained from the discrete simulation model and compared. However, if the variability was not high enough because of not only the processing times but also the delays caused by the routings and sequences in the polishing line, it would be difficult to accurately conclude over which one is the best strategy to be selected to study the different available processes.

The Discrete Simulation Model

The user interface and the discrete simulation model can be seen in Figure 12, and its representation in dynamic simulation for both PTO's and covers in Figure 14. For the discrete simulation model, the changes done over the model cannot be shown during the simulation run, and only the selected work-in-process (WIP) and total production values were displayed. In comparison with the current model built in XLS and @Risk software, this discrete simulation model was more flexible since it allowed keeping track of detailed information by resource, work center, and routings. The models built in XLS and @Risk did not provide enough information in order to fully understand the potential problems that could occur inside the line because of the complexity to be coded, its lack of flexibility, and its limitation to a small level of detail and did not allow to fully represent the real complexity of a manufacturing system with an advanced algorithm that interacts directly with the graphic environment.

However, the statistical information was tracked internally and displayed at the end of the simulation run, and the researcher simply needs to identify the previously selected variables to monitor and considered the rest of the information as guidance since it is difficult to optimize or improve every single part of the system without affecting others.

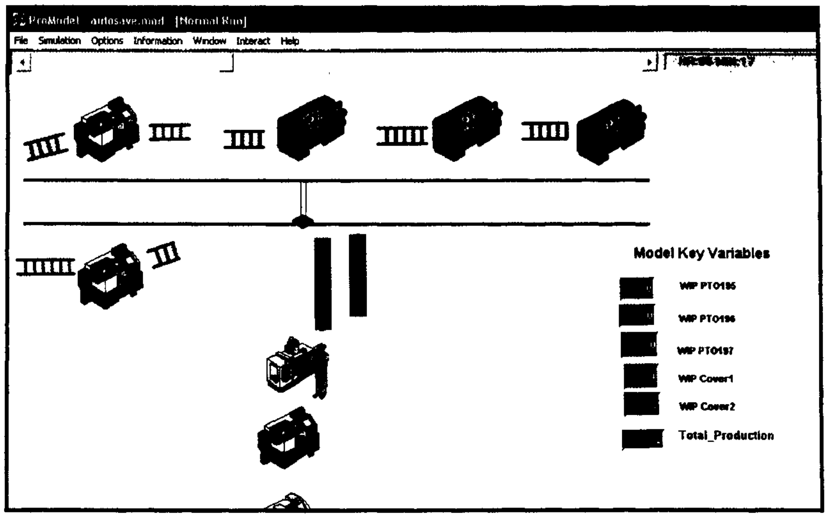

Figure 12. Simulation run for the discrete model

The selected variables were the processing times for each of selected work centers, using a range of values from low to high, with a 1% of expected variation, which was the company's standard that included shutdowns, maintenance and blockage. Figure 13 shows those ranges as well as the optimization module using full factorial designs that will be the initial point to look for optimized levels for the polishing line; however, this approach is believed to generate little impact over the system.

Input Factor Selection

Selected	Name	Lower Bound	Upper Bound	Data Type
	A195	73.69	74.18	Real
	B195	25.87	26.14	Real
	A196	60.42	61.04	Real
	B196	20.52	20.75	Real
	A197	76.12	76.12	Real
	B197	23.05	23.29	Real
	Cover	70.82	71.54	Real

Figure 13. Full factorial optimization module for promodel

At the end of the simulation run, the model generated output reports describing production levels, resource and machine utilization, inventory and work-in-process levels, and total cycle time, which was a function of all the individual process cycle times. The model generated this information in a text file that could be easily shared on the network or saved into a local drive. A copy of the output appears in Appendix A.

On Figure 14 the first run without optimization was performed in order to analyze the behavior of the simulated system under current working conditions. Each part was represented by its color, and the graph represented the average number of parts in work-in-process in time measured in hours. The 30 simulated days were represented using replications for the same 8-hour periods, and using processing times based on a normal distribution with a standard deviation of .01.

The graph represents each variable using the following nomenclature:

- WIP1= Work-in-process of PTO195
- WIP2= Work-in-process of PTO196
- WIP3= Work-in-process of PTO197
- WIP4= Work-in-process of Cover1
- WIP5= Work-in-process of Cover2

It was evident how an initial step function is generated for WIP3, WIP4 and WIP5, and not for WIP1 and WIP2, that was more stable. After one hour the model stabilized generating an average of 8 parts in work-in-process for the first group and almost 2 parts for the other group.

The difference in behavior depended on the availability of parts in the queue as well as their processing times and the availability of the worker to control and handle the request of all workstations and the automatic conveyor.

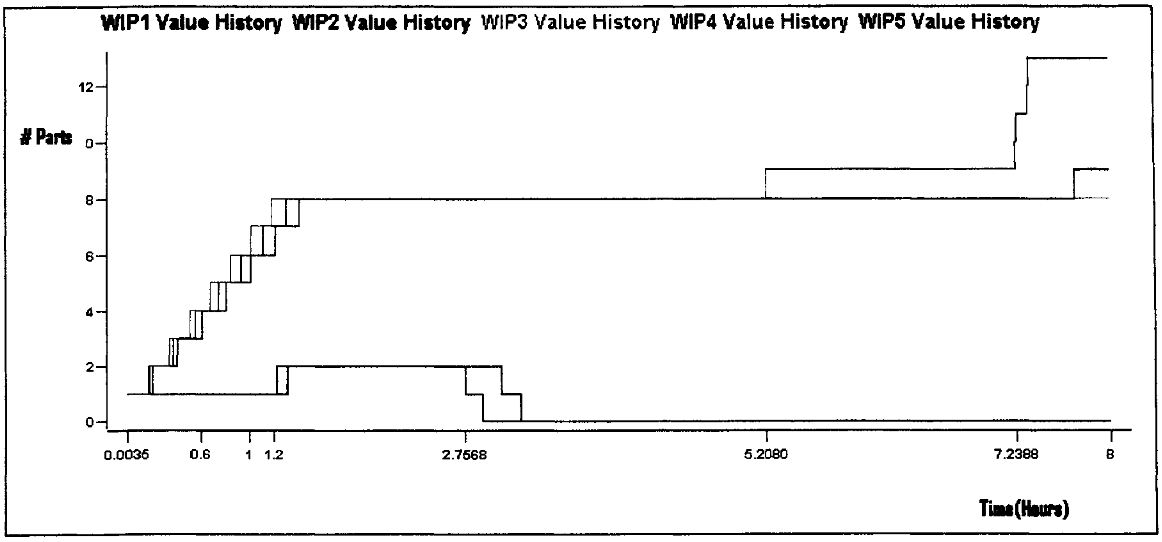

Figure 14. Work-in-process levels (WIP) for each part type

Figure 15 shows the utilization for each work center as a percentage of the total available time, which provided a brief overview of how close the system reflected the real performance of the polishing line of 99%. The results of the discrete simulation model are presented in Tables 4, 5, 6, 7 and 8 reflecting the differences between the actual system and the simulation model. However, it is important to consider that the submitted values are approximations since the company does not perform any work-study or detail analysis over its processes in order to improve processing options.

The values of work center utilization were quite close to the real or "expected values" but there are some differences in utilization that were corrected with the optimization, but they are limited to the availability of the company to meet the suggested improved parameters.

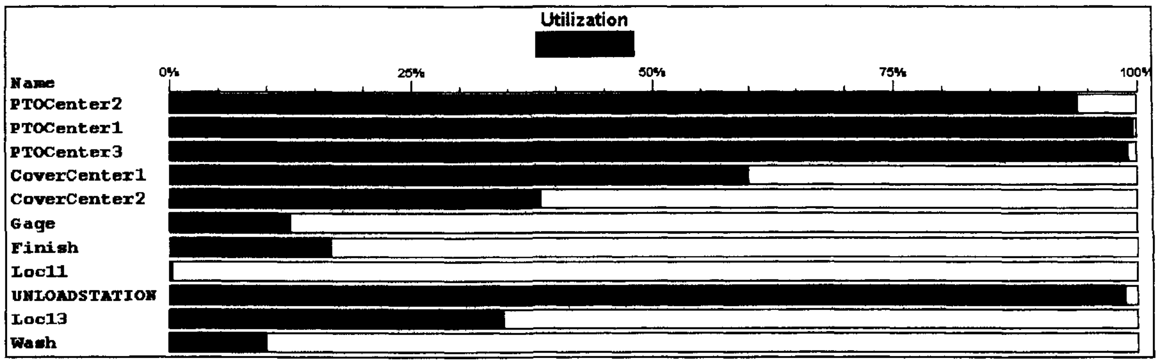

Figure 15. Utilization per work center

Table 4. *Production levels for the discrete model and the actual system*

Part Type	Expected Production (parts/day)	Model Production (parts/day)	Standard Deviation	Expected Average Number of Parts in WIP Status (parts/day)	Model Number of Parts in WIP Status (parts/day)	Standard Deviation
PTO195	8	7.99	0.04	2	2.55	0.2
PTO196	8	7.98	0.10	1	1.55	0.30
PTO197	8	7.96	0.40	8	7.80	0.25
Cover1	8	7.98	0.25	12	10.88	0.40
Cover2	8	7.99	0.34	9	8.2	0.82

Table 5. *Utilizations per work center for the discrete model and the actual system*

Part Type	Expected Utilization (%)	Model Utilization (%)	Standard Deviation
PTOCenter1	99.0	98.96	0.03
PTOCenter2	99.0	98.6	0.02
PTOCenter3	99.0	98.0	0.016
CoverCenter1	99.0	70.0	0.021
CoverCenter2	99.0	60.0	0.012

Table 6. *Production levels for the discrete model and the actual system after full factorial optimization*

Part Type	Expected Production (parts/day)	Model Production (parts/day)	Standard Deviation	Expected Average Number of Parts in WIP Status (parts/day)	Model Number of Parts in WIP Status (parts/day)	Standard Deviation
PTO195	8	7.99	0.04	2	2	0.001
PTO196	8	7.98	0.10	1	1.03	0.01
PTO197	8	7.96	0.40	8	8.2	0.02
Cover1	8	7.98	0.25	12	12.56	0.2
Cover2	8	7.99	0.34	9	9.01	0.03

Table 7. *Utilizations per work center for the discrete model and the actual system after optimization*

Part Type	Expected Utilization (%)	Model Utilization (%)	Standard Deviation
PTOCenter1	99.0	99.0	0.01
PTOCenter2	99.0	99.0	0.01
PTOCenter3	99.0	99.0	0.01
CoverCenter1	99.0	75.0	0.02
CoverCenter2	99.0	70.0	0.03

Table 8. *Optimized values for the processing times for each work center*

	Initial Values (Min)	Factorial Optimization (Min)
A195	74.44	73.80
B195	26.14	25.89
A196	61.04	60.34
B196	20.75	20.67
A197	76.12	75.74
B197	23.29	23.24
Cover	71.53	70.51

The System Dynamic Model

The initial discrete model was useful to comprehend the initial system, and to optimize the selected variables using full factorial designs. However, the initial managerial required a genetic algorithm model be developed capable of interacting with the new SAP system; therefore the system dynamic model needed to be simplified in order to integrate the flow of the line, and the work-in-process.

Figure 16 shows a simplification of the model into a dynamic flow diagram that can be directly linked to the SAP platform into their main database using the software Powersim (see the complete model in Figure B1 in Appendix B). The dynamic model was developed after the system has been clearly identified using the state transition diagrams presented in Figure 7 and 8. This simplification responds to orientation towards improvement of the flow inside the line based on the work in process (WIP), and processing times for each of the polishing centers.

The processing time would be considered to be the rates that move the parts from workstation to next and the accumulation of inventory in the line. The flows and rates were part of the optimization (improvement) strategies using genetic algorithms, which constituted the second part of the study.

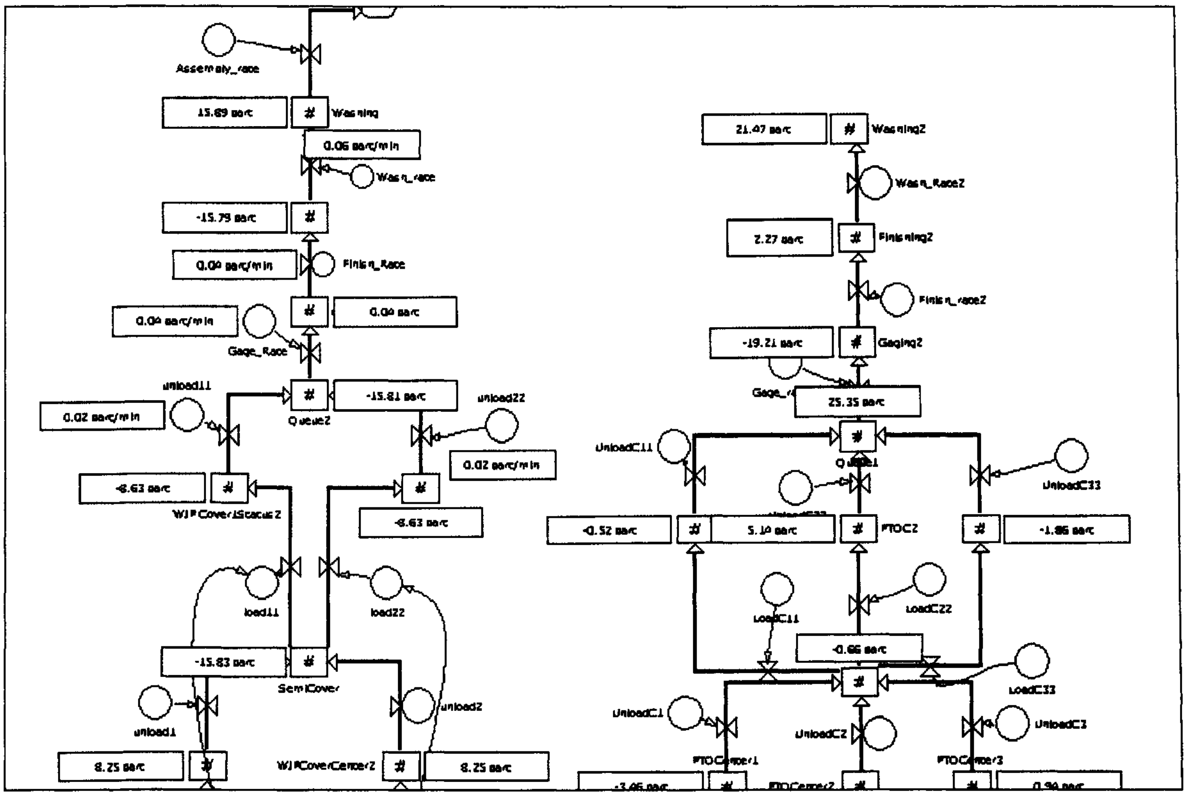

Figure 16. System dynamic model for the polishing line

Both models, discrete and dynamic, have the same outputs and processing times, based on the Tables 1 and 2 from Chapter III. However, their approach was totally different. The first one was oriented towards consideration of low-level decisions, but the other one was more oriented to the analysis of information inside and outside the line.

Table 9 and 10 show the final output coming out of the system dynamic model that, as well as the discrete model, makes the comparison between required production levels and the information generated from the system dynamic model.

For this reason, this model was more appropriate for high-level strategic decisions, because it allowed one to connect the data for each individual work center to the SAP system, which linked costs and other transactional information to this planning system that are uploaded from the SAP BW system.

The discrete system was useful if the specific changes to the line have been developed using the dynamic system, but a lower of level planning was required. For example, once that it was determined that the production rate for cover1 could be improved by reducing the cycle time of operation 2 and its impact validated by the rest of the system performance, it was important to schedule the task it did not affect the rest of the flow in the line.

This could be achieved if the new rate was introduced into the system, and operational optimization was desired, instead of focusing on overall line performance. Figure 17 validated this information showing that the same performance viewed in the discrete simulation model was also affecting the dynamic simulation model for each of the individual WIPs, replicated 30 times for 8 hours each.

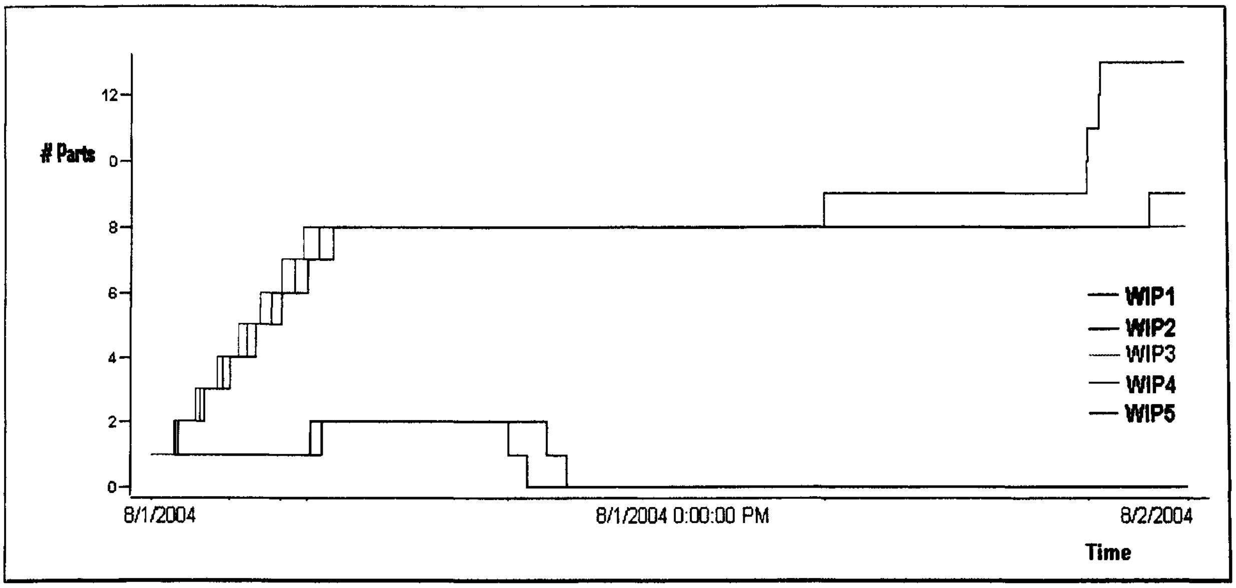

Figure 17. Dynamic model for the work-in-process levels (WIP) for each part type

Table 9. *Production levels for the dynamic model and the actual system*

Part Type	Expected Production (parts/day)	Model Production (parts/day)	Standard Deviation	Expected Average Number of Parts in WIP Status (parts/day)	Model Number of Parts in WIP Status (parts/day)	Standard Deviation
PTO195	8	7.28	0.03	2	2	0.001
PTO196	8	7.26	0.09	1	1	0.05
PTO197	8	7.27	0.38	8	8.01	0.002
Cover1	8	7.7	0.17	12	11.99	0.010
Cover2	8	7.8	0.34	9	8.989	0.025

Table 10. *Utilizations per work center for the dynamic model and the actual system*

Part Type	Expected Utilization (%)	Model Utilization (%)	Standard Deviation
PTOCenter1	99.0	98.96	0.03
PTOCenter2	99.0	98.6	0.04
PTOCenter3	99.0	90.0	0.02
CoverCenter1	99.0	70.0	0.01
CoverCenter2	99.0	60.0	0.01

The Powersim software allowed the researcher to look for optimized scenarios using its optimization module (Figure 18), in order to construct the genetic algorithm based on the developed model for the polishing line (Figure 16). The researcher will focus on improvement of the processing time and work in process levels inside the line, with the same ranges used in the discrete simulation model, and shown in Figure 12.

As the final outcome, it was desirable that the assembly queue be maximized in order to determine the maximum production that is possible from the polishing line. For that reason, the variables washing2 and washing were optimized (improved) because they were the variables that the polishing line was supposed to increase. In this way, the results of using the same range of values applied Promodel but this time applied to the system dynamics model.

The results were shown in Table 11, where the maximum possible outcome based on the previously defined constraints the washing2 and washing values for PTO and Cover, respectively are 15 and 24.47 parts. These results mean that at the end of the line the maximum number of possible parts to be produced by the polishing line were approximately 40 (8 parts of each type).

In this way, the modification of the assembly line using the current values of the machinery and considering the low allowed variation in the polishing approximately only 37 parts can be produced during a regular work schedule of 8 hours, meaning that close to 3 parts need to be produced in extra time. The approximation of the model reflects that the system is working to maximum capacity and that no improvement is possible considering the types of machines and levels of production of the line, as well as its low variability.

This conclusion did not differ much from values reached with the full factorial optimization model, and further analysis needed to be made in order to improve the approximation of the processing, logic, and flow of the current polishing line.

Table 11 shows the suggested levels using genetic algorithms in order to improve the polishing line performance according to the above conclusions using 3 parents, 300 generations and 15 offspring as the standard for each generation considering that the sample size was sufficient because it is bigger than 30 and because of the low variability of the system (refer to Appendix C for the variable codification).

Tables 12 and 13 show that the optimization strategy using genetic algorithms does not improve significantly the final output of the simulation model. The initial low variability of the system plays an important role in this final output and that made it difficult to compare this results with those coming out of the discrete simulation model.

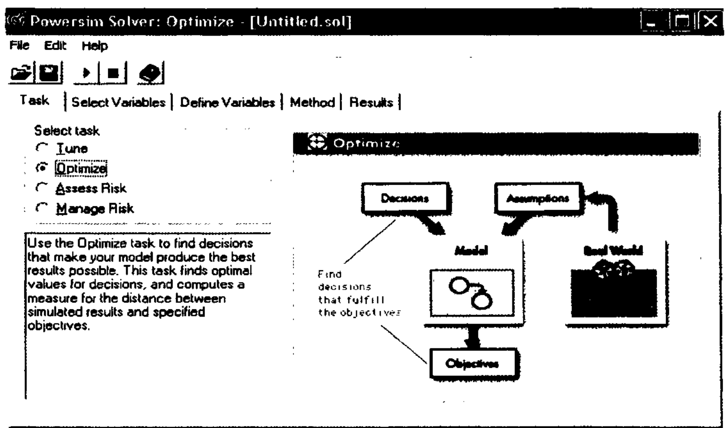

Figure 18. Optimization module of powersim for genetic algorithms
Source: Powersim corporation

Table 11. *Final values of the genetic algorithm optimization module*

Washing2	22.335	PTOC3	1.440	PTO195_rate	0.457
Washing	15.888	PTOC2	-1.322	LoadC33	0.282
WIPCoverCenter2	8.250	PTOC1	2.159	LoadC3	0.617
WIPCover2Status2	-8.629	UnloadC33	0.384	LoadC22	0.356
WIP Cover1Status2	-8.629	Wash_Rate2	1.035	LoadC2	0.383
SemiPTO	-9.280	Wash_rate	0.056	LoadC11	0.362
WIPCoverCenter1	8.250	load11	0.011	LoadC1	0.375
SemiCover	-15.829	load22	0.011	Load2	0.011
RawPTO	5.223	unload1	0.006	Load1	0.011
RawCover	-16.368	UnloadC3	0.316	Gage_rate2	0.157
Queue2	-15.806	UnloadC2	0.504	Finish_Rate	0.045
PTOCenter3	-0.442	UnloadC1	0.523	Finish_rate2	0.737
Queue1	24.222	UnloadC11	0.331	Cover1	0.006
PTOCenter2	4.405	PTO196_rate	0.470	Assembly_rate	0.047
PTOCenter1	2.664	PTO197_rate	0.412		

*Note: refer to appendix C for nomenclature

Table 12. *Production levels for the dynamic model and the actual system after optimization*

Part Type	Expected Production (parts/day)	Model Production (parts/day)	Expected Average Number of Parts in WIP Status (parts/day)	Model Number of Parts in WIP Status (parts/day)
PTO195	8	7.33	2	1.99
PTO196	8	7.33	1	.78
PTO197	8	7.33	8	7.7
Cover1	8	7.5	12	11.5
Cover2	8	7.5	9	8.88

Table 13. *Utilizations per work center for the dynamic model and the actual system after optimization*

Part Type	Expected Utilization (%)	Model Utilization (%)	Standard Deviation
PTOCenter1	99.0	98.96	0.01
PTOCenter2	99.0	98.6	0.02
PTOCenter3	99.0	90.0	0.03
CoverCenter1	99.0	70.0	0.02
CoverCenter2	99.0	60.0	0.01

The Structural Equation Modeling Model (Causal Model)

As part of the current research a causal correlation model for a manufacturing line was developed using the previous generated information. The idea was to have a deeper understanding of the factors that "cause" the performance of the different manufacturing variables. In order to create the model based on the previous information, the initial data would be utilized and the variation of the simulated discrete model would be combined in order to create the model. In Figure 19 shows those causal blocks created based on discrete and dynamic simulation models in order to derive and create a causal structures that explains the behavior of the current polishing line.

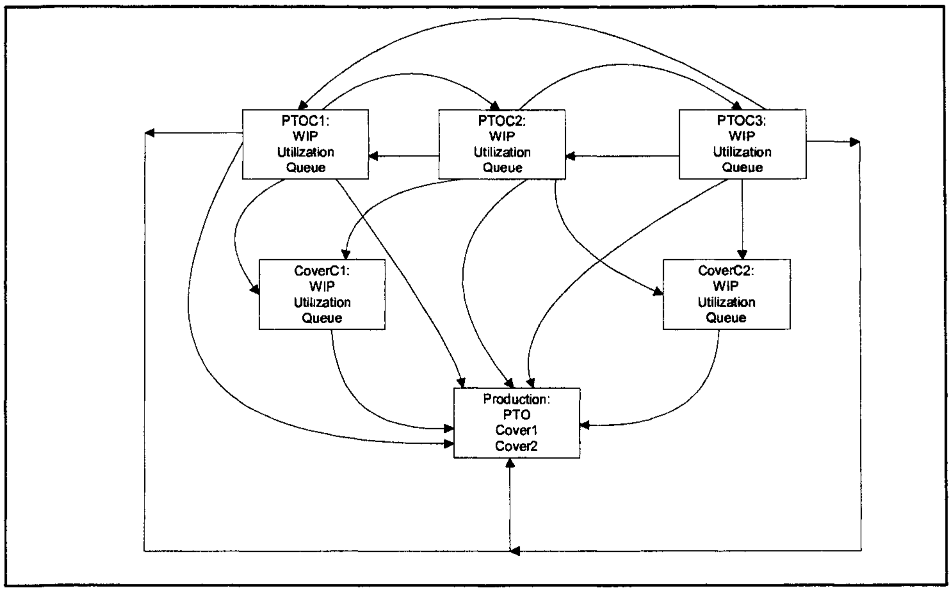

Figure 19. Causal structural model for the manufacturing polishing line

In order to perform the causal analysis Table C1, see Appendix C, a population of 5000 samples was generated for work-in-process (WIP), utilization, and processing times for each work centers. The analysis was centered on these three main variables and their influence on the production levels for each of the product types PTO195, PTO196, PTO197, Cover1, and Cover2.

The generated random values provided a detailed understanding of the existing correlations inside the manufacturing line that defined the causal-correlation model to be presented at the end of this chapter. The results of the correlation analysis are presented in Table C1, in Appendix C, and created the basis in order to generate inferences regarding the impact that each variable has over the process performance.

In order to analyze the different selected variables by a computer program, these results need to be analyzed using a standard coding system in order to identify it in the analysis. For that reason, Appendix C shows this coding system defining each individual variable utilized in the generation of the causal-correlation model analyzed using Statistica Software.

In this way, using the correlation values from Table C1, the significant factors are shown in order to reflect that its relation is statistically significant ($p<0.05$), and that it is important to explore its influence in more detail. Figure 19 presents a path diagram that represented a possible causal structure for the selected area of study. Because of the issues properly described in the literature review, this diagram was only one of the many possible alternatives based on the selected level of statistical significance ($p<0.05$).

In general the idea of examining correlations between variables was not a new thing. Even though that correlation does not necessarily imply causation, the same analysis could be used to "infer" causation as it was explained in the literature review.

In Figure 19 an alternative causal structure for the manufacturing line is presented using only those relationships shown to be significant based on the correlation coefficients (with values higher than 0.02). This level of correlation was small and close to insignificant and increased in variability up to 30% was added in order to identify the causal correlations that would not show clearly because of the reduced amount of data and low level of variability of the current system. In this way, 13 variables were identified using the eigenvalues mathematical criteria in order to quantify its impact over the statistical model (see Figure 21). According to Bollen (1989), in order to consider the eigenvalues significant its value was bigger or equal to 2, meaning that the set of selected values shown in Figure 18, only WIP and Queue size of cover center 2 did not show a significant impact over the polishing line performance even at levels of 30% variation (response variables PTO195, PTO196, PTO197, Cover1 and Cover2).

Figure 20 represents an initial causal structure for the control of the polishing line, and a way to clarify the impact of the different set of variables identified in the process. In this way, it is possible to determine the relationships that exist within the polishing line, that control its behavior and that allowed the improvement of its final outputs.

The values used to calculate the eigenvalue curve have a low level of correlation because of the effect of variability in the system. However, the increased variability reflects the existence of a possible causal structure shown in Figure 20 that might represent the best way to handle and control the polishing line in case that any changes are introduced in the future. This figure might suggest causation based on correlation, but the logic analysis performed using the supervisor insight validates the found structures in order to clarify the behavior of the line.

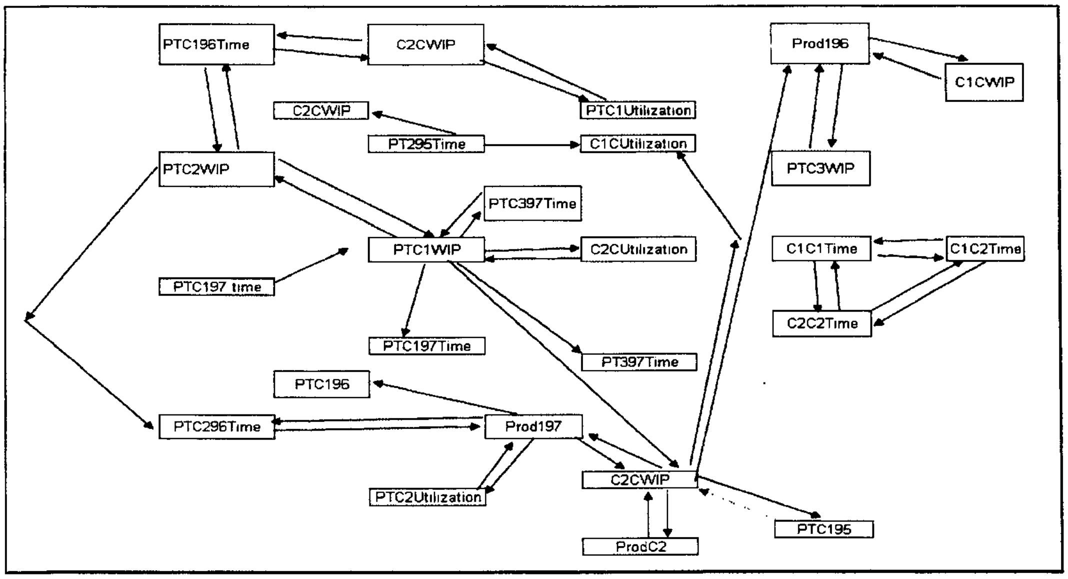

Figure 20. Alternative causal structure for the polishing line

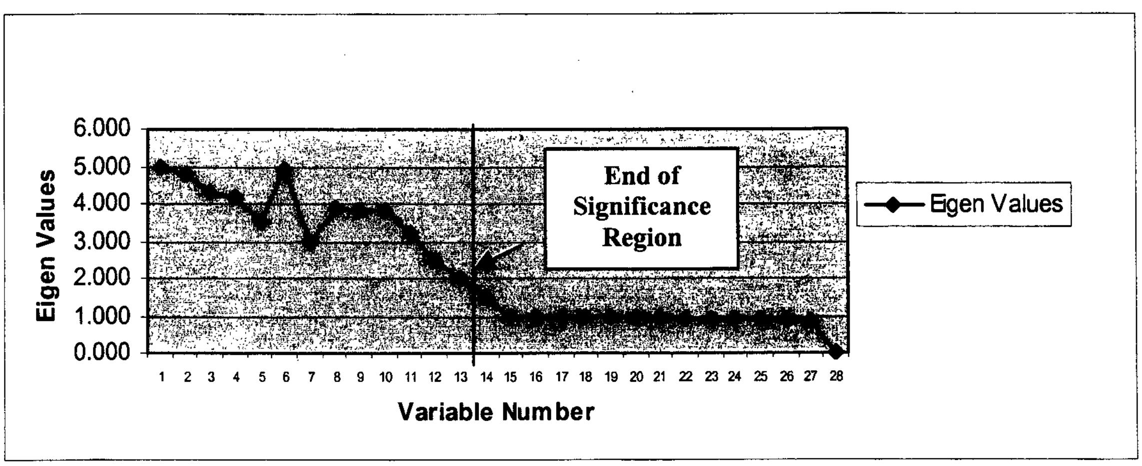

Figure 21. Eigenvalues for the causal-correlation model of the polishing line

From Figure 20 and Table D1, in the Appendix D, one can see the most significant variables (those that have the correlation coefficient with a minimum value equal or higher to 0.04 (absolute) and a maximum value lower than 1). For example, for the processing time at work center 3 for PTO197 affects significantly the work in process (WIP) for the PTO work center 1 with a coefficient of 0.05. This relationship might indicate that any variations in the processing time for work center 3 will affect importantly the level of WIP in work center 1. Although the relationship between the processing times for work centers 1 and 2 though is 1, it should not be considered meaningful since having both the same characteristics will have the same effect over the system.

The inverse relationship between the utilization for the PTO work center 1 and the work in process (WIP) for work center 2 was also significant, this could be explained by the fact that with a higher utilization of work center 1 the queue size for work center 2 would be inversely affected. Generating a causal correlation structure improved management of the effect of each work center and its associated variables could be understood based on its impact on the overall line performance.

In this way, the improvement or change in the manufacturing line can be developed based on the impact that each variable has over the line performance. The correlation coefficients can potentially suggest causation within the polishing line, and a change in the current variables will affect the relationships with other variables.

For example, if another machine was supposed to be added into the line, its impact over the flow and the key selected variables of work in process, utilization, processing time, and production levels, need to be restudied in order to determine how the rest of the variables would be affected. From a production stand point as showed in Table C1, see Appendix C, shows the major influence for the final production levels for each of the product types is caused by the following relationships:

- Production of the PTO195 part did not have a significant effect over any other major variables in the system.
- Production of PTO196 is significantly influenced by the work in process (WIP) levels of the Cover work center 1.
- Production of PTO197 is highly influenced by the processing time of the PTO work center 2 when producing PTO196 and for its utilization, and also with a major influence from the WIP levels at the Cover work center 2.
- Production of Cover 1 was not significantly influenced by any major factors within the polishing line; however, this issue might be caused because of inaccuracy from the original data that affected the researcher along this project.
- Production times for each cover center affected each others processing times. However, this relationship was clear since there are only two work centers, if any one malfunctions the queue size was increased and the production of both cover parts was affected. This is obvious since there are only two work centers for production of covers, in comparison to three for the production of PTOs.

It is important to consider that a model that is consistent with reality must also be consistent with the data (Bollen, 1989). But even if the data were consistent with a model, this does not imply that the model is consistent with reality. In the case of this model, the selected structure seems to be logically related to reality, especially with respect to the cover work centers.

It seems that their processing times are interrelated, which is logical given that depending on the time from one there would be a higher queue in the other. However, it is possible that these processing times are not connected with any other part of the main model, which causes the researcher to suspect that there are other variables that affect these work centers that are not considered yet in the model, unfortunately no additional data were available to continue the analysis validation study of the simulated and real data.

However, it is important to notice that as can be seen in the Appendix D, the overall line behavior even though that the random numbers are generated using a normal distribution, in overall there is a lack of fit of the line with the normal distribution. The explanation is because of the combination of the different times is not stable around all the simulation runs, there are delays that affect its performance and thus affects the statistical values of the monitored variables.

Besides, if there were a part in movement between one or two work centers in the limit when that part is finishing and the other one is arriving, there would be a block station status. This will mean that the work center is not operative for a short period of time, and it will cause an additional delay between the switch between processing and free state. These problems are clearly reflected in the significant loop found between C1C2Time (processing time for part Cover1 in work center 1), C1C2Time (processing time for part Coverl in Work Center 2), and C2C2Time (processing time for part Cover2 in Work Center 2) shown in Figure 22.

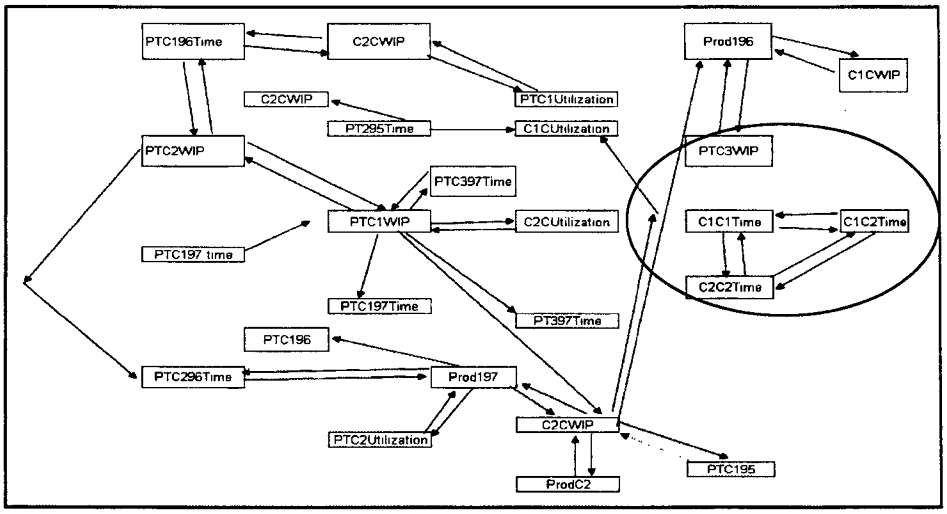

Figure 22. Material flow deficiencies

This isolated control loop reflects these problems that were natural to any process when it was operating over capacity. The only solution would ideally eliminate the blocking time while improving the flow within the line, but these problems will always affect the variability of the system.

Using the current model, it was detected that around 5% of the time there is at least one of this type of failures in the line, and thus the performance will deviate from an ideal smooth move of materials inside the polishing line affecting the collection of statistics during the simulation run. However, if the variability due to this factor causes the system to increase the answer does not rely on the optimization of the processing times, since the variability of the system by itself is very small, the answer of the increasing the Drivetrain Output may be simply improvement of the flow of material within the line in order to avoid the lack of capacity during this cycles.

In this way, addition of another load/unload workstation might as well as a secondary automatic transporter will resolve the production problem since the current processes were performing at maximum capacity, and the relationship between variables clearly identifies that those deviations were attributed to this factors, and the available capacity in the process is quite limited.

In summary, the development of a dynamic simulation model and its optimization has been reached with an initial causal-correlation structure that might indicate the variables that are the most sensitive to variation in the polishing line. It is clear that even though it was simple to understand, it was difficult to quantify the interrelationships between the selected group of variables and the final process performance.

The results of the Structural Modeling Equations are shown in Appendix E in Table E1, and determine the initial causal structure identified with the model. The significant effects are highlighted in red in order to show the R Square and the significance levels with 5% (if $p<0.05$ is significant). In addition, as it can be seen in Figure 23, the results coming from the structural modeling equation model reflects the effects that each individual variable have in the system, which complements the findings identified in Appendix D, Figure D1 and D2, because of the lack of normal fit might also be caused of the big differences in the mean.

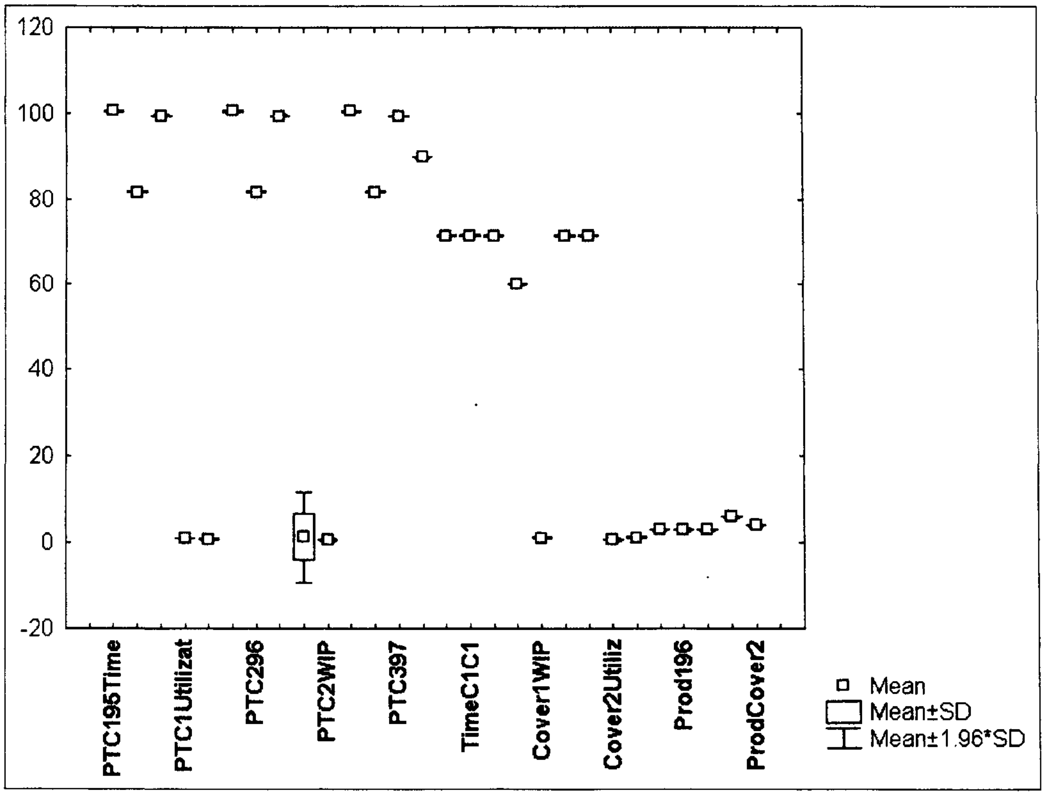

Figure 23. Effect size for all the variables included in the study (source data in Appendix E)

In this way, the structural design has low correlation coefficients because of its low variability and its big differences in mean. However, the structural model presents an initial solution to explore in order to develop more advanced algorithms or detailed scenarios by the company. Part of the problem of developing such an advanced methodology is that in a small level of application the effects of variability and the algorithms required to control the involved variables will increase the analysis time, same principle applied to artificial intelligence projects where high-level analysis can be easily performed in comparison with a simple problem.

For example, if an AI algorithm or structural modeling software is built to control or analyze the production of the whole plant, will give better results rather than studying how only one operation performs. In relation to the project, the level of detail for the selected polishing line was too narrow and this is just one of the reasons why the impact of the final results are small because of the complexity of the decision making inside the polishing line. The machine utilization of the work centers was increased with the additional transporter, and thus improving the Drivetrain Buffer (total production for each finished part type) production levels at the end of the line.

Finally, it was important to consider that this model now can be linked to the table related to SAP Software since the interface of the system allows it. The use of advanced database systems, like OLAPs, allowed the present model to be shared within the company and populating it with SAP and add the same analysis to other assembly or polishing lines because the logic and routings were substantially similar.

CHAPTER V

CONCLUSIONS AND RECOMENDATIONS

Conclusions

This research was the initial study of the possible application and combination of three different areas in industrial environments: discrete simulation, structural modeling equations, and dynamic simulation.

The current research identified the constraints inherent to the polishing line of the automotive manufacturer, in order to establish an initial simulation model and improvement strategies that allow management to have a base model that replicates the key processes of other assembly and polishing lines of the company.

The answers for the research questions are stated as follows:

1. What were the most important variables that affect inventory levels of an assembly line of an automotive manufacturer?

Based on the study, the main variables that management was interested to investigate and were essential for the performance of the line were: work-in-process for each part type, work station and operator utilization, arrival rates of the parts into the line, processing times for each work station and the unload/loading times, routing priorities, and the Drivetrain Buffer (the total production of finished parts for each type of product).

2. What were the significant effects of the causal relationships identified in order to determine an initial model structure?

It is important to consider that due to the low variability of the selected polishing line, many of the results might be close to reality because the system can be controlled and simulated without major difficulty, in comparison with variations of performance with 30% to 100%. Even though that the intermediate results look quite nonlinear, in overall the design of the simulation models was focused more in the analysis and discovery of the system, rather than how exact the data was because of the lack of information to validate it.

The causal-correlation model developed provides an initial understanding of the statistical significant variables and its relationships within the polishing line. In this way, management will have a better idea of the impact that a change of one of the final 13 most important variables will have over the line and how each of them impacts the final production of each of the part types.

Based on the causal relationship model using structural equations modeling the following relationships were identified:

- Production of the PTO195 part did not have a significant effect over any other major variables in the system.
- Production of PTO196 was significantly influenced by the work-in-process (WIP) levels of the Cover work center 1.
- Production of PTO197 was highly influenced by the processing time of the PTO work center 2 when producing PTO196 and for its utilization, and also with a major influence from the WIP levels at the Cover work center 2.

- Production of Cover 1 was not significantly influenced by any major factors within the polishing line; however, this issue might have been caused because of inaccuracy from the original data that affected the researcher along this project.
- Production times for each cover center affected each others processing times. However, this relationship was clear since there are only two work centers, if any one malfunctions the queue size was increased and the production of both cover parts was affected. This is obvious since there are only two work centers for production of covers, in comparison to three for the production of PTOs.

3. What constraints restrict the behavior and improvement of the selected variables?

Based on Figures 6 and 7 using the state transition diagrams, the constraints of the system were identified and included part of the simulation algorithms. For example, in Region A in Figure 6 the system constraints were considered in order to determined the available capacity of the Load/Unload stations, as well as the others work stations, considering either PTO parts are in the system and it is not allowed to include not higher or lower than two parts, or either one or two parts for Cover parts. However, the system did not allow including parts of PTO and Covers combined in the Unloading/Loading workstation, and the production rate for a given part type was determined by the slowest operation.

The same constraints were included in order to establish the logic that controlled the transporter to move inside the polishing line. Besides, the processing constraints shown in Region C for Figure 6 displayed the change of status for the part once it was rotated in the Unload/Load station. For example, once a raw part entered the system, its status variable changed from one to two once processed the first time, in this way this constraints limited the priority rules in the processing sequences since this is the way to determine if the part was new in the system or work-in-process, updating the proper statistics during the simulation run.

The queue size for all the operations within and outside the line was controlled if the material flow within the line was improved with the addition of another unload/load workstation in order to increase the number of parts in the system in comparison with the current levels. However, the current data measurement and historical data makes it difficult to totally support this argument because there is no availability of proper instrumentation in order to perform such analysis. With the use of the developed models and Six Sigma tools (scatter plot diagram, structural equation modeling, path analysis, simulation, moving average, standard deviation) it was possible to replicate similar processes in other parts of the company, and create virtual manufacturing strategies for process, product, assembly, flow, and capacity optimization.

4. What levels of the selected variables could be used in order to improve production levels?

Using the system dynamics and full factorial simulation results, Table 8 and Table 11 there was enough information in order to determine the improved behaviors of the line. However, neither of those search methods gave a significant difference in order to determine which one was the best in order to apply it to the polishing line because of it the low variability. The results of both discrete and dynamic simulation models showed the WIP can be reduced up to 5% for PTO parts and 3% for Cover parts if the utilization of the work centers is improved up to 98% with an additional transporter.

Even though that machine utilization seems to be over 90% in many work centers, in some cases these levels went down as low as 40%, because the machine was idle because the transporter was busy loading, unloading, moving, or waiting for a specific part and that work center has low priority in comparison with other work centers. However, even though that the changes made under the current conditions did not provide enough information about the real behavior of the line, it was expected that the implementation was directed to improve the production rate at least 13 % per product family.

Finally, the new knowledge generated from this research is mainly focused to identify the possibility of combining three different methodologies into one single effort towards an aggressive system and process optimization with the usage of advanced statistical techniques that are not common to industrial environments to explore the capabilities of the different mathematical techniques to optimize a process.

Recommendations

The applicability to support managerial decisions with simulated models needs to be validated under real world circumstances, and must consider the issue of variability as the most important factor to control.

All simulation parameters (processing times, routings, loops, initial inventories, and others) need to be revisited in order to make sure that they are the main parameters that influence the performance of the polishing line and their behavior due to seasonality of the requirements of the polishing line.

The application of the current project to implement and plan manufacturing strategies before the allocation of resources into a specific production plan will improve the production efficiency and reduce the machine downtimes and shutdowns. The development of a large simulation algorithm that controls the total production plant is not suggested because of its complexity and its difficulty of modification.

The division of the plant in production groups will allow management to allocate, measure, control, and monitor resources in a better way in virtual environments rather than a complete simulation model of the facility. The application of similar computer based models in combination with Six Sigma tools would be quite beneficial because it will allow management to direct its process optimization efforts with a more strategically oriented approach. The utilization of @Risk Software should be limited to managerial models, not to operational models related to control flow, routings, capacity, and constraints because of its limited discrete and dynamic capabilities.

In addition, in order to improve the material flow inside the line an another transporter and unload/load station is suggested to be added if the production volume is desired to be increased. Since the current system is working close to its maximum capacity and its capability to improve the current output is difficult because of its low variability.

The structural modeling equations model as well as the complete simulation models will need to be reanalyzed using the additional transporter and the new load/unload station, because it will increase an important change in the algorithm and will also change the behavior of the selected response variables.

The application of the current procedure requires not only knowledge of the current processes, but an extensive training in software simulation and model building. It is suggested to train at least one expert in the company using these types of advanced Six Sigma techniques since currently there is a lack of knowledge in the corporation in order to continue the development of the current research.

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APPENDIX A

EXAMPLE OF ONE SIMULATION OUTPUT

SIMULATION AND SEQUENCING MODEL SIMULATION

```
--------------------------------------------------------------------------------
General Report
Output from D:\Doctorate Work\JOHN DEERE \WAS.MOD
Date: Jan/09/2005   Time: 01:01:05 PM
--------------------------------------------------------------------------------
Scenario        : Normal Run
Replication     : 1 of 1
Simulation Time : 40.40918333 hr
--------------------------------------------------------------------------------
```

LOCATIONS

Location Name	Scheduled Hours	Capacity	Total Entries	Average Minutes Per Entry	Average Contents	Maximum Contents	Current Contents	% Util
PTOCenter2	35.40918333	1	211	2.000000	0.19863	1	0	19.86
PTOCenter1	35.40918333	1	424	2.000000	0.399143	1	0	39.91
PTOCenter3	35.40918333	1	0	0.000000	0	0	0	0.00
CoverCenter1	35.40918333	1	0	0.000000	0	0	0	0.00
CoverCenter2	35.40918333	1	0	0.000000	0	0	0	0.00
Gage	35.40918333	1	531	1.426940	0.356642	1	1	35.66
Finish	35.40918333	1	530	1.293560	0.322697	1	1	32.27
Loc11	35.40918333	1	529	0.269000	0.0669793	1	0	6.70
UNLOADSTATION	35.40918333	2	1063	2.456259	1.22897	2	1	61.45
Loc13	35.40918333	2	1063	0.170891	0.0855037	2	0	4.28
Wash	35.40918333	1	529	0.145807	0.0363051	1	0	3.63
ENTRY	35.40918333	1	425	0.266692	0.0533496	1	0	5.33
Loc1	35.40918333	2	214	1.214883	0.122372	1	0	6.12

Loc3	35.40918333	2	0	0.000000	0	0	0	0.00
Loc2	35.40918333	999999	848	0.266164	0.106238	2	0	1.68
Loc4	35.40918333	999999	422	0.139436	0.0276962	1	0	0.30
Loc5	35.40918333	999999	0	0.000000	0	0	0	0.00
Total Count	35.40918333	1	0	0.000000	0	0	0	0.00

LOCATION STATES BY PERCENTAGE (Multiple Capacity)

Location Name	Scheduled Hours	% Empty	% Partially Occupied	% Full	% Down
UNLOADSTATION	35.40918333	20.28	36.55	43.17	0.00
Loc13	35.40918333	92.55	6.35	1.10	0.00
Loc1	35.40918333	87.76	12.24	0.00	0.00
Loc3	35.40918333	100.00	0.00	0.00	0.00
Loc2	35.40918333	89.38	10.62	0.00	0.00
Loc4	35.40918333	97.23	2.77	0.00	0.00
Loc5	35.40918333	100.00	0.00	0.00	0.00

LOCATION STATES BY PERCENTAGE (Single Capacity/Tanks)

Location Name	Scheduled Hours	% Operation	% Setup	% Idle	% Waiting	% Blocked	% Down
PTOCenter2	35.40918333	19.86	0.00	80.14	0.00	0.00	0.00
PTOCenter1	35.40918333	39.91	0.00	60.09	0.00	0.00	0.00
PTOCenter3	35.40918333	0.00	0.00	100.00	0.00	0.00	0.00
CoverCenter1	35.40918333	0.00	0.00	100.00	0.00	0.00	0.00
CoverCenter2	35.40918333	0.00	0.00	100.00	0.00	0.00	0.00
Gage	35.40918333	29.96	0.00	64.34	5.38	0.33	0.00
Finish	35.40918333	29.87	0.00	67.73	2.39	0.00	0.00
Loc11	35.40918333	6.70	0.00	93.30	0.00	0.00	0.00
Wash	35.40918333	0.00	0.00	96.37	3.63	0.00	0.00

ENTRY	35.40918333	0.00	0.00	94.67	5.33	0.00	0.00
Total Count	35.40918333	0.00	0.00	100.00	0.00	0.00	0.00

RESOURCES

Resource Name	Units	Scheduled Hours	Number Of Times Used	Average Minutes Per Usage	Average Minutes Travel To Use	Average Minutes Travel To Park	% Blocked In Travel	% Util
Res1	1	35.40918333	1912	0.043677	0.027794	0.000000	0.00	6.43
Employee	1	35.40918333	2865	0.067539	0.125026	0.000000	0.00	25.97

RESOURCE STATES BY PERCENTAGE

Resource Name	Scheduled Hours	% In Use	% Travel To Use	% Travel To Park	% Idle	% Down
Res1	35.40918333	3.93	2.50	0.00	93.57	0.00
Employee	35.40918333	9.11	16.86	0.00	74.03	0.00

FAILED ARRIVALS

Entity Name	Location Name	Total Failed
PTO195	ENTRY	213
PTO196	ENTRY	1
PTO197	ENTRY	142
Cover1	ENTRY	35
Cover2	ENTRY	142

ENTITY ACTIVITY

Entity Name	Total Exits	Current Quantity In System	Average Minutes In System	Average Minutes In Move Logic	Average Minutes Wait For Res, etc.	Average Minutes In Operation	Average Minutes Blocked

PTO195	212	0	11.144660	1.502986	0.000000	8.987000	0.654675
PTO196	105	1	14.850000	1.630000	0.000000	13.111000	0.109000
PTO197	0	0	-	-	-	-	-
Cover1	212	2	13.018712	2.022132	0.294189	8.719000	1.983392
Cover2	0	0	-	-	-	-	-

ENTITY STATES BY PERCENTAGE

Entity Name	% In Move Logic	% Wait For Res, etc.	% In Operation	% Blocked
PTO195	13.49	0.00	80.64	5.87
PTO196	10.98	0.00	88.29	0.73
Cover1	15.53	2.26	66.97	15.23

VARIABLES

Variable Name	Total Changes	Average Minutes Per Change	Minimum Value	Maximum Value	Current Value	Average Value
WIP1	426	4.974315	0	2	2	1.08917
WIP2	0	0.000000	0	0	0	0
WIP3	636	3.336119	0	213	212	106.698
WIP4	316	6.709082	0	106	106	53.0517
WIP5	0	0.000000	0	0	0	0
Total	317	6.694136	0	317	317	156.996

□

APPENDIX B

DYNAMIC SIMULATION MODEL

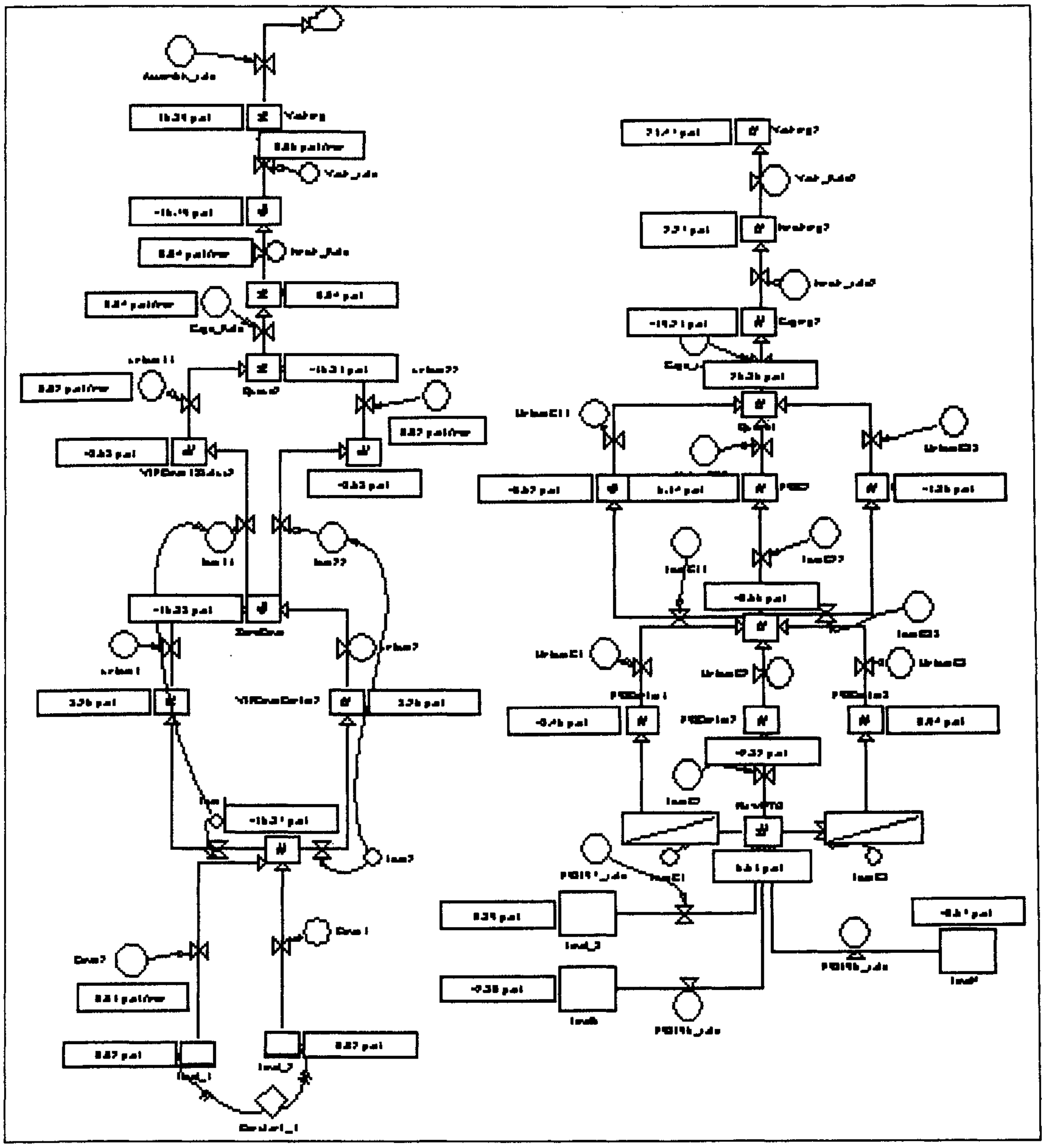

Figure B1. Complete system dynamic model

APPENDIX C

NOMENCLATURE FOR THE VARIABLES IN THE DYNAMIC SIMULATION MODEL

Table C1. Nomenclature for the variables in the Dynamic Simulation Model

Washing2	Cover parts in washing	PTOC3	PTO Part 197	PTO195_rate	Arrival Rate PTO195
Washing	PTO parts in washing	PTOC2	PTO Part 196	LoadC33	Loading Rate of Work Center 3 PTO's status 1
WIPCoverCenter2	WIP in Cover Center 2	PTOC1	PTO Part 195	LoadC3	Loading Rate of Work Center 3 PTO's status 2
WIPCover2Status2	WIP in Cover Center 2 with Status 2	UnloadC33	Unload rate for PTO Work Center 3	LoadC22	Loading Rate Work Center 2 Status 2
WIP Cover1Status2	WIP in Cover Center 1 with Status 2	Wash_Rate2	Washing Rate for PTO's	LoadC2	Loading Rate Work Center 2 Status 1
SemiPTO	PTO parts with Status 1	Wash_rate	Washing Rate for Covers	LoadC11	Loading Work Center 1 Status 2
WIPCoverCenter1	WIP Cover Center 1	load11	Loading rate for Work Center 1 Cover	LoadC1	Loading Work Center 1 Status 1
SemiCover	Cover Parts with Status 1	load22	Loading rate for Work Center 2 Cover	Load2	Loading Cover Status 1
RawPTO	PTO parts ready to process	unload1	Unloading rate for Work Center 1 Cover	Load1	Loading Cover Status 2
RawCover	Cover parts ready to process	UnloadC3	Unloading rate for Work Center 2 Cover	Gage_rate2	Gaging Rate
Queue2	Cover parts waiting for Gaging Station	UnloadC2	Unloading rate for Work Center 3 PTO	Finish_Rate	Finishing Rate for PTOs
PTOCenter3	PTO Work Center 3	UnloadC1	Unloading rate for Work Center 2 PTO	Finish_rate2	Finishing Rate for Covers
Queue1	PTO Parts waiting for Gaging Station	UnloadC11	Unloading rate for Work Center 1 PTO	Cover1	Cover Arrival Rate
PTOCenter2	PTO Work Center 2	PTO196_rate	Arrival Rate of PTO196	Assembly_rate	Assembly Rate
PTOCenter1	PTO Work Center 1	PTO197_rate	Arrival Rate of PTO197		

APPENDIX D

RESULTS FOR THE CAUSAL CORRELATION MODEL

Table D1. Correlation Values for the Dynamic Simulation Model

	PTC195	PTC196	PTC197	PTC1Utilizat	PTC1WIP	PTC295	PTC296	PTC297	PTC2Utiliz	PTC2WIP	PTC395	PTC396	PTC397	PTC3Utiliz	PTC3WIP
PTC195	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
PTC196	0.0010	1.0000	0.0069	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	-0.0313	0.0100	0.0100	0.0100	0.0100	-0.0098
PTC197	0.0010	0.0010	1.0000	-0.0123	-0.0376	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
PTC1Utilizat	0.0010	0.0010	-0.0123	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0071
PTC1WIP	0.0010	0.0010	-0.0376	0.0117	1.0000	0.0100	0.0100	0.0100	0.0100	0.0287	0.0100	0.0100	0.0439	0.0100	-0.0111
PTC295	0.0010	0.0010	0.0010	0.0117	0.0100	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	-0.0061
PTC296	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	-0.0104
PTC297	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0010
PTC2Utiliz	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100	-0.0070
PTC2WIP	0.0010	-0.0313	0.0010	0.0117	0.0287	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100	0.0100	0.0100	0.0100	0.0100
PTC395	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100	0.0100	0.0100	0.0083
PTC396	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100	0.0100	0.0071
PTC397	0.0010	0.0010	0.0010	0.0117	0.0439	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100	0.0211
PTC3Utiliz	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.0000	0.0100
PTC3WIP	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.0000
TimeC1C1	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0102
TimeC1C2	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0102
Cover1Utiliz	0.0010	0.0010	0.0010	0.0117	0.0100	0.0306	0.0100	0.0100	0.0100	-0.0278	0.0100	0.0100	0.0100	0.0100	0.0100
Cover1WIP	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
TimeC2C1	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
TimeC2C2	0.0010	0.0010	0.0010	0.0117	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Cover2Utiliz	0.0010	0.0010	0.0010	0.0117	-0.0302	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Cover2WIP	0.0010	0.0291	0.0010	-0.0410	0.0100	0.0298	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Prod195	0.0010	0.0100	0.0010	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
Prod196	0.0010	0.0100	0.0010	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0188	0.0100	0.0104	0.0106	0.0100	0.0311
Prod197	0.0010	0.0100	0.0010	0.0205	0.0100	0.0100	0.0293	0.0100	0.0306	0.0100	0.0100	-0.0053	-0.0057	0.0100	0.0100
PCover1	0.0010	0.0100	0.0010	-0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
PCover2	0.0010	0.0100	0.0010	0.0010	-0.0100	0.0100	0.0100	0.0100	0.0200	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100

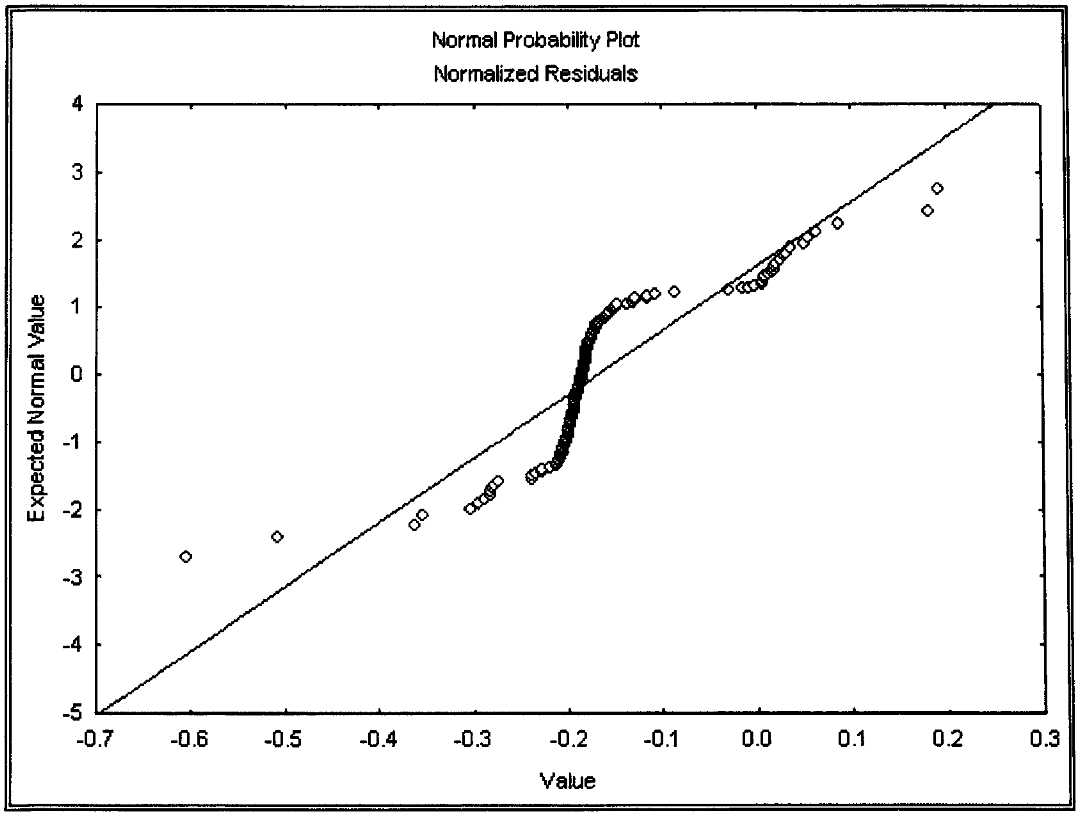

Figure D1. Normalized residuals for the processing times for the PTO parts.

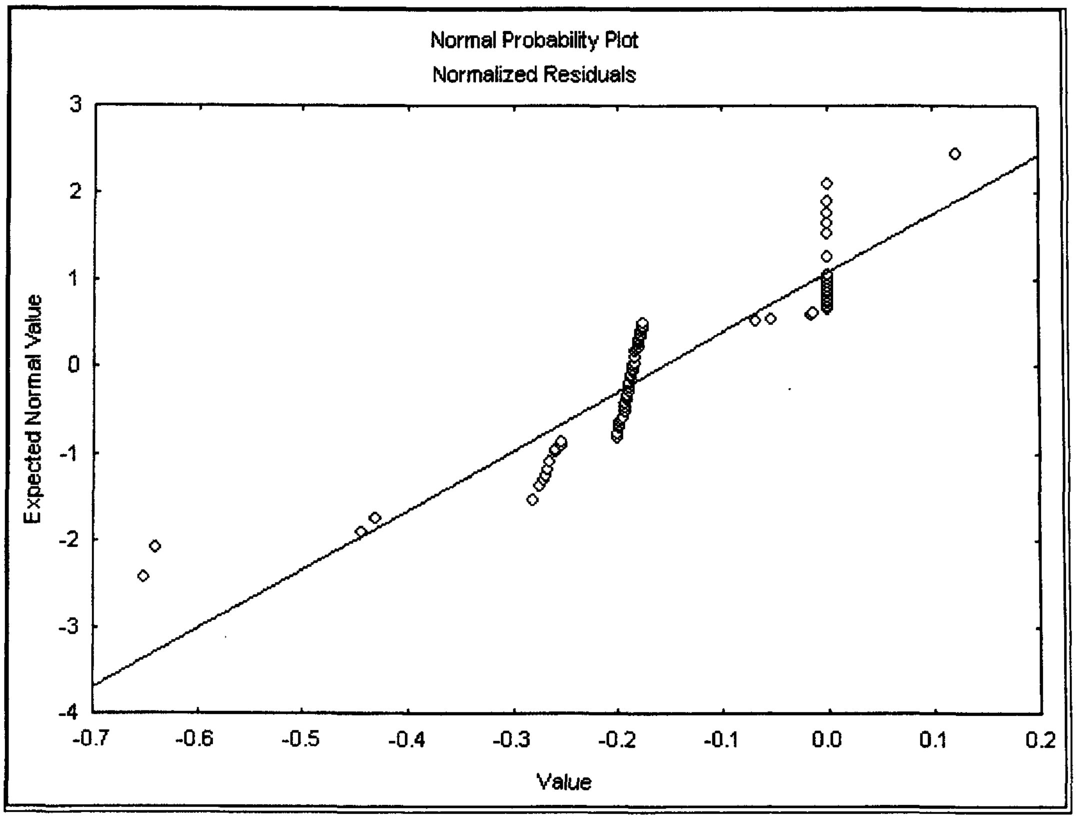

Figure D2. Normalized residuals for the processing times for the cover parts.

APPENDIX E

FINAL RESULTS FOR THE STRUCTURAL EQUATION MODELING MODEL

Table E1. *Final results for the structural modeling equation model*

Ridge Regression Summary for Dependent Variable: Prod196 (WAS FILE.sta)
I=.10000 R= .06942981 R^2= .00482050 Adjusted R^2= .00022059
F(23,4976)=1.0480 p<.39854 Std.Error of estimate: .09845

N=5000	Beta	Std.Err. of Beta	B	Std.Err. of B	t(4976)	p-level
Intercept			-1.05978	5.227899	-0.20272	0.839365
PTC195Time	0.014562	0.013500	0.01438	0.013334	1.07870	0.280772
PTC196	0.000868	0.013512	0.00086	0.013386	0.06421	0.948805
PTC197	0.004307	0.013508	0.00418	0.013113	0.31886	0.749849
PTC1Utilizat	0.002059	0.013503	0.19827	1.300233	0.15249	0.878808
PTC1WIP	0.002052	0.013524	0.00204	0.013454	0.15171	0.879418
PTC295Time	-0.016024	0.013512	-0.01561	0.013159	-1.18598	0.235688
PTC296	-0.016044	0.013508	-0.01570	0.013219	-1.18775	0.234987
PTC297	-0.013868	0.013496	-0.01372	0.013355	-1.02756	0.304206
PTC2Utiliz	-0.016477	0.013503	-0.00030	0.000247	-1.22021	0.222442
PTC2WIP	0.017091	0.013511	0.01699	0.013428	1.26498	0.205936
PTC395	0.003329	0.013497	0.00331	0.013427	0.24667	0.805172
PTC396	0.009127	0.013500	0.00890	0.013161	0.67604	0.499048
PTC397	0.008108	0.013516	0.01621	0.027020	0.59989	0.548607
PTC3Utiliz	0.017165	0.013503	0.01692	0.013313	1.27119	0.203722
PTC3WIP	0.028137	0.013493	0.02734	0.013112	2.08523	0.037100
TimeC1C1	0.005276	0.032369	0.00518	0.031778	0.16300	0.870528
TimeC1C2	0.005276	0.032369	0.00518	0.031778	0.16300	0.870528
Cover1Utiliz	-0.003820	0.013506	-0.00379	0.013397	-0.28282	0.777327
Cover1WIP	-0.029555	0.013499	-0.02884	0.013170	-2.18946	0.028610
TimeC2C1	0.002194	0.013498	0.00213	0.013128	0.16255	0.870879
TimeC2C2	-0.009077	0.013504	-0.00896	0.013329	-0.67222	0.501472
Cover2Utiliz	-0.019754	0.013507	-0.01953	0.013356	-1.46244	0.143684
Cover2WIP	0.009901	0.013517	0.00956	0.013055	0.73250	0.463895

*Note: The values in red represent those variables of the model used to construct the SEM model because their effect is significance at the P-level < 0.05.

(Table continues)

Table E1. *Final results for the structural modeling equation model*

	Variables currently in the Equation; DV: Prod196 (WAS FILE.sta) Ridge regression, lambda=.1000000						
Variable	Beta in	Partial Cor.	Semipart Cor.	**Tolerance**	R-square	t(4976)	p-level
PTC195Time	0.014562	0.015290	0.015255	1.097431	-0.097431	1.07870	0.280772
PTC196	0.000868	0.000910	0.000908	1.095393	-0.095393	0.06421	0.948805
PTC197	0.004307	0.004520	0.004509	1.096009	-0.096009	0.31886	0.749849
PTC1Utilizat	0.002059	0.002162	0.002156	1.096942	-0.096942	0.15249	0.878808
PTC1WIP	0.002052	0.002151	0.002146	1.093491	-0.093491	0.15171	0.879418
PTC295Time	-0.016024	-0.016810	-0.016772	1.095487	-0.095487	-1.18598	0.235688
PTC296	-0.016044	-0.016835	-0.016797	1.096105	-0.096105	-1.18775	0.234987
PTC297	-0.013868	-0.014565	-0.014532	1.098024	-0.098024	-1.02756	0.304206
PTC2Utiliz	-0.016477	-0.017295	-0.017256	1.096856	-0.096856	-1.22021	0.222442
PTC2WIP	0.017091	0.017930	0.017889	1.095547	-0.095547	1.26498	0.205936
PTC395	0.003329	0.003497	0.003488	1.097927	-0.097927	0.24667	0.805172
PTC396	0.009127	0.009583	0.009561	1.097326	-0.097326	0.67604	0.499048
PTC397	0.008108	0.008504	0.008484	1.094800	-0.094800	0.59989	0.548607
PTC3Utiliz	0.017165	0.018018	0.017977	1.096849	-0.096849	1.27119	0.203722
PTC3WIP	0.028137	0.029548	0.029489	1.098446	-0.098446	2.08523	0.037100
TimeC1C1	0.005276	0.002311	0.002305	0.190878	0.809122	0.16300	0.870528
TimeC1C2	0.005276	0.002311	0.002305	0.190878	0.809122	0.16300	0.870528
Cover1Utiliz	-0.003820	-0.004009	-0.004000	1.096447	-0.096447	-0.28282	0.777327
Cover1WIP	-0.029555	-0.031023	-0.030963	1.097606	-0.097606	-2.18946	0.028610
TimeC2C1	0.002194	0.002304	0.002299	1.097713	-0.097713	0.16255	0.870879
TimeC2C2	-0.009077	-0.009529	-0.009507	1.096784	-0.096784	-0.67222	0.501472
Cover2Utiliz	-0.019754	-0.020727	-0.020682	1.096153	-0.096153	-1.46244	0.143684
Cover2WIP	0.009901	0.010384	0.010359	1.094686	-0.094686	0.73250	0.463895

(Table continues)

Table E1. *Final results for the structural modeling equation model*

	Ridge Regression Summary for Dependent Variable: Prod197 (WAS FILE.sta I=.10000 $R=.06966199$ $R^2=.00485279$ Adjusted $R^2=.00025304$ $F(23,4976)=1.0550$ $p<.38968$ Std.Error of estimate: .09966					
N=5000	**Beta**	Std.Err. of Beta	B	Std.Err. of B	t(4976)	p-level
Intercept			-0.339344	5.292217	-0.064121	0.948876
PTC195Time	-0.002237	0.013499	-0.002236	0.013498	-0.165675	0.868420
PTC196	0.000733	0.013512	0.000735	0.013551	0.054239	0.956747
PTC197	-0.004792	0.013508	-0.004710	0.013275	-0.354784	0.722766
PTC1Utilizat	0.020035	0.013502	1.953045	1.316230	1.483818	0.137921
PTC1WIP	0.009823	0.013524	0.009893	0.013619	0.726371	0.467645
PTC295Time	-0.003950	0.013511	-0.003895	0.013321	-0.292367	0.770019
PTC296	0.027702	0.013508	0.027443	0.013381	2.050851	0.040334
PTC297	0.003342	0.013496	0.003348	0.013520	0.247661	0.804407
PTC2Utiliz	0.028058	0.013503	0.000520	0.000250	2.077936	0.037766
PTC2WIP	-0.001015	0.013511	-0.001021	0.013594	-0.075141	0.940105
PTC395	0.001190	0.013496	0.001198	0.013593	0.088135	0.929773
PTC396	-0.005067	0.013500	-0.005001	0.013323	-0.375360	0.707409
PTC397	-0.005248	0.013516	-0.010620	0.027352	-0.388285	0.697822
PTC3Utiliz	0.019465	0.013503	0.019427	0.013477	1.441539	0.149495
PTC3WIP	0.009055	0.013493	0.008907	0.013273	0.671049	0.502221
TimeC1C1	-0.005335	0.032369	-0.005302	0.032169	-0.164834	0.869082
TimeC1C2	-0.005335	0.032369	-0.005302	0.032169	-0.164834	0.869082
Cover1Utiliz	0.009011	0.013505	0.009049	0.013562	0.667247	0.504646
Cover1WIP	0.009435	0.013498	0.009319	0.013332	0.698986	0.484593
TimeC2C1	-0.011351	0.013498	-0.011176	0.013289	-0.840963	0.400409
TimeC2C2	-0.003152	0.013503	-0.003149	0.013493	-0.233418	0.815447
Cover2Utiliz	0.015920	0.013507	0.015935	0.013521	1.178591	0.238617
Cover2WIP	0.035633	0.013516	0.034841	0.013216	2.636279	0.008408

(Table continues)

Table E1. *Final results for the structural modeling equation model*

Variable	Beta in	Partial Cor.	Semipart Cor.	Tolerance	R-square	t(4976)	p-level
	Variables currently in the Equation; DV: Prod197 (WAS FILE.sta) Ridge regression, lambda=.1000000						
PTC195Time	-0.002237	-0.002349	-0.002343	1.097431	-0.097431	-0.165675	0.868420
PTC196	0.000733	0.000769	0.000767	1.095393	-0.095393	0.054239	0.956747
PTC197	-0.004792	-0.005029	-0.005017	1.096009	-0.096009	-0.354784	0.722766
PTC1Utilizat	0.020035	0.021030	0.020984	1.096942	-0.096942	1.483818	0.137921
PTC1WIP	0.009823	0.010297	0.010272	1.093491	-0.093491	0.726371	0.467645
PTC295Time	-0.003950	-0.004145	-0.004135	1.095487	-0.095487	-0.292367	0.770019
PTC296	0.027702	0.029061	0.029003	1.096105	-0.096105	2.050851	0.040334
PTC297	0.003342	0.003511	0.003502	1.098024	-0.098024	0.247661	0.804407
PTC2Utiliz	0.028058	0.029444	0.029386	1.096856	-0.096856	2.077936	0.037766
PTC2WIP	-0.001015	-0.001065	-0.001063	1.095547	-0.095547	-0.075141	0.940105
PTC395	0.001190	0.001249	0.001246	1.097927	-0.097927	0.088135	0.929773
PTC396	-0.005067	-0.005321	-0.005308	1.097326	-0.097326	-0.375360	0.707409
PTC397	-0.005248	-0.005504	-0.005491	1.094800	-0.094800	-0.388285	0.697822
PTC3Utiliz	0.019465	0.020431	0.020386	1.096849	-0.096849	1.441539	0.149495
PTC3WIP	0.009055	0.009512	0.009490	1.098446	-0.098446	0.671049	0.502221
TimeC1C1	-0.005335	-0.002337	-0.002331	0.190878	0.809122	-0.164834	0.869082
TimeC1C2	-0.005335	-0.002337	-0.002331	0.190878	0.809122	-0.164834	0.869082
Cover1Utiliz	0.009011	0.009459	0.009436	1.096447	-0.096447	0.667247	0.504646
Cover1WIP	0.009435	0.009908	0.009885	1.097606	-0.097606	0.698986	0.484593
TimeC2C1	-0.011351	-0.011921	-0.011893	1.097713	-0.097713	-0.840963	0.400409
TimeC2C2	-0.003152	-0.003309	-0.003301	1.096784	-0.096784	-0.233418	0.815447
Cover2Utiliz	0.015920	0.016706	0.016667	1.096153	-0.096153	1.178591	0.238617
Cover2WIP	0.035633	0.037346	0.037282	1.094686	-0.094686	2.636279	0.008408

(Table continues)

Table E1. *Final results for the structural modeling equation model*

N=5000	Ridge Regression Summary for Dependent Variable: ProdCover2 (WAS FILE.s l=.10000 R= .07185989 R^2= .00516384 Adjusted R^2= .00056552 F(23,4976)=1.1230 p<.30962 Std.Error of estimate: .09962					
	Beta	**Std.Err. of Beta**	**B**	**Std.Err. of B**	**t(4976)**	**p-level**
Intercept			2.112728	5.289908	0.39939	0.689624
PTC195Time	0.022040	0.013497	0.022032	0.013492	1.63294	0.102544
PTC196	0.008336	0.013510	0.008358	0.013545	0.61704	0.537234
PTC197	-0.019828	0.013506	-0.019480	0.013269	-1.46806	0.142151
PTC1Utilizat	0.016412	0.013500	1.599397	1.315656	1.21567	0.224170
PTC1WIP	-0.012247	0.013522	-0.012330	0.013613	-0.90576	0.365106
PTC295Time	-0.008354	0.013509	-0.008234	0.013315	-0.61840	0.536337
PTC296	-0.003557	0.013505	-0.003522	0.013376	-0.26334	0.792298
PTC297	-0.010173	0.013494	-0.010188	0.013514	-0.75389	0.450952
PTC2Utiliz	0.022569	0.013501	0.000418	0.000250	1.67169	0.094649
PTC2WIP	0.002160	0.013509	0.002173	0.013588	0.15993	0.872943
PTC395	-0.011048	0.013494	-0.011124	0.013587	-0.81872	0.412985
PTC396	0.005911	0.013498	0.005832	0.013317	0.43794	0.661450
PTC397	0.016750	0.013514	0.033889	0.027340	1.23953	0.215209
PTC3Utiliz	0.006891	0.013501	0.006876	0.013471	0.51043	0.609773
PTC3WIP	0.001360	0.013491	0.001337	0.013268	0.10079	0.919724
TimeC1C1	-0.007114	0.032364	-0.007068	0.032155	-0.21980	0.826032
TimeC1C2	-0.007114	0.032364	-0.007068	0.032155	-0.21980	0.826032
Cover1Utiliz	-0.006779	0.013503	-0.006805	0.013556	-0.50203	0.615672
Cover1WIP	0.022715	0.013496	0.022429	0.013326	1.68305	0.092427
TimeC2C1	-0.008480	0.013496	-0.008347	0.013283	-0.62839	0.529779
TimeC2C2	0.001284	0.013501	0.001283	0.013487	0.09510	0.924237
Cover2Utiliz	-0.021793	0.013505	-0.021808	0.013515	-1.61366	0.106665
Cover2WIP	-0.030874	0.013514	-0.030180	0.013210	-2.28458	0.022379

(Table continues)

Table E1. *Final results for the structural modeling equation model*

Variable	Variables currently in the Equation; DV: ProdCover2 (WAS FILE.sta) Ridge regression, lambda=.1000000						
	Beta in	Partial Cor.	Semipart Cor.	Tolerance	R-square	t(4976)	p-level
PTC195Time	0.022040	0.023143	0.023089	1.097431	-0.097431	1.63294	0.102544
PTC196	0.008336	0.008747	0.008725	1.095393	-0.095393	0.61704	0.537234
PTC197	-0.019828	-0.020807	-0.020758	1.096009	-0.096009	-1.46806	0.142151
PTC1Utilizat	0.016412	0.017231	0.017189	1.096942	-0.096942	1.21567	0.224170
PTC1WIP	-0.012247	-0.012839	-0.012807	1.093491	-0.093491	-0.90576	0.365106
PTC295Time	-0.008354	-0.008766	-0.008744	1.095487	-0.095487	-0.61840	0.536337
PTC296	-0.003557	-0.003733	-0.003724	1.096105	-0.096105	-0.26334	0.792298
PTC297	-0.010173	-0.010687	-0.010660	1.098024	-0.098024	-0.75389	0.450952
PTC2Utiliz	0.022569	0.023691	0.023637	1.096856	-0.096856	1.67169	0.094649
PTC2WIP	0.002160	0.002267	0.002261	1.095547	-0.095547	0.15993	0.872943
PTC395	-0.011048	-0.011606	-0.011576	1.097927	-0.097927	-0.81872	0.412985
PTC396	0.005911	0.006208	0.006192	1.097326	-0.097326	0.43794	0.661450
PTC397	0.016750	0.017569	0.017526	1.094800	-0.094800	1.23953	0.215209
PTC3Utiliz	0.006891	0.007236	0.007217	1.096849	-0.096849	0.51043	0.609773
PTC3WIP	0.001360	0.001429	0.001425	1.098446	-0.098446	0.10079	0.919724
TimeC1C1	-0.007114	-0.003116	-0.003108	0.190878	0.809122	-0.21980	0.826032
TimeC1C2	-0.007114	-0.003116	-0.003108	0.190878	0.809122	-0.21980	0.826032
Cover1Utiliz	-0.006779	-0.007117	-0.007098	1.096447	-0.096447	-0.50203	0.615672
Cover1WIP	0.022715	0.023853	0.023798	1.097606	-0.097606	1.68305	0.092427
TimeC2C1	-0.008480	-0.008908	-0.008885	1.097713	-0.097713	-0.62839	0.529779
TimeC2C2	0.001284	0.001348	0.001345	1.096784	-0.096784	0.09510	0.924237
Cover2Utiliz	-0.021793	-0.022870	-0.022816	1.096153	-0.096153	-1.61366	0.106665
Cover2WIP	-0.030874	-0.032370	-0.032303	1.094686	-0.094686	-2.28458	0.022379