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# SIMULATION INTELLIGENCE AND MODELING FOR MANUFACTURING UNCERTAINTIES

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## ABSTRACT

The realistic simulation modeling becomes very essential and effective for designing and managing of manufacturing systems, which needs to be addressed manufacturing dynamics. This research includes manufacturing uncertainties in the form of simulation intelligence to improve the system's performance in the high-mix low-volume manufacturing systems. It shows how simulation modeling can be used to evaluate alternative designs in a dynamic uncertain manufacturing environment. Fuzzy rule based machine, labor and logistics uncertainties are addressed in this study. A combination of product mix and production volume is analyzed using intelligent simulation model for an optimal designing of the production system to meet future customer demands. Intelligent knowledge system shows significant close to real-life scenario. The proposed intelligent simulation modeling is validated with real life application.

## 1 INTRODUCTION

In the 21st century high-mix low-volume manufacturing, competitive advantage is required to win the battle for customers in the global marketplace. During the past decade, the manufacturing industry has undergone a dynamic transformation. Recently, traditional manufacturers are inherently subject to high-mix, low volume manufacturing as a business model. Mahoney (1998) presented manufacturing operations to facilitate the management decision-making process in a high-mix low-volume manufacturing environment. Nagano (1999) presented real-time production control for low volume and high product mix manufacturing. Current trend of information technology as well as automation technology, companies are urging a solution to produce varieties of products with low volume as market demand is fast changing into it. Simulation has been commonly used to study behavior of real world manufacturing system to gain better understanding of underlying problems and to provide recommendations to improve the systems. To observe real manufacturing systems is very expensive and sometimes cumbersome. Therefore, a simulation model is an easier way to build up models for representing real life scenarios to identify bottlenecks, to enhance system performance in terms of productivity, queues, resources utilization, cycle times, lead time, etc. Azadeh (2000) develops an integrated simulation model for a heavy continuous rolling mill system and generates a set of optimum production alternatives. Choi (2002) discusses the initial efforts to implement simulation modeling as a visual management and analysis tool through the use of scenarios by varying the number of assembly machines and processing time. Altiparmak (2002) uses simulation metamodels to improve the analysis and understanding of decision-making processes of an asynchronous assembly system to optimize the buffer sizes in the system. Wiendahl (1991) uses the simulation tools in the field of assembly planning and due to different objectives of the different efforts in simulation, the tools are divided into the four-hierarchy classes assembly shop, cell, station and component. In lean manufacturing environments of advanced manufacturing systems, the flexible production line is designed to manufacture a variety of products in timely manner with minimal inventories. A large number of factors are critical in the effective operations of such flexible production lines including number of product options, manufacturing operation of each, product type, workstation capacity, processing time of the operations at each station, material handling capacity at each work station, and overall material handling capacity. This problem becomes more critical for high-mix low-volume manufacturing due to the changing needs in today's supply system. The challenges is due to the combinatorial nature of highly complicated constraints such as unpredictable machine breakdowns (machine dynamics), unavailability of human resources (labor dynamics), varying operational requirements (operation dynamics), schedule variation of logistics for material arrival and shipping (logistics dynamics), and unpredictable customer orders (demand dynamics), etc. The mentioned manufacturing dynamics are addressed in this research. The machine dynamics, the labor dynamics, the operational dynamics and the logistics dynamics are considered for better representation of the manufacturing behavior in the modeling. Three intelligent modules (labor, machine and logistics) using fuzzy rules are developed using Arena simulation to model real-life scenario.

The paper is organized as follows: Section 2 presents the manufacturing systems uncertainty where fuzzy rule based machine, labor and logistics intelligence are included into the simulation-modeling environment. Section 3 describes the problem statement and the simulation model development for base model, redesigned model and intelligent model. Section 4 is devoted to the validation of the proposed modeling in terms on throughput and cycle time and comparison of the proposed intelligent model with and without uncertainty consideration. The last part provides conclusions.

## 2 MANUFACTURING SYSTEMS UNCERTAINTY

The variation with in the systems, with in the operations are exist in manufacturing systems. Some variations are dependent and some are independent. The dependent variations are more critical to manage as it depends on various factors or sub-systems. Time varying (dynamic) behavior of factory floor is becoming a growing concern in today's competitive manufacturing environment. Forrester (1961) defines industrial dynamics as the study of the information-feedback characteristics of industrial activity to show how the decision and actions interact to influence the success of the enterprise. Lane (1997) precisely summarizes Forrester's approach and use computer simulation the means of inferring the time evolutionary dynamics endogenously. System dynamics has been applied to a wide range of problem domains. Sterman (1989) suggests that the decision-making process is dominated by locally rational heuristics due to the complexity of the system and time pressure. Industrial dynamics show how the decisions interact to influence the success of the enterprise. Interaction between system components can be more important than the components themselves. Dynamic model deals with time varying interactions. The close dynamic model is one that functions without connection to externally supplied variables that are generated outside the model. The close model can exhibit interesting and informative behavior without receiving an input variable from an external source.

Manufacturing flexibility is a difficult and multifaceted concept that because of its inherent complexity and fuzziness. Fuzzy logic offers a suitable framework for measuring flexibility in its various aspects, which deals with the measurement of machine flexibility. If the data and knowledge are not precise, fuzzy-logic modeling should be employed by transforming the human expertise into IF-THEN rules and membership functions. Uncertainty is handled by probability theory under the assumption that probabilities can be obtained precisely. Mandelbaum and Buzacott (1990) examine the meaning and use of flexibility in decision-making processes for real-world problems with increased complexity. Fuzzy modeling implication methods are used in a flexibility measurement methodology that is easy for a manager to interpret and use. Sethi and Sethi (1990) used flexibility for various types of machining operations in uncertain manufacturing environment and argued that it allows production with improvement. Yang and Peters (1998) proposed robust machine parameters over a rolling horizon planning time window. Human operator, expertise, analogy and intuition play a preponderant role in the piloting, the control and the decision-making in a production system characterized by uncertain environment. Li et. al. (1994) considered uncertain future demand, machine breakdowns, and processing time estimates, which cause any detailed schedule to become outdated, and the effects may propagate throughout the schedule, affecting product delivery dates. A fuzzy optimization is developed using lagrangian relaxation technique to evaluate the performance in a dynamic environment. Ramakrishnan and Wysk (2002) developed a real-time simulation-based architecture for deriving active control policies for manufacturing systems. Evans and Karwowski (1986) define labor dynamics of individual personalities prevail which is differing from machine dynamics. Aggarwal (1993) mentioned, the life time of the machine can be broken into five fuzzy time periods as "very new", "new", "normal", "old", "very old". An effective approach for scheduling considering uncertain arrival times, processing times, due dates, and part priorities which is based on a combined Lagrangian relaxation and stochastic dynamic programming (Luh 1999).

Fuzzy Logic can be useful in modeling and solving scheduling problems with uncertain processing times, constraints, and set-up times. The uncertainties can be represented by fuzzy numbers using the concept of an interval of confidence and integrated with other methodologies (e.g., search procedures, constraint relaxation). Slany (1994) stresses the imprecision of straightforward methods presented in the mathematical approaches and introduces a method known as fuzzy constraint relaxation, which is integrated with a knowledge-based scheduling system. His system was applied to a steel manufacturing plant. Grabot and Geneste (1994) use fuzzy logic principles to combine dispatching rules for multi-criteria problems. On the other hand, Krucky (1994) addresses the problem of minimizing setup times of a medium-to-high product mix production line using fuzzy logic. A realistic model in simulation is still under study. Most of the commercial simulation software does not provide the functionalities to include unexpected variations in the system, i.e., dynamics. So a combination knowledge-based-system for dynamics representation appears to be a promising approach for solving real-life problems such as manufacturing scheduling. Representing the objects, events, and major decision rules used will help make the model more understandable; this can also make the underlying model more robust and reactive by considering fuzzy rules to predict real situations. As realistic models of discrete event simulation are still under development to capture all static and dynamic information, an intelligent simulation model is proposed to represent a more realistic model and design optimal production requirements for product mix and dynamic scheduling systems, which may help the manager to make real-time operational decisions.

### 2.1 Uncertainly Representation

Machine uncertainty, labor uncertainly and logistics uncertainty are considered for simulation intelligence. Analogous to a real world dynamics can be constructed into two components. One component is in charge of physical entities as body while the other is concerned with controlling the activity and performance of the body; as brain. The brain accommodates the integrated mapping knowledge about the mapping field and the integrated inference mechanism to use the knowledge. The body encompasses an entity processing mechanism, feature set, and attribute set of the real-life element. This structure diagram is shown in Figure 1. The behavior of the body is controlled by the brain via feature set, while the brain uses the mapping knowledge to drive the feature value on the basis of attribute set from the body. Typical categorization of machine knowledge is shown in Table 1. For labor knowledge, feature set is considered as processing time, rejection rate, effectiveness, absentee, and physical attribute set is considered as skill, age, working environment, and workmanship respectively. For logistics knowledge, feature set is considered as supplier behavior profile, timely delivery, delivery time, cost, and physical attribute set is considered as commitment, network, and transportation.

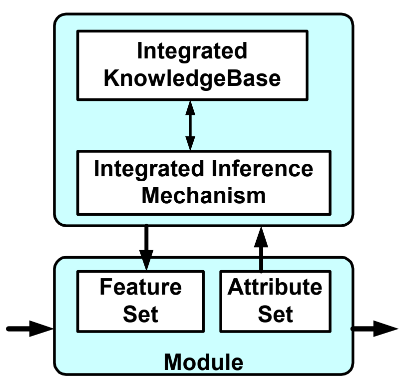


Figure 1: Structural Diagram of Module Design

Fuzzy membership functions are used for uncertainty representation. Five fuzzy sets are used to represent input (I) such as skill as VL (very low), L (low), M (middle), H(high), and VH (very high) and output (O) such as maintenance time. According to experience, fuzzy membership

Table 1: Intelligent Machine Configurations

| **Feature set** | **Feature value** | **Physical attribute set** | **Attribute value** |
|---|---|---|---|
| Time between failure | Very long<br>Long<br>Medium<br>Short<br>Very short | Machine life time | Very new<br>New<br>Medium<br>Old<br>Very old |
| Processing time | High<br>Medium<br>Low | Flexibility | Low<br>Medium<br>High |
| Setup time | High<br>Medium<br>Low | Flexibility | Low<br>Medium<br>High |
| Maintenance time | Short<br>Medium<br>Long | Maintenance labor | Skill<br>Ok<br>New |

functions are shown below.

$$F_{in} = \frac{I_1}{VL} + \frac{I_2}{L} + \frac{I_3}{M} + \frac{I_4}{H} + \frac{I_5}{VH}$$

$$F_{out} = \frac{O_1}{VL} + \frac{O_2}{L} + \frac{O_3}{M} + \frac{O_4}{H} + \frac{O_5}{VH}$$

where VL = Very low , L = Low, M = Middle, H = High, VH = Very High, $F_{in}$ = Input, $F_{out}$ = Output, $I_1$, $I_2$, $I_3$, $I_4$, $I_5$ = Fraction of input, $O_1$, $O_2$, $O_3$, $O_4$, $O_5$ = Fraction of output

It is obvious that there is some relationship between input (skill) and output (maintenance time). In a general way, if the demand is high, the supplier commitment will be high..

### 2.2 Simulation module design

A module in Arena is simply a modeling construct that is used to represent some components of a system. There are two types of modules: base modules and derived modules. Base modules are the lowest level modules in Arena and correspond directly to the SIMAN blocks and elements. Derived modules are built up from base modules. The logic of the module can be developed when the new resource or module is defined by using base blocks. A module has operands that define values associated with the module. The module creator defines the characteristics of each operand, including the position of the dialog box, user prompt, default value, permissible values, etc. The operands of a derived module may supply values for operands of its component modules from which it is constructed. Dialog boxes are forms that display parameter choices and solicit and accept input (Collins 1993). After building the derived modules, all modules are gathered in a template.

As a manufacturing system becomes more complex, more and more activities and behavior cannot properly be described by simply using fixed delay or random statistical distribution. Various types of knowledge are needed to represent the systems. System dynamics exists within the production scenario regardless of the change in time dependent or time independent. Conventionally, dynamics are represented as random variables. The dynamics' qualitative relation tendency to upper and lower bounds are known, but the quantitative relations are unknown. These types of dynamics are called fuzzy dynamics. The three dynamics will be considered for product mix and dynamic scheduling:.

### 2.2.1 Machine uncertainties

The machine dynamic behavior is the most important factor in manufacturing systems. The machine lifetime, breakdown conditions, maintenance, time between failures, time between repairs, and quality are necessary to address in order to improve the accuracy of simulation resources. Those must take into account fuzzy dynamics for a realistic scenario. A simulation resource is defined for machine dynamics in order to represent all behavior changes in the machine. The feature set and attribute set are used to represent above-mentioned issue. The key behavior and characteristics of the machine include past processing time, part rework rate, machine down time, and machine maintenance period. A feature may be time varying, state varying, or invariant parameter. The attribute set is a collection of the all-important information about a resource. Machine knowledge is defined with the range of machine life (Max-Min), reject number (Max-Min), fault time (Max-Medium-Min), etc. Machine fault times at different life spans are considered for machine fuzzy knowledge and the machine working state. Down time is the non-operating period when the machine is idle or under maintenance. Change-over time depends on the complexity of the product. Some products may require changes in the entire software program and fixtures while others may only be required to make modifications on program configuration. Maintenance period is the time spent for preventive maintenance activities. Maintenance has two possibilities: good or poor. If maintenance is good, then the fault time and reject number will be low. Otherwise, maintenance is poor, resulting in normal fault time and reject number. Further, maintenance time will depend on the worker's skill level. The machine dynamics configuration is done in the Arena simulation template-building environment. The dialog interface for simulation modeling of dynamic machine behavior is represented in Figure 2. The user can assign the desired parameter and choose different combinations of fuzzy sets for the machine configuration. This designed module could be also used as internal operations of any simulation modules where the behavior will act as a background.

### 2.2.2 Labor uncertainties

Labor dynamics are considered for better representation of the operator's performance on the shop floor. The technicians/operators are classified as skilled, medium, and normal. The working environment is also another factor for labor dynamics. The working environment is considered as good, okay and poor. The absentee rate is also another factor in shop floor assembly systems. The absentee rate is considered as long, medium, or short. The age of the operator/technician also affects the operation. Maintenance technician skill levels are also considered for non-fuzzy knowledge. The satisfaction of the operation gives them encouragement to do the right job at the right time. The labor dynamics operand window is shown Figures 3.

### 2.2.3 Logistics uncertainties

The behavior/pattern of the suppliers and customers affects logistic decisions. Inbound and outbound logistics are needed for capturing upstream and downstream logistics dynamics. The delivery pattern, routing, and priority are set into the model. The service level will be set as a specific level for a different group of customers and suppliers.

## 3 VALIDATION

Validation is necessary to show that the proposed model has the acceptable level of confidence in the performances. Validation is also concerned with whether the proposed model is indeed an accurate representation of the real system. There are several ways to validate the model. Balci (1989) shows how to assess the acceptability and credibility of simulation results. If the interval is too large, the model might not show real representation. Statistical methods are used to check for accuracy of results. There are a few goodness-of-fit tests, such as the chi-square *t*-test, which could be applied to fit distribution. A t-test validation technique is used to see whether the proposed simulation model shows significant improvement or not. Comparison between the actual throughput and the simulated one is used for the proposed model validation. The cycle time comparison is done, which also proves the validity of the intelligent simulation model.

### 3.1 Capacity Comparison

Because the operation sequence of each product is different and operation time is different, the production capacity of the system varies. Thus the capacity of each product is identified first for product mix and production volume. We assume four different types of power drive products and consider a typical sequence for those products, and identifying each capacity per day. A steady-state system is identified first to eliminate initial bias. All replications are run for an equivalent of 80 hours of production. The data from the simulation model is gathered from the consecutive 10 replications of 16 hours (double shift), 80 hours (weekly, double shift) and 500 hours (yearly, double shift). The replications can be identified to obtain a satisfactory confidence interval for the power drive cases. Figure 4 presents the throughput of the different scenarios of power drive assembly systems. The output has improved significantly from scenario 1 to scenario 6, since the bottleneck station has been identified and balanced by adding one station and reorganized material management systems. By improving material management systems, the non-value-added time is reduced, which leads to improvement in the operation time. The improvement of

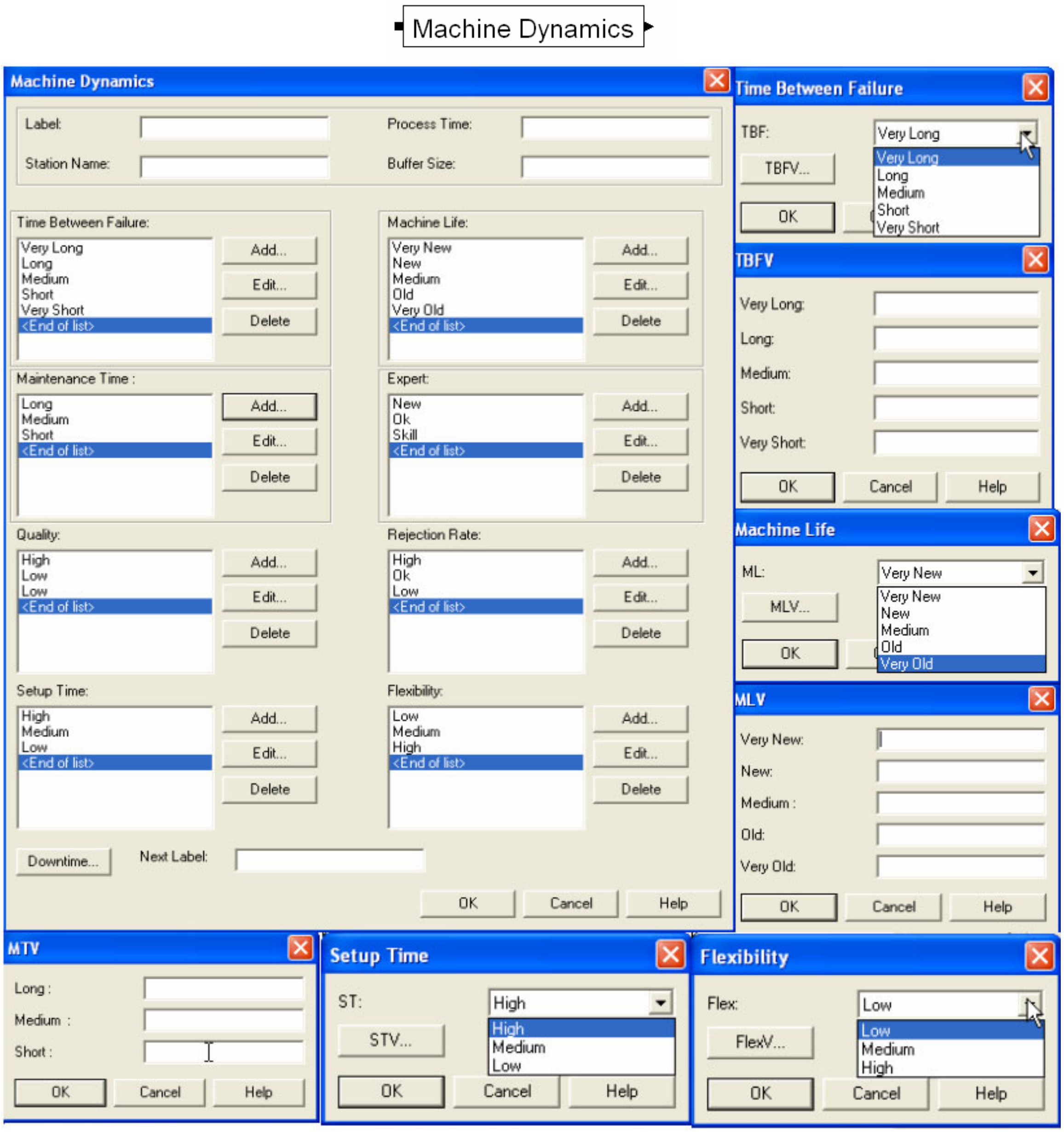


Figure 2: Machine Dynamics Configuration

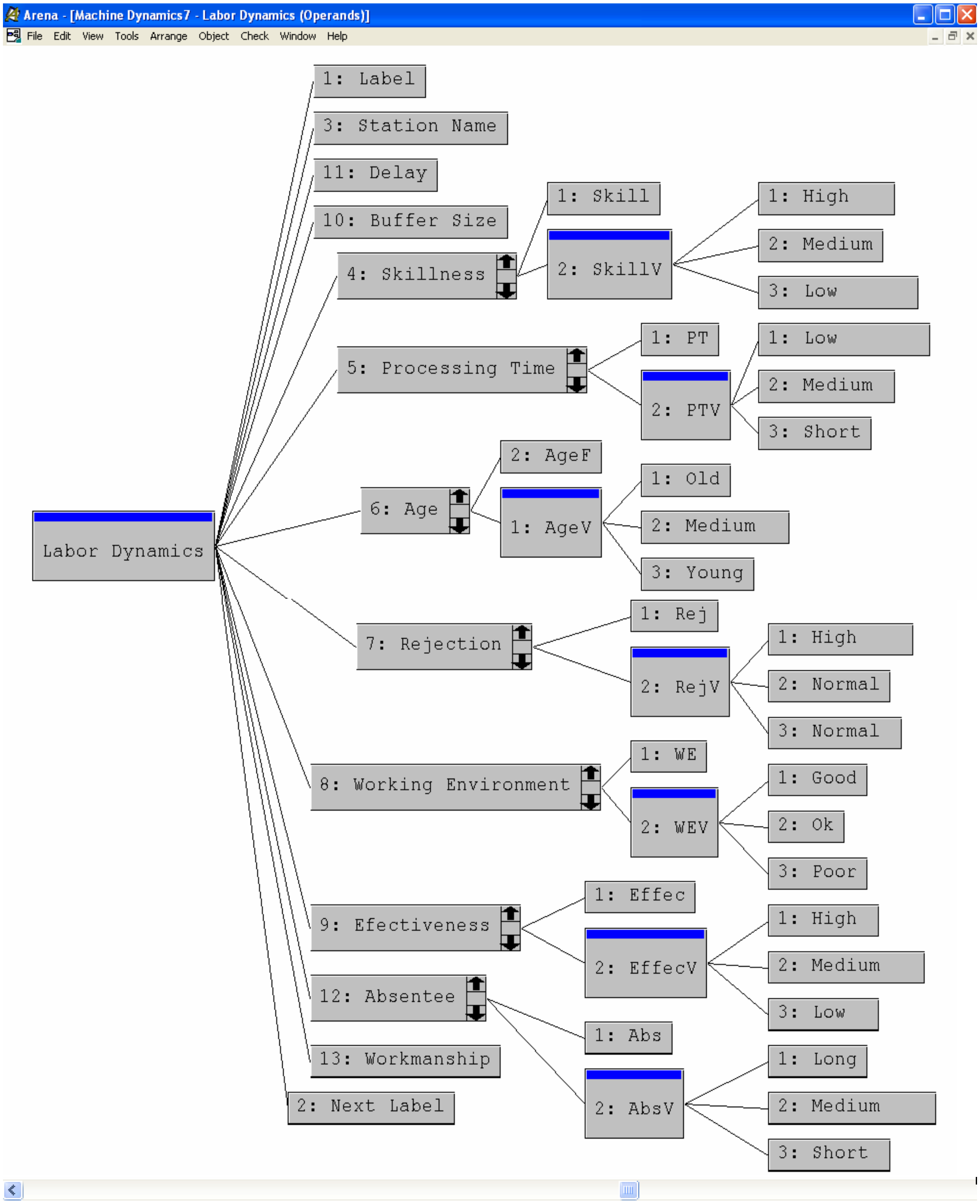


Figure 3: Labor Dynamics Operand Window

throughput is found after using the proposed model strategy, which represents a more realistic scenario, and eliminating the bottleneck of the systems. The capacity of the production line is set into a database. If the environment of the assembly systems changed, the model could be run to get new or modified capacity and revise the production scheduling. In this way, we can get real-time capacity status for the power drive assembly. If any new product comes, it can be identified from the flow sequence, then it can easily be modeled from the proposed power drive modeling systems to analyze the system to get better performance and identify how to fit into the existing assembly line to identify the capacity level for that particular product. The simulation model is a tool to do the "what if" analysis. A similar analysis is done for three production scenarios to identify the optimal buffer size to meet the expected future customer's need.

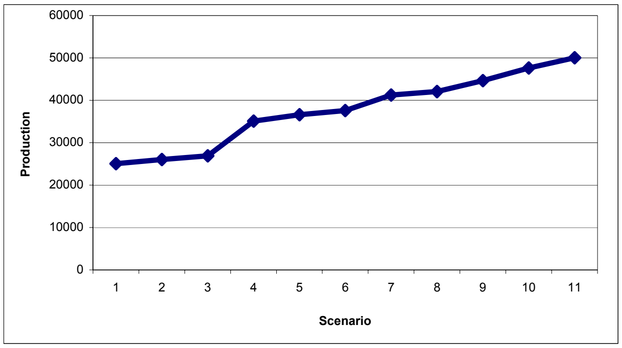


Figure 4: Annual Production Comparison

## 3.2 Throughput

The throughput validation has been done through statistical analysis. A paired t-test is considered to test the difference between the real-life throughput and the simulated throughput. The production throughput of the power drive is used to compare the results of the actual, proposed simulation with and without dynamics consideration. The simulation environment is also used in the same scenario, including machine and labor dynamics. The production environment is considered for four weeks (one month), each week for five days, and each day for two shifts for throughput validation purposes. A degree of confidence level must also be considered for the analysis. A 95% confidence interval is considered for throughput and cycle time analysis. The sample mean of the difference is 42.7. The sample variance is 17642. The sample standard deviation is 132.8. The test statistic is 1.017. The t distribution critical value for 9 degrees of freedom and a 95% confidence interval is 2.262. From the t-test, the calculated value of the test statistic is t = 1.017 and the t distribution critical value is $t_{9,0.025} = 2.262$. As the calculated value of the test statistic is less than the t distribution critical value ($t < t_{9,\ 0.025}$), the result falls within the 95% confidence interval. Since the calculated value of the test statistic does not fall in the rejection region, we do not reject it. Thus, data does not present sufficient evidence to indicate that the results can be rejected. The confidence interval of throughput is $851.2 < \mu < 892.4$. The confidence interval for actual throughput is $702.3 < \mu < 955.9$. The actual data range is high, because sometimes one week's production is counted in another week, and there is variation in customer orders and systems. The t-test for simulated output and actual output falls within the confidence interval. Thus, the model does have an accuracy level to indicate that it is valid.

Comparison of the model with and without uncertainty is considered. The sample mean of the difference is 15.6. The sample variance is 751.6. The sample standard deviation is 27.42. The test statistic is 1.799. The t distribution critical value for 9 degrees of freedom and 95% confidence interval is 2.262. From the t-test, the calculated value of the test statistic is t = 1.799 and t distribution critical value $t_{9,\ 0.025} = 2.262$. Since the test statistic for *t* with 9 degrees of freedom, with *n* = 10, is 1.799, the calculated value is 1.799 < 2.262. This means that there is no significant difference between the cases. As the calculated value of the test statistic is less than the t distribution critical value ($t < t_{9,\ 0.025}$), the result falls within the 95% confidence interval. Since the calculated value of the test statistic does not fall in the rejection region, there is no sufficient evidence to reject the result. The confidence intervals of throughput for the simulation model with dynamics and without dynamics are $815.2<\mu<897.2$ and $815.2<\mu<851.1$, respectively. The t-test for simulated output and actual output falls within the confidence interval. Thus, the both models do have an accuracy level to indicate that they are valid. The t-distribution is considered to check the confidence level of the simulation output without considering dynamics. The sample mean of the simulated throughput without dynamic consideration is 871.8. The sample variance is 424.18. The sample standard deviation is 20.6. The test statistics is 6.56. From the calculation, it is found that the test statistics value is 6.56. The sample mean of the throughput with dynamic consideration is 856.2. The sample variance is 865.29. The sample standard deviation is 29.42. The test statistics is 2.91. From the t-test, the calculated value of the test statistic is $t_1 = 6.56$ without dynamics and $t_2 = 2.91$ with dynamics. As the calculated value of the test statistic ($t_2$) of with dynamics is less than the calculated value of the test statistic ($t_1$) without dynamics ($t_2 < t_1$), the dynamic results are closer to real systems. Initially we have found that the simulated results validated the real systems, while the later part shows the dynamic model is a closer representation of the actual systems.

## 3.3 Cycle Time

The cycle time comparison is done both with dynamics and without dynamics in the model scenario. It is found that balancing the line and dynamics consideration significantly impacts the cycle time scenario. Figure 5 represents the cycle time variation without dynamics and line balancing. Figure 6 depicts the cycle time scenario with the consideration of dynamics and line balancing. It can be easily identified from the figures that the cycle time variation in Figure 5 is much higher than in Figure 6. After line balancing and dynamic consideration, cycle time becomes more stable.

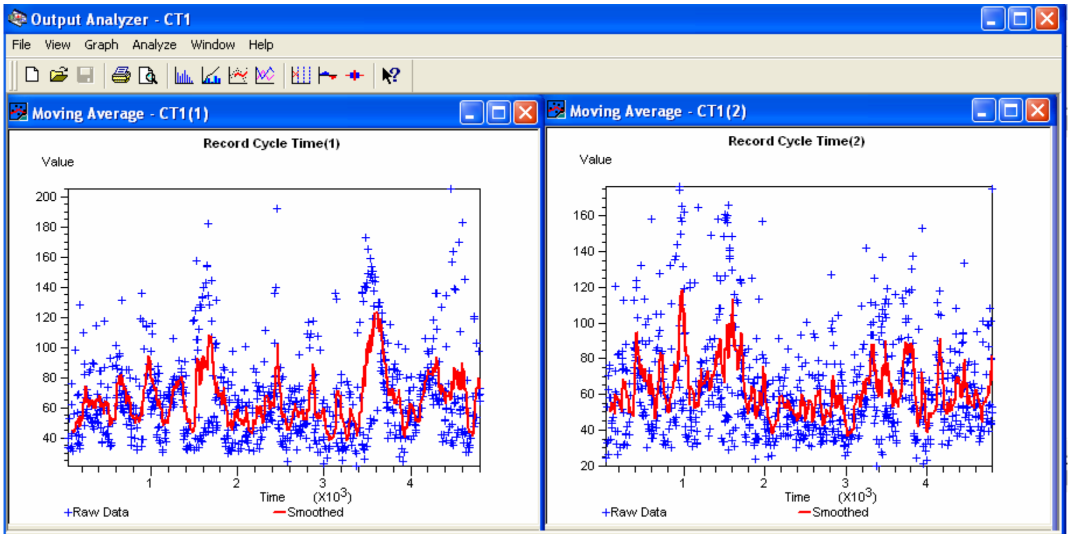


Figure 5: Cycle Time Variation without Uncertainties and Line Balancing

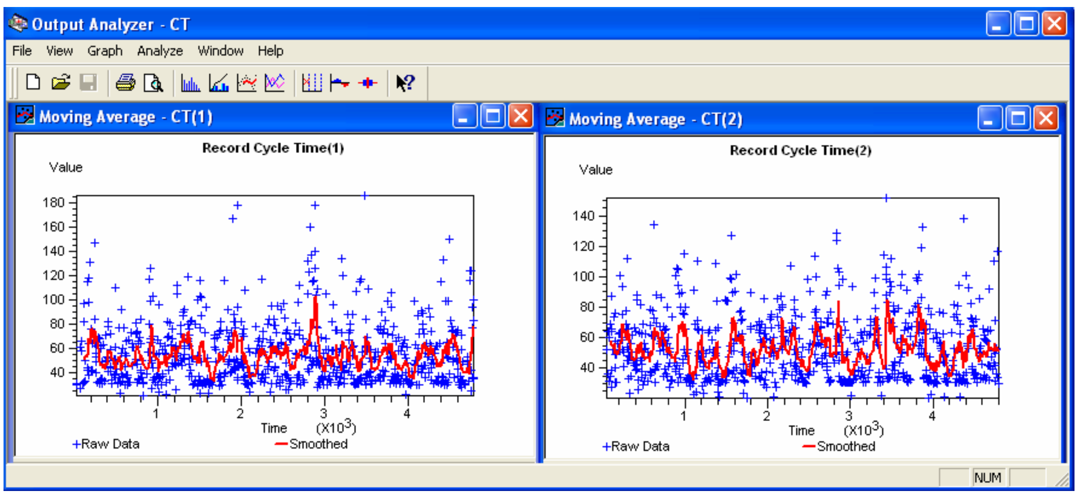


Figure 6: Cycle Time Scenario with Uncertainties and Line Balancing

## 4 CONCLUSIONS

Simulation intelligence for manufacturing uncertainties is represented in this research. Intelligent simulation modules are developed to represent factory floor dynamics for labor and machine dynamics Fuzzy-rule-based systems are used for uncertainty representation. This proposed modeling technique would improve the modeling accuracy in terms of more realistic presentation of all activities. As knowledge acquisition and representation will be used to acquire the knowledge for better representation of the manufacturing scenario in the model. Using those intelligent modules, the intelligent simulation models are constructed in such a way that each model investigates dynamic performance of the overall system. Thus the work develops an intelligent modeling tool in simulation, where the user can build up a more realistic model to identify bottlenecks and enhance system performance in terms of productivity, queues, and work in process (WIP) as well as cycle time. A base model and a reconfigured/redesigned model are developed to compare the performances such as capacity, utilization, queue, etc. the models show significant improvement in reconfigurable/redesigned systems. The best satisfaction of the production requirements is identified. An optimal buffer size also identified for the production requirements. Throughput and cycle time validation are done for the proposed modeling to show the significant improvement. A real-life case study of power drive assembly system is considered to validate the proposed approach. The work of this research study may be extended with real-time integration of the factory floor as well as to add more features to handle uncertainty, and give more numerical examples, which may lead to building more robust systems.

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