International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 02 - Issue 06 || June 2016 || PP. 59-78

Simulation Framework for Manufacturing Systems with complex material Handling

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Abstract: This paper addresses the problem of manufacturing systems and their associated sub-assemblies and/or raw materials. A manufacturing system is a set of policies that monitors and controls finished products and raw materials. It determines how much of each item should be manufactured or be kept in warehouses, when low items should be replenished, and how many items should be assembled or be ordered when replenishment is needed.

Practical manufacturing systems rarely optimize or even represent very precise descriptions of realistic situations. The art of model design is to develop commonsense approximations that give enough information to facilitate managerial decision making. A system with a high degree of intelligence is more robust and able to perform better performance in terms of lower cost and higher efficiency.

The integration concept of manufacturing processing has enjoyed increased popularity among researchers and manufacturers. Integrated manufacturing system is a set of mathematical models and policies that monitors and controls raw items, subassemblies, and finished products. Although such systems provide a better utilization of resources they have a number of drawbacks due to the complexity of real-world problems. Using intelligent simulation techniques will lead to better automated systems.

The framework allows the complex simulation model to be manageable for the purpose of adaptation to the changing environment variables. Moreover, the framework employs a material handling request-driven approach in order to implement both push and pull flows of production loads. The framework performed a steady state simulation to furnish top management with a clear understanding of the cost associated with warm up period. The steady state simulation also provides top managements with clear picture of how to make their production line more efficient in terms of profits as well as enabling to remove any processes that are overly complicated.

Keywords: manufacturing, raw material, discrete simulation, finished product, optimality, constraints, intelligent techniques, warm-up.

1. Introduction

Before starting the discussion of manufacturing systems and how a simulation framework can handle such systems, one needs to introduce a number of terms including modeling. A model may be viewed as a representation of real life activities while a system can be viewed as a section of reality. A common property of all physical systems is that they are composed of components interacting with one another. The physical laws that govern their behavior determine the nature of the interactions in these systems.

A system, in our case, is an organized group of entities such as people, equipment, methods, principles, and parts, which come together and work as one unit. A simulation model characterizes a system by mathematically describing the responses that can result from the interactions of a system’s entities. The set of values of variables in a system at any point in time is called the state of the system at that point in time.

In this paper, we suggest a framework that allows for the simulation-based performance assessment of complex manufacturing systems with Automated Material Handling Systems (AMHS). A simulation may be performed through solving a set of equations (a mathematical model), constructing a physical model, staged rehearsal, games such as war games, or a computer graphics model. simulations are very useful tools that allow experimentation without exposure to risk, they are gross simplifications of the reality because they include only a few of the real-world factors, and are only as good as their underlying assumptions.

Therefore, we consider a coupling architecture that connects simulation models of the manufacturing base system and the AMHS with a shop-floor control system. The center point of this architecture is a blackboard-type data layer between the shop-floor control system and the two simulation engines. We provide detailed information on how the different subsystems communicate and how each system triggers events of the other systems. We show by means of a case study how this framework supports the required performance assessment [1].

Simulation in manufacturing systems is defined as a planned system that enables a computer model of any manufacturing system to analyze and obtain important information from it. However, their use has been limited due to the complexity of some software packages and the lack of preparations that users have in the field of probability and statistics. This technique represents a valuable tool used by engineers when evaluating the effect of capital investment in equipment and physical facilities like factory plants, warehouses, and distribution centers. Simulation can also be used to predict the performance of an existing or expected system and to compare alternative solutions for a particular design problem [2].

In order to have clear picture of the underlying framework, one need to express the simulation system state as a collection of variables, stochastic that can change randomly, and deterministic that is not influenced by probability. The variables represent all the necessary information required to describe a system at any point in time.

In simulation system, a discrete event is an instantaneous action that occurs at a unique point in time. A part arriving at a delivery dock, a customer arriving at a bank, and a machine finishing a cycle of production are examples of discrete events. A continuous event continues uninterrupted with respect to time. The temperature of water in a lake raising and lowering during a day, the flowing of oil into a tanker, and chemical conversions are simple examples [3]. Simulation has been a widely used tool for manufacturing system design and analysis for more than three decades. During this period, simulation has proven to be an extremely useful analysis tool **[**4].

Agent technology has also been recognized as a promising paradigm for next generation of manufacturing systems. Researchers have attempted to apply agent technology to manufacturing enterprise integration, enterprise collaboration (including supply chain management and virtual enterprises), manufacturing process planning and scheduling, shop floor control, and to manufacturing paradigms as an implementation methodology **[5]**.

2. Steady State and Background

A steady state simulation implies that the System State is independent of its initial start-up conditions. The discussion of the steady state simulation supports our work by providing a clear understanding of cost associated with manufacturing plant through the practical understanding of warm up period. The steady state simulation also will provide top managements with clear picture of how to make their production line more efficient. Steady state experiments help making production line more efficient by remove any processes that are overly complicated.

A steady state simulation is essential needed to show any inconsistencies in the environment of manufacturing process. For example, steady state will furnish top management with sufficient items of information regarding the efficiency and skill of their employees and whether they properly trained in order to maximize efficiency on the production line. The steady state simulation will confirm that the better trained your employees are the better they will be able to do their jobs productively and effectively. This step alone could increase the efficiency of your production process and make your manufacturing plant more profitable.

Analyses of manufacturing models based on output data generated the steady state conditions are achieved. Figure 1 shows a simple C++ program simulating die values. Figures 2, 3, and 4 below show that die values remain at 3.5 approximately.

```
Main ()
{
  srand(time(0));
  double sum ; long int  C, Iter, freq[arraysize];
  for (  C = 100; C<= 1000000; C*=1.5){
        sum = 0; for(int j=1; j<=6; j++) freq[j] = 0;
        for( long int roll = 1; roll <= C; roll++) ++freq[1+ rand()%6];
        for(int i = 1; i <= 6; i++ ) sum += freq[i]*i;
    cout << C<<'\t'<<sum/C<<endl;
  }
}
```

Figure 1: simulation of die values

We run the piece of code in figure 1 a number of times as described in the following experiments

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www.ijlret.com || Volume 02 - Issue 06 || June 2016 || PP. 59-78

Experiment 1: In this experiment, we run the program a number of times with initial value = 100 and final value = 1000000 and increment calculated as C = C * 1.5. Averages of iterations of the outer loop are computed. The x-axis represents iteration numbers. Averages are graphed in figure 2.

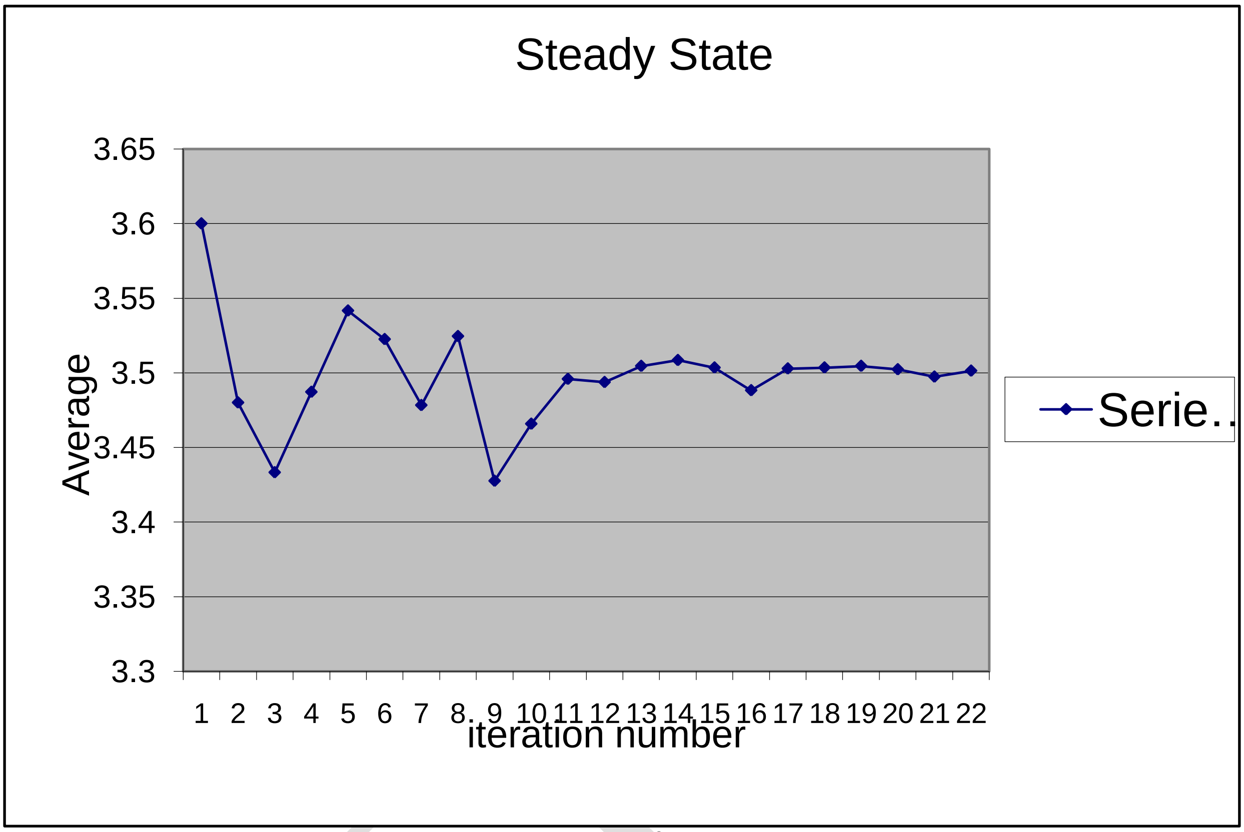

Figure 2: Output of experiment 1

Experiment 2: In this experiment, we run the program a number of times with

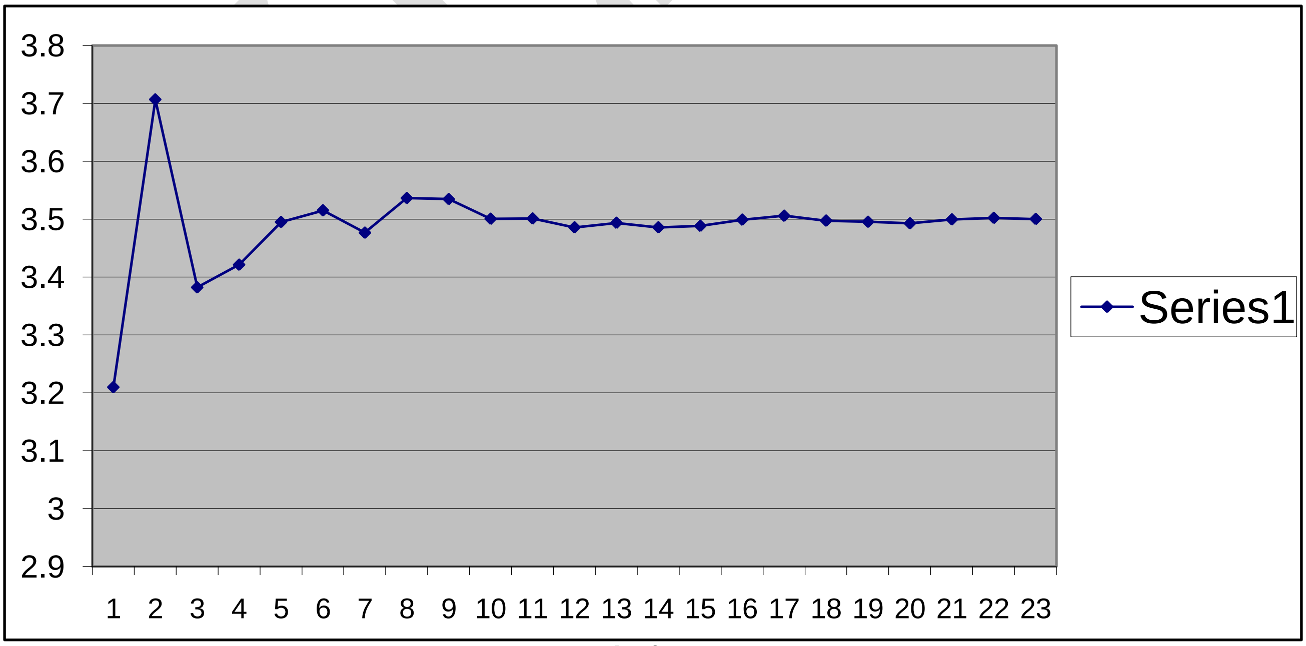

Figure 3: Graph of experiment 2

different initial and final values. Averages of iterations of the outer loop are computed. The x-axis represents iteration numbers. Averages are graphed in figure 3.

Experiment 3: This experiment is similar to the above two experiment except that the initial, final, and increment values are different. Output of this experiment is drawn in figure 4.

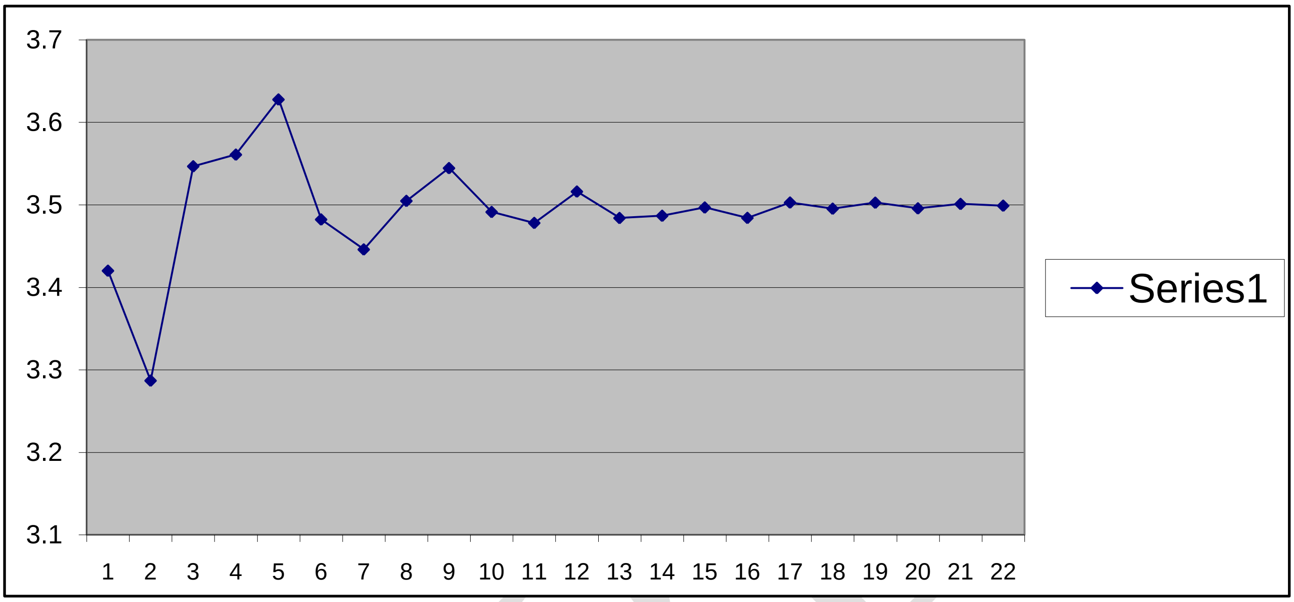

Figure 4: Graph of experiment 3

A terminating simulation runs for a predetermined length of time or until a specific event occurs. Analyses and conclusions are based on output values produced at the stopping point. The results of terminating simulation are usually dependent upon the initial values and quantities used when starting the model. The start-up condition should accurately reflect start-up circumstance exhibited in the real world system, which is being studied. The decision to employ a steady state or terminating simulation is made during the preliminary planning strategies of a simulation protect.

Warm-up period is the amount of time that a model needs to run before statistically data collection begins. Model verification is the operation of the model in its intended manner. Consider a system consisting of a conveyor feeding parts to a machine. A simulation model is developed to analyze parts queuing on the conveyor.

The model can be deemed verified when it reflects the following conditions.

1. Parts arrive at a desired rate.
2. Parts serviced at a desired rate.
3. Parts queued are counted correctly.

Model validation implies that the results generated coincide with the results produced by the system being represented by the model. Sometimes simulation is used to analyze theoretical systems, which do not physically exist. Model validation is not possible prior to hypothesis testing. In these cases, model builders must rely on system experts to establish the reasonableness of the results. Model verification becomes a major element for establishing rational validity.

Random number stream is a sequence of random numbers where each succeeding number is calculated from the previous one. The initial number is referred as the *random number seed*. Random number with values between zero and 1 play an important role in extracting values from probability distributions. Model runs a model run involves operating a simulation for a specified period of time with a unique set of random values. An independent Model replication entails operating the same model for the same period of time with a different set of random values. Multiple model replications are always required when analyzing results from a stochastic simulation.

In previous paragraphs a number of experiments have been conducted. The experiments are based on computerized mathematical technique that allows researchers to account for risk in quantitative analysis and decision making. The technique is used by professionals in such widely disparate fields as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transportation, and the environment. The simulation experiments furnish the decision-makers with a range of possible outcomes and the probabilities they will occur for any choice of action. They can extend to show the extreme possibilities along with all possible consequences.

From experience with the above experiments, one can derive techniques that can be exploited to model human reasoning in order to model the intangible aspects of a system. Such simulation techniques can reduce subjective decisions and increases the potential for real-time automation [8]. They have capabilities for assisting, constructing, and maintaining simulation system. They allow human expertise to be coded for future use in inference mechanism. They help organize manufacturing processes and produce a flexible system based on a set of manufacturing rules [9].

The current available tools and techniques for solving manufacturing problems have a number of drawbacks such as large integer problems and an inefficient implementation with some interfacing obstacles [9]. They require sufficient items of information of the specified domain [10].

The framework embodies a dynamic system where the raw materials are not known in advance. Hence, the system should provide alternatives for different criteria. That is, different types of raw materials, different number of identical raw materials used in the manufacturing of sub-assemblies and/or finished manufactured products.

Today's manufacturing and business systems are complex and encompassing many different sub-systems such as production process, sub-assembly, material handling, material storage, shop floor control, and order release. The manufacturing systems in today's world are so complex that attempting to capture descriptions from a single domain expert or from any one point of view cannot be guaranteed to be complete. In most organizations, different domain experts are involved in designing, implementing, and maintaining the different systems and sub-systems**.** Accountability is key issue in manufacturing industries. One need to encapsulate items of information associated with each step of the manufacturing process to carry a history with raw material, sub-assembly, floor work, finished products, departments, storage, time required, number of items and even the plan for manufacturing a unit. This accountability is considered a reference for future follow ups and future improvements or we may call it knowledge collection or representation.

Knowledge collection from disparate sources, model building validating, challenging tasks of large-scale simulation modeling and multiple-scenario simulation runs to find best solutions are generally distributed between several specialized tools. Because manufacturing and business systems are complex systems encompassing many different sub-systems and because different domain experts are involved in designing, implementing, and maintaining the different sub-systems, it is becoming imperative that descriptions from different domain experts are captured, stored, integrated with data from legacy information systems and used to design multiple simulation models of the enterprise systems. This paper presents the concept and a framework for capture and maintenance of multiple descriptions and its applicability in manufacturing systems modeling and simulation [18].

The design of manufacturing systems is a complex and critical activity entailing decisions with an impact on a long time horizon and a major commitment of financial resources. Indeed, the modeling, simulation and evaluation of manufacturing systems are relevant activities both in the design and the operational phases of an industry [19].

The most important objective of simulation in manufacturing is to understand the change to the whole system since it is easy to understand the difference made by changes in the local system but it is hard or impossible to assess the impact of this change in the overall system. Simulation gives us some measures and analysis of such impact:

- Parts produced per unit time
- Time spent in system by parts
- Time spent by parts in queue
- Time spent during transportation from one place to another
- In time deliveries made
- Build up of the inventory
- Inventory in process
- Percent utilization of machines and workers.

Some other benefits include Just-in-time manufacturing, calculation of optimal resources required; validation of the proposed operation logic for controlling the system, and data collected during modeling that may be used elsewhere.

The following is an example: In a manufacturing plant one machine processes 90 parts in 9 hours but the parts coming to the machine in 9 hours is 140. So there is a buildup of inventory. This inventory can be reduced by employing another machine occasionally. Thus we understand the reduction in local inventory buildup. But now this machine produces 140 parts in 9 hours which might not be processed by the next machine and thus we have just shifted the in-process inventory from one machine to another without having any impact on overall production

Simulation is used to address some issues in manufacturing as follows: In workshop to see the ability of system to meet the requirement, to have optimal inventory to cover for machine failures. Figure 5 shows the use of simulation in manufacturing [6].

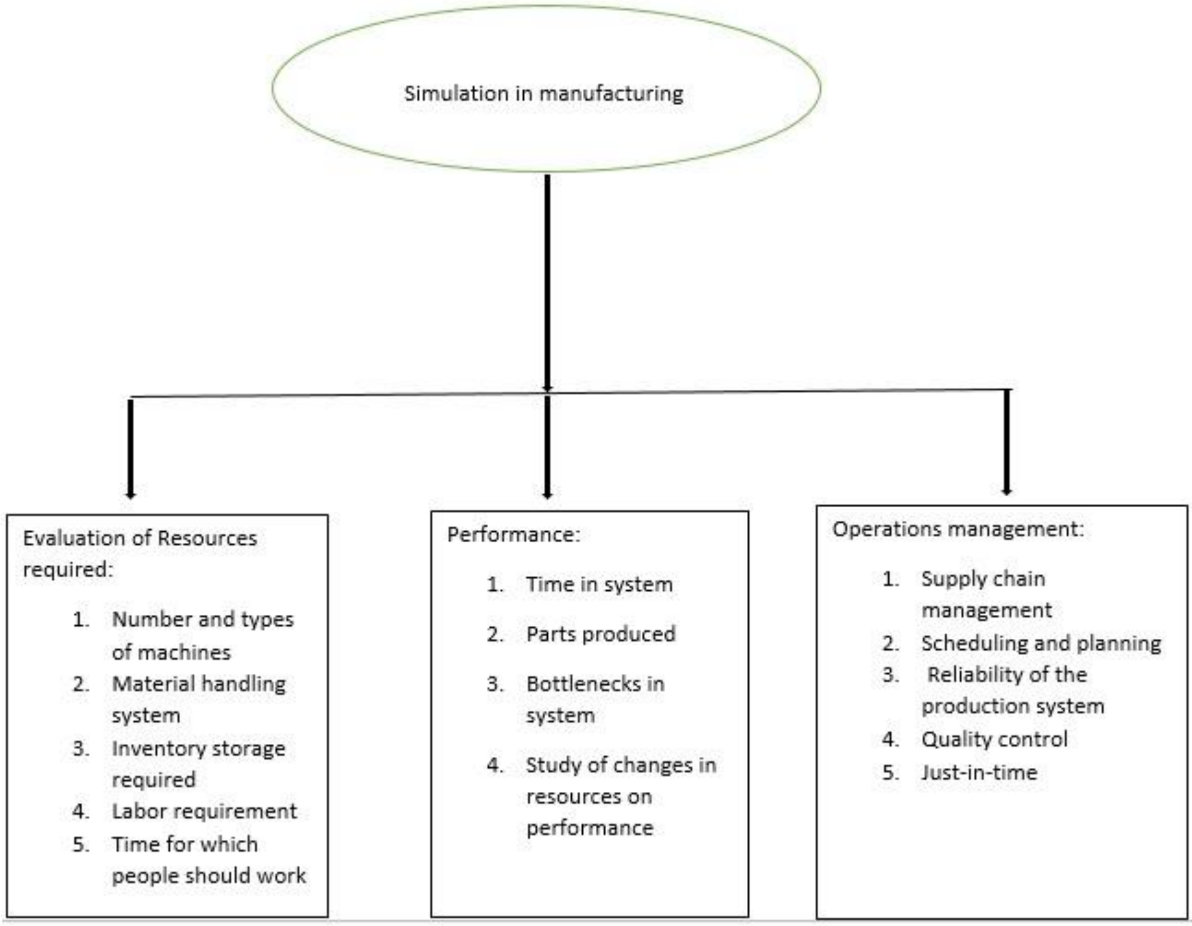

Figure 5: Use of simulation in manufacturing

Simulation is not strictly a type of model. Models in general represent reality, whereas simulation typically imitates it. Simulation is a technique for conducting experiments. To simulate means to assume the appearance of the characteristics of reality. Simulation involves testing specific values of the decision or uncontrollable variables in the model and observing the impact on the output variables. Simulation is usually used only when a problem is too complex to be treated by numerical or analytical optimization techniques [7]. The framework is equipped with capabilities to plug in arbitrary shop floor control systems.

3. Construction of Simulation Framework

A manufacturing plant or factory is an industrial site, usually consisting of buildings and machinery, or more commonly a complex having several buildings, where workers manufacture goods or operate machines processing one product into another. Factories arose with the introduction of machinery when the capital and space requirements became too great for workshops. Most modern factories have large warehouses or warehouse-like facilities that contain heavy equipment used for assembly line production. Large factories tend to be located with access to multiple modes of transportation, with some having rail, highway and water loading and unloading facilities.

Factories may either make discrete products or some type of material continuously produced such as chemicals, pulp and paper, or refined oil products. Discrete products may be final consumer goods, or parts and sub-assemblies which are made into final products elsewhere. Factories may be supplied parts from elsewhere or make them from raw materials. Continuous production industries typically use heat or electricity to transform streams of raw materials into finished products [24].

One of the most used techniques by manufacturing system designers is the discrete event simulation. This type of simulation allows assessing the system's performance by statistically and probabilistically reproducing the interactions of all its components during a determined period of time. In some cases, manufacturing systems need a continuous simulation approach. This is the cases where the states of the system change continuously, like, for example, in the movement of liquids in oil refineries or chemical plants. As continuous simulation cannot be modeled by digital computers, it is done by taking small discrete steps. This is a useful feature, since there are many cases where both, continuous and discrete simulation, have to be combined. This is called hybrid simulation [26], which is needed in many manufacturing industries [11, 12].

The process of manufacturing of a complex product requires a wide range of knowledge and information updating. It is of great importance to know how the assemblies of the system be integrated as well as their individual effects on the overall manufacturing production system. This integrated system would be more efficient if a complete understanding of the behavior of all raw material units, sub-systems and the relationships among them is automatically available.

The proposed manufacturing system has two main models:

a. The finished products model, and
b. The raw materials model.

The sub-system or sub-assembly model is considered a model for final product which may be produced from raw materials or mixed raw materials with sub-assemblies. The sub-system or sub-assemblies may need to go through one or more floor shops or factories in order to be manufactured. At each floor shops a number of actions, procedures, and rules have to be adopted. These activities and the accountability for them should be recorded and can be queried whenever a decision on them is required.

3.1 Finished Product Model

The finished product model has three main cost components. These cost components include [13]:

Setup cost: This is the cost of changeover a production line from making one product to making a different product. Set up costs favor large production runs result in larger inventory. The low setup costs favor smaller runs with fewer inventories. Set up cost is not always straight forward to calculate or estimate. It may be a complicated mathematical function that has no analytical solution. In this case a mathematical simulation technique needs to be adopted. The warm-up period discussed the simulation experiments is one element of set up cost as well as deficiencies in production line due to processes that are overly complicated.

Holding costs: These are the costs that organizations incur in purchase and storing of the inventory. They include the costs of financing the purchase, storage, handling, taxes, obsolescence, pilferage, breakage, spoilage, reduced flexibility and opportunity cost. Holding costs are also known as carrying costs. High holding costs favor low inventory levels and frequent orders, while low holding costs favor holding large quantities of inventory. Inventory management is primarily about specifying the size and placement of stocked goods. Inventory management is required at different locations within a facility or within multiple locations of a supply network to protect the regular and planned course of production against the random disturbance of running out of materials or goods.
The scope of inventory management also concerns the fine lines between replenishment lead time, carrying costs of inventory, asset management, inventory forecasting, inventory valuation, inventory visibility, future inventory price forecasting, physical inventory, available physical space for inventory, quality management, replenishment, returns and defective goods and demand forecasting and also by replenishment Or can be defined as the left out stock of any item used in an organization. Above variables that contribute to the holding cost may be hard to compute or estimate, and each variable may need to be fitted into a probabilistic distribution. The values of variables will be generated by running simulation tools on the probabilistic distribution until a steady state is reached.

Shortage costs: This is the cost of not having stocks when they are needed. These costs include loss of goodwill, loss of a sale, loss of a customer, loss of profit, and late penalties. Many of these costs are difficult or impossible to measure with any accuracy without using simulation techniques.

The basic function of production is to insulate the production process from changes in the environment. This is shown in sketch in figure 6 [25].

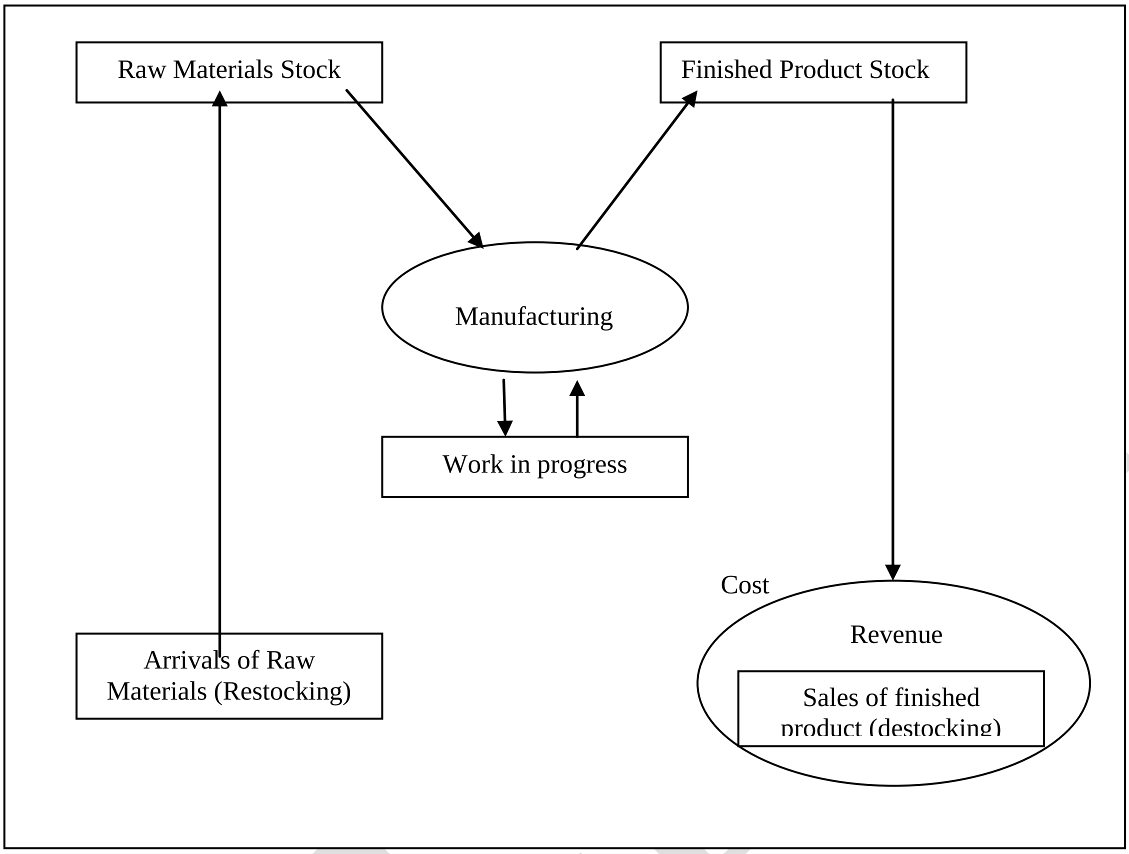

Figure 6: Manufacturing processes

The finished product model has the form:

Total Finished Cost = Setup cost + holding cost + shortages cost

From figure 7, the following model which represent the finished product total cost, is outlined in equation 1.

Rule 1:

$$\textbf{Total Finished Cost} = \frac{DC_1}{Q} + \frac{(P_1 Q - S)^2}{2P_1 Q} C_2 + \frac{S^2}{2P_1 Q} C_3 \quad \ldots \quad (1)$$

Variables explanation:

D = finished product demand per unit time,
Q = finished production quantity,
C1= set-up cost per item per cycle (or order),
C2= holding cost per item per unit time,
C3= shortages cost per unavailable unit per unit time,
S = shortages quantity,
P_1 = (1 - D / P), where P is production rate per unit time.

In real life situations, all above variable values are not known in advance and they are following a probabilistic distribution. It would impossible to estimate their values without using simulation.

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 02 - Issue 06 || June 2016 || PP. 59-78

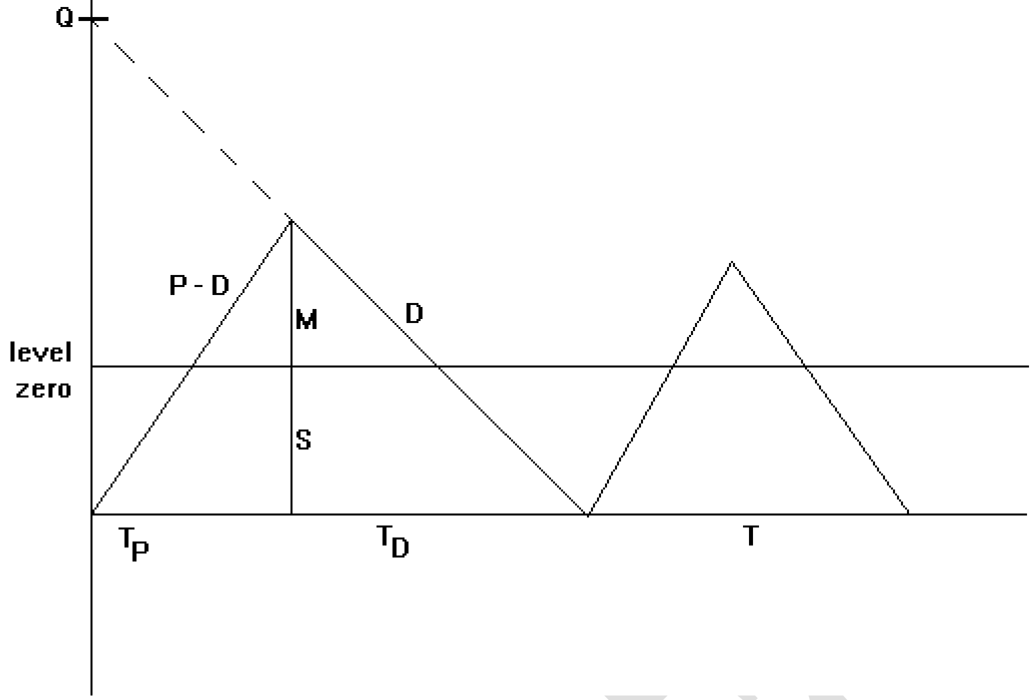

Figure 7: Finished Production Cycle

T is the length of the production cycle, T_P is the actual production time, and T_D is the demand time when there is no production processing [9].

3.2 Raw Material Model

A finished product model is developed through the process of a very complicated interaction of raw materials. Each unit of a finished product may be produced by combining, on average, hundreds of items (raw materials). The number of items from each type required is not evenly distributed. In order to facilitate the formulation and the understandability of the simulated model, we assume that assembled component Aj is made up by raw materials and/or assembled components R1, R2, ..., Rj of kind J_w out of kind w where J = 1, 2 ,3, ..., i_m and $1 <= i_m <= m$.

Finished product P_i is made up by assembled components and/or raw materials A_1, A_2, ..., A_m of kind i_m from kind m. This is characterized in figure 8.

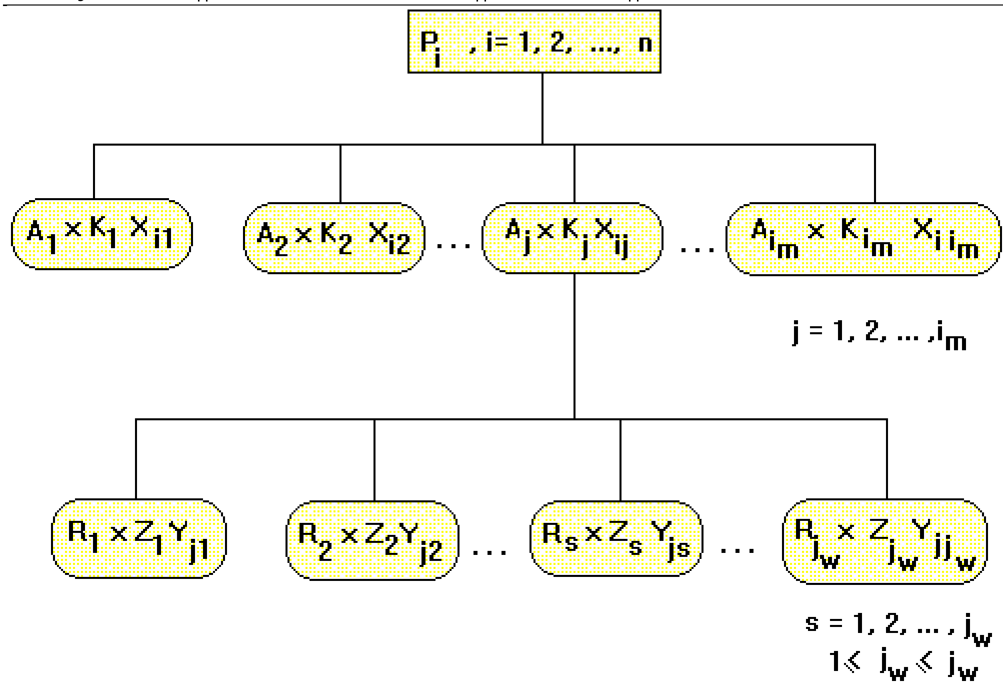

Figure 8: Structure of raw materials and assembled components

The branching of the tree may continue to a finite number of levels. K_j and Z_j are decision variables indicating the time between raw material j releases for level 1 and level 2 respectively. Form figure 9, the raw material model is:

Total Raw Material Costs = Ordering Costs + Holding Costs

We assume no shortages of raw materials are permitted as situations in real life do not permit shortages of raw materials; otherwise production processes will be stopped. The model would be:

$$\text{Total Raw Material Cost} = \sum_{j=1}^{M} RMC_j(T, K_j)$$

Where **RMCj** is the cost for the raw material number j. The above formula can be described as follows [3]

Rule 2:

$$\text{Total Raw Material Cost} = \sum_{J=1}^{M} \frac{O_j}{TK_j} + \frac{1}{2}\sum_{J=1}^{M}\left[X_j \frac{DT}{P} K_j + Zb_j\right] hc_j , \qquad K_j < 1$$

Or,

Rule 3:

$$\text{Total Raw Material Cost} = \sum_{J=1}^{M} \frac{O_j}{TK_j} + \frac{1}{2}\sum_{J=1}^{M}\left[X_j \frac{DT}{P} + X_j T(K_j - 1) + Zb_j\right] hc_j , \qquad K_j >= 1$$

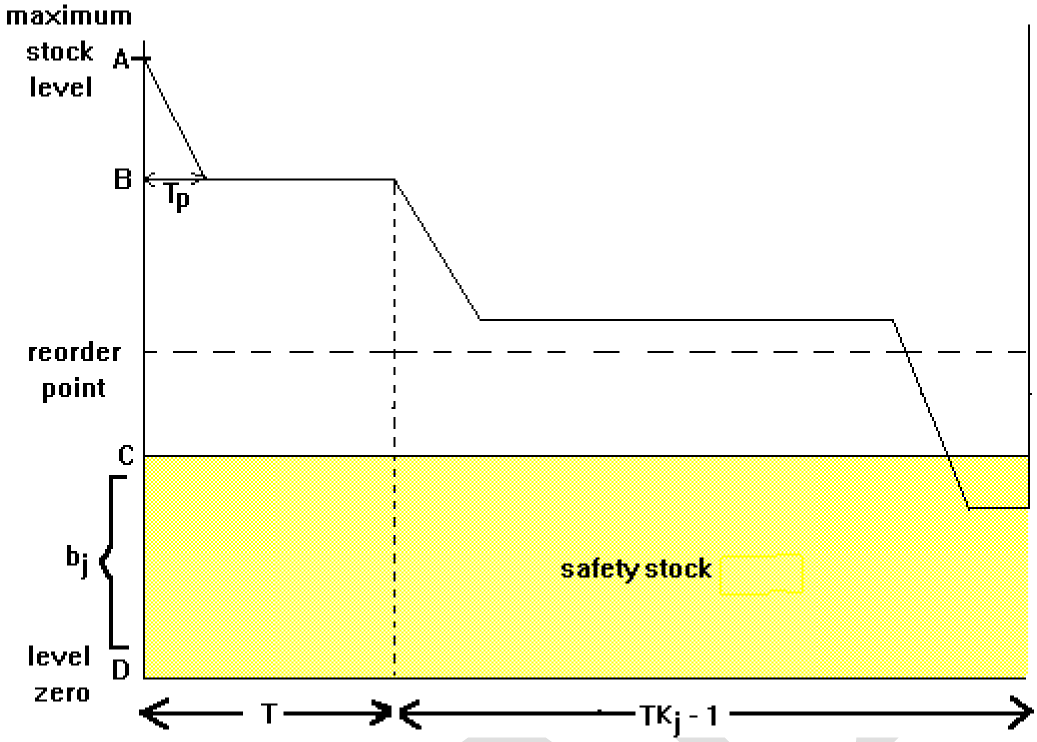

Figure 9: Raw Material Cycle Sketch

The symbols A, B, C, and D are variables used to help in formulating the raw materials costs model. K_j is a real number refers to the number of production cycles between any two consecutive replenishments of raw materials.

O_j is the ordering cost for raw material j which is the cost of placing an order for an item. Ordering costs apply to items the organization purchase. Ordering costs include placing an order, tracking the order, shipping costs, receiving and inspecting the order, and handling the paperwork. b_j is the safety stock for raw material j.

A number of fixed costs were not explicitly mentioned in the formulation of the model. These costs may include labor, machinery, overheads ... etc. These costs have no effects on the solution of the model. They, the fixed costs, can be added to the total variable costs or they can be added to the set-up costs (administrative costs), holding costs, or shortages costs.

4. Simulating the Integrated Model

When finished products and raw materials models are combined, the following integrated model is produced.

Total Variable Cost = Integrated Model Cost = Finished Product Total Cost
+ Raw Material Total Cost

In other words,

Rule 4:

$$Tvc\,(T, K_j, S) = \frac{C_1}{T} + \frac{(P_1DT - S)^2}{2P_1DT} C_2 + \frac{S^2}{2P_1DT} C_3 + \sum_{J=1}^{M} RMC_j\,(T, K_j)$$

$$= \frac{C_1}{T} + \frac{1}{2} P_1 DT C_2 - SC_2 + \frac{S^2}{2P_1DT}(C2 + C3) +$$

$$\sum_{J=1}^{M} \frac{O_j}{TK_j} + \frac{1}{2} \sum_{J=1}^{M} \left[X_j \frac{DT}{P} K_j + 2b_j \right] hc_j \quad , \quad K_j < 1$$

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www.ijlret.com || Volume 02 - Issue 06 || June 2016 || PP. 59-78

OR,
Rule 5:

$$Tvc\,(T, Kj, S) = \frac{C_1}{T} + \frac{1}{2} P_1 DT C_2 - SC_2 + \frac{S^2}{2P_1 DT}(C2 + C3) + \sum_{J=1}^{M} \frac{0_j}{TK_j}$$
$$+ \frac{1}{2}\sum_{J=1}^{M}\left[X_j \frac{DT}{P} + X_j T(K_j - 1) + 2b_j\right] hc_j\,, \quad K_j >= 1 \qquad \ldots(3)$$

Rule 4 is Rule 1 and Rule 2.
Rule 5 is Rule 1 and Rule 3.
Rule 6: if K_j is less than 1 then Trigger Rule 4.
Rule 7: if K_j is Greater or equal to 1 then Trigger Rule 5.

To accomplish the optimal solution from the proposed model, a cost function of state m is computed as follows:

$$\text{let} \quad \underline{f}^{(m)} = \begin{bmatrix} T^{(m)} \\ k_1^{(m)} \\ \vdots \\ k_n^{(m)} \\ S^{(m)} \end{bmatrix}$$

therefore,

$$\underline{f}^{(m+1)} = \underline{f}^{(m)} + \Delta\underline{f}^{(m)}$$

Transformation from one state to the next one is continued until the optimal solution is deducted.

For the best decisions, it is necessary to study every aspect of alternatives thoroughly. However, the volume of data increases significantly as the number of alternatives and variables associated with the data increases. Because previously introduced generic simulators have difficulties in handling large volumes of data, simulation analyses are often limited and not satisfactory. In addition, the statistical functions of commercial simulation packages used in semiconductor line modeling leave something to be desired. That is, they are not easy to use and not particularly powerful [14].

5. Scientific Validity of the manufacturing system

Although analytical solutions are available to many production problems, other real life problems become complicated or impossible to analytically solve. It provides a mental picture of the manufacturing processing. It improves manufacturing capability and flexibility and hence reduces total cost, increases equipment utilization [15].

Items of information about the nature of states, the cost of transforming from one state to another and the characteristics of the objectives can be used to guide the simulation actors more efficiently. These items are expressed in the form of a heuristic evaluation function f (k, g), a function of iteration (nodes) and the objectives. This approach helps pruning fruitless paths. This is a best-first search that provides guidelines with which to estimate costs [16].

For each iteration along the path to the objective goal, the heuristic estimation function is
$f(k, g) = f_1(k, g_1) + f_2(k, g_2)$

Where both $f_1(k, g_1)$, $f_2(k, g_2)$ are estimates of cost from the beginning to node k and from node k to last node. Validation is an important step toward robustness [20, 21].

The proposed framework provides methods for verification and validation of the simulation manufacturing System that is based on an existing framework for modeling and simulation. The framework addresses problems arising especially in recently emerging Systems of Systems such as cyber-physical autonomous cooperative systems. The design of such systems presents challenges to the currently employed independent use of simplified models for formal verification or brute-force simulations which are severely limited in the range of conditions they can test. The proposed framework is applied to integration of formal analytic and simulation verification methods where there is a need to have confidence that the properties proved for idealized abstract models also hold in more realistic models which gave rise to the abstractions. Taking both logical and probabilistic perspectives clarifies the situation and suggests where more research is needed [20].

The Discrete Event System Specification (DEVS) is used to create models whose behavior is defined in response to events in the simulated environment. DEVS models can be used to simulate systems as diverse as natural disasters and traffic patterns. We present an application that uses formatted messaging to interact with a DEVS model running on the RISE server. The purpose of this is to demonstrate that *while only risking the virtual lives of avatars. When properly applied, Modeling and simulation capabilities provide critical insight that allows leaders to make smart decisions about how to accomplish the mission and increase human performance more quickly and at lower cost and risk than reliance on real-world testing [22]*. A DEVS model can be executed as part of a larger, web-enabled synthetic environment, such as a military planning exercise [21].

Developing solutions to complex problems in government and industry is a daunting task that often requires tremendous investment in time and resources to solve. Modeling and simulation has incredible potential to streamline development and cut costs by conducting virtual experiments that give insight into performance under various test conditions. As many program managers in the federal acquisition process can attest, realistic testing of live equipment in an operational environment can be some of the most expensive parts of a development program. Modeling and simulation can provide insight into mission success of systems without the need to actually build and test the system in the real world. Similarly, Modeling and simulation tools can evaluate human effectiveness under various scenarios

5.1 Optimality Criteria

The necessary and sufficient conditions for a function f(x_1, x_2, ..., x_n) to be optimal at a point $x^*=(x_1^*, x_2^*, \ldots, x_n^*)$, such that its n partial derivatives are zero, the *Hessian matrix* (the second-order partial derivatives) *principal minors* must strictly be positive for a minimum point and negative for a maximum. In our case, the function is Tvc with three variables T*, S*, and K_j^* (J=1,2,..., M). Hessian matrix is:

$$\begin{pmatrix} \frac{\partial^2}{\partial S^2} & \frac{\partial^2}{\partial S \partial T} & \frac{\partial^2}{\partial S \partial Kj} \\ \frac{\partial^2}{\partial T \partial S} & \frac{\partial^2}{ST^2} & \frac{\partial^2}{\partial T \partial Kj} \\ \frac{\partial^2}{\partial Kj \partial S} & \frac{\partial^2}{\partial Kj \partial T} & \frac{\partial^2}{\partial Kj^2} \end{pmatrix}$$

The principal minors of the Hessian matrix are

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 02 - Issue 06 || June 2016 || PP. 59-78

$$\Delta_1 = \frac{\partial^2}{\partial S^2}$$

$$\Delta_2 = \begin{vmatrix} \frac{\partial^2}{\partial S^2} & \frac{\partial^2}{\partial S \partial T} \\ \frac{\partial^2}{\partial T \partial S} & \frac{\partial^2}{ST^2} \end{vmatrix}$$

$$\Delta_3 = \begin{vmatrix} \frac{\partial^2}{\partial S^2} & \frac{\partial^2}{\partial S \partial T} & \frac{\partial^2}{\partial S \partial Kj} \\ \frac{\partial^2}{\partial T \partial S} & \frac{\partial^2}{ST^2} & \frac{\partial^2}{\partial T \partial Kj} \\ \frac{\partial^2}{\partial Kj \partial S} & \frac{\partial^2}{\partial Kj \partial T} & \frac{\partial^2}{\partial Kj^2} \end{vmatrix}$$

If the conditions $\Delta_1 > 0$, $\Delta_2 > 0$, and $\Delta_3 > 0$ hold then the point (T^*, S^*, Kj^*) is a minimum. These conditions are computed using numerical differentiation of $\mathbf{O}(h^4)$ i.e. using the central-difference formula:

$$f'' = (-f_2 + 16f_1 - 30f_0 + 16f_{-1} - f_{-2})/(12h^2) + \mathbf{O}(h^4)$$

5.2 Constraints

However, even if production capacity itself keeps increasing by consistent improvement of manufacturing processes and process equipments, an increase of material handling capacity does not meet that of production capacity because of limited space. Therefore, material handling capacity is not sufficient to comfortably fulfill on-time delivery to process equipments. In other words, limited material handling capacity may lead to starvation of highly expensive process equipments. Consequently, in order to assess production performance involved in production capacity (or turn-around time) of a material handling simulation is required to be integrated with production simulation [17]. These restriction variables such as space, time, capacity, and other key resources can affect manufacturing performance. Restrictions may be imposed on any variable. For example, K_j may be constrained into

$$L_j <= K_j <= U_j,$$

Constraints may be imposed on T, S, or the total raw material.

$$\sum_{j=1}^{i_m} X_{ij} < \text{Storage Available} \quad , \; i=1,2,\ldots, m \quad 1=<i_m=< m$$

6. Results of Computational Experiments

For each simulation scenario Experiments have been conducted to demonstrate the viability of the proposed simulation model.

<u>simulation scenario 1</u>: In this example, Consider the items of information listed below:

m = 4, c1=56, c2=2.59, c3=1.9, p=380, d:=165, p1= 1.0-d/p,

Raw Material Demand:

x[1]:= 495; x[2]:= 825; x[3]:=165; x[4]:=330;

Holding Costs:

hc[1]:=0.005; hc[2]:=4.221; hc[3]:=0.401; hc[4]:=10.024;
Ordering Costs:
o[1]:=40.87; o[2]:=32.91; o[3]:=14.19; o[4]:=12.23;
Safety Stocks:
b[1]:= 495; b[2]:=825; b[3]:=165; b[4]:=330;

After running the simulated model the following output is outlined below:
Minimum costs = $758.442
Optimal Production Cycle = 0.55 months
Shortages Allowed are: 38 units
Reorder Raw Material (1) After 78 Days
Reorder Raw Material (2) After 12 Days
Reorder Raw Material (3) After 36 Days
Reorder Raw Material (4) After 12 Days

simulation scenario 2: In this experiment, consider the problem listed below:

m= 6; c1:=34;c2:=1.59;c3:=1.2; p:=4400;d:=1155; p1:= 1.0-d/p;
Raw Material Demand:
x[1]:= 1155;x[2]:= 1155; x[3]:=2310;x[4]:=2310;x[5]:=1155;x[6]:=3465;
Holding Costs:
hc[1]:=0.05;hc[2]:=0.021;hc[3]:=0.001;hc[4]:=0.002;
hc[5]:=0.003;hc[6]:=0.01;
Ordering Costs:
o[1]:=4.87;o[2]:=2.91;o[3]:=1.19;o[4]:=3.23;o[5]:=2.74;o[6]:=4.46;
Safety Stocks:
b[1]:=10;b[2]:=20;b[3]:=10;b[4]:=10;b[5]:=10;b[6]:=10;

After running the simulated model the following output is outlined below:

Minimum costs = $248.836
Optimal Production Cycle = 0.37 months
Shortages Allowed are: 182 units
Reorder Raw Material (1) After 33 Days.
Reorder Raw Material (2) After 39 Days
Reorder Raw Material (3) After 81 Days
Reorder Raw Material (4) After 96 Days
Reorder Raw Material (5) After 87 Days
Reorder Raw Material (6) After 42 Days

simulation scenario 3: In this experiment, consider the problem outlined below:
m:= 10; c1:=34;c2:=1.59;c3:=1.2; p:=4400;d:=1155; p1:= 1.0-d/p;
x[1]:= 1155;x[2]:= 1155; x[3]:=2310;x[4]:=2310;x[5]:=1155;x[6]:=3465;
x[7]:= 3465; x[8]:=4620; x[9]:= 2310; x[10]:=1155;
hc[1]:=0.05;hc[2]:=0.021;hc[3]:=0.001;hc[4]:=0.002;hc[5]:=0.003;
hc[6]:=0.01;hc[7]:=0.12; hc[8]:= 0.076; hc[9]:=0.0025; hc[10]:=0.11;
o[1]:=4.87;o[2]:=2.91;o[3]:=1.19;o[4]:=3.23;o[5]:=2.74;o[6]:=4.46;
o[7]:=4.43; o[8]:=3.21; o[9]:=8.76; o[10]:=5.01;
b[1]:=10;b[2]:=20;b[3]:=10;b[4]:=10;b[5]:=10;b[6]:=10;
b[7]:=10; b[8]:=20; b[9]:=10;b[10]:=20;

Subject to the following constraints
T > 0.0 and T <= 0.5,
S >= 0 and S <= 144,
1 <= K1 <= 1.6
1 <= K2 <= 2.3
1 <= K3 <= 3.2
1 <= K4 <= 1.9

1 <= K5 <= 1.6
1 <= K6 <= 2.6
1 <= K7 <= 1.4
1 <= K8 <= 1.6
0 <= K9 <= 2.5
1 <= K10 <= 1.6

After running the simulated model the following output is outlined below:

Minimum costs = $383.70
Optimal Production Cycle = 0.325 months
Shortages Allowed are: 134 units
Reorder Raw Material (1) After 40 Days
Reorder Raw Material (2) After 42 Days
Reorder Raw Material (3) After 42 Days
Reorder Raw Material (4) After 42 Days
Reorder Raw Material (5) After 42 Days
Reorder Raw Material (6) After 42 Days
Reorder Raw Material (7) After 39 Days
Reorder Raw Material (8) After 39 Days
Reorder Raw Material (9) After 60 Days
Reorder Raw Material (10) After 48 Days

The proposed model provides insight that could be not obtained by separated modules or other methods. The model provides users with a flexible approach of imposing and satisfying constraints.

From simulation scenario 2, one can conclude that optimal production cycle length (T^*) is 0.37 months and optimal backorders (S^*) permitted is 182 units. $K_j{}^*$ values are as listed above. The total variable cost is 248.836 Dinars. These numbers are the optimal ones while any other combinations would increase the total variable costs. In order to convince general readers, an evidence of optimality is provided and a number of case studies for sensitivity analysis is conducted.

simulation scenario 4: A firm is specialized in selling cranes. The sale follows a uniform distribution of values between 1 and 3 cranes per day. After placing an order for a new shipment of cranes, arrival time follows a normal distribution with a mean of 2 weeks and a standard deviation of 0.6 weeks. In the past, the manager has placed an order when the quantity has dropped to 21. Set up a simulation and experiment with various reorder quantities to see which values seems to work best.

Sales Uniform Distribution

Minimum	1
Maximum	3

Normal Arrival Distribution

Mean	2.0
Standard Deviation	0.6

Reorder Quantity	21
Starting Quantity	44

Results

Average Inventory	28.7
Minimum Inventory	0.0

Maximum Inventory	55.0
Number of Stockouts	16

0=No, 1=Yes

Day	Inventory	Sales	Ending Inventory	Orders Pending	Orders	Days Till Arrival	Arrival Date
1	44	1	43	0	0	0	0
2	43	1	42	0	0	0	0
3	42	3	39	0	1	13	16
4	39	1	38	1	0	0	16
5	38	3	35	1	0	0	16
6	35	1	34	1	0	0	16
7	34	3	31	1	0	0	16
8	31	2	29	1	0	0	16
9	29	2	27	1	0	0	16
10	27	1	26	1	0	0	16
11	26	2	24	1	0	0	16
12	24	2	22	1	0	0	16
13	22	2	20	1	0	0	16
14	20	1	19	1	0	0	16
15	19	1	18	1	0	0	16
.	.	.	.	.	.	.	
975	26	2	24	1	0	0	978
976	24	3	21	1	0	0	978
977	21	1	20	1	0	0	978
978	41	1	40	0	1	9	987
979	40	1	39	1	0	0	987
980	39	1	38	1	0	0	987
981	38	2	36	1	0	0	987
982	36	1	35	1	0	0	987

Extension to Simulation Scenario 4: expand the experiment varying the reorder point as well as the reorder quantity. Experiment with various values. Set up a data table to report results.

Sales Uniform Distribution

Minimum	1
Maximum	3

Normal Arrival Distribution

Mean	2.0
Standard Deviation	0.6

Reorder Quantity	21
Reorder Point	30

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Starting Quantity	44

Results

Average Inventory	19.4
Minimum Inventory	0.0
Maximum Inventory	51.0
Number of Stockouts	31

Day	Inventory	Sales	Ending Inventory	Orders Pending (0=No, 1=Yes)	Orders	Days Till Arrival	Arrival Date	Arrivals
1	44	1	43	0	0	0	0	0
2	43	2	41	0	0	0	0	0
3	41	3	38	0	0	0	0	0
4	38	1	37	0	0	0	0	0
5	37	2	35	0	0	0	0	0
6	35	3	32	0	0	0	0	0
7	32	3	29	0	1	13	20	0
8	29	3	26	1	0	0	20	0
9	26	1	25	1	0	0	20	0
10	25	1	24	1	0	0	20	0
.	.	.	.	.	.	.	.	.
975	11	3	8	1	0	0	981	0
976	8	3	5	1	0	0	981	0
977	5	3	2	1	0	0	981	0
978	2	2	0	1	0	0	981	0
979	0	0	0	1	0	0	981	0
980	0	0	0	1	0	0	981	0
981	21	3	18	0	1	10	991	21
982	18	3	15	1	0	0	991	0

When optimality criteria is applied the following numerical results is obtained: $\Delta_1 = 0.08781833$, $\Delta_2 = 52.00098$, and Δ_3 is positive for all Kj, j=1,...,M. The minor values for j=1,2,..., 6 are 953.0471, 331.406, 13.88616, 23.11795, 16.06441, 455.7297 respectively. As the principal minors are strictly positive, the point (T^*, S^*, Kj^*) is a minimum of the function Tvc(T^*,S^*,Kj^*). The above statements prove that the proposed model has actually optimal solutions.

From experience with the proposed manufacturing system one can find that it satisfies the most important three criteria; **effectiveness** in which the quality of the output corresponds to the given goal and **efficiency** in which one can measure how long users take to complete the product and the mental resources they need to spend on interaction with the product; and **ease of use** in terms of general attitudes towards the product and specific attitudes towards or perception of the interaction with the tool.

Processing a large amount of items of information about system components, control variables, and the interdependency structures create new challenges on the shoulder of engineers and managers. The proposed system provides a traceability capability for components and their relationships. It provides manager and engineer with sufficient items of information in order to detect inconsistencies. I.e. it has reasoning capabilities on the system objects.

The work in this paper considers the integrated problem of locating distribution centers in urban areas and the corresponding freight distribution (vehicle routing). The combined problem is solved by using a hybrid algorithm which employs Monte Carlo simulation to induce biased randomness into several stages of the optimization procedure. The approach is then validated using real-life data and comparing our results with results from other works already available in the existing literature [23].

7. Conclusions and Suggestions

The paper addressed an important application issue: how well an integrated model can describe the real world applications. The idea was to integrate the finished products, sub-assemblies and raw materials in one model. Simulation is used to generate a number of scenarios in what-if-analysis approach in order to deal with uncertainty.

Simulation is important for any intelligent system involving uncertainty. Simulation is applicable to complex situations where mathematical techniques do not work or hard to analytically or numerically optimize. Simulation is used in two general types of situations:

- The probability distributions cannot be expressed in mathematical forms as we have seen in our models.
- The model is too complex. There are too many components, and the model is thus impossible to solve using mathematical methods.

Introducing artificial intelligence in the simulated applications provides a laboratory to generate and examine models and what-if scenarios that involve many uncertainties. The intelligent system can examine not only results but assumptions, particularly as far as probabilities are concerned.

Material handling capacity is taken into consideration on performance assessment involved in production capacity, and the framework also allows the complex simulation model to be manageable for the purpose of adaptation to the changing environment. Moreover, the framework employs a material handling request-driven approach rather than a process request-driven approach in order to implement both push and pull flows of production loads. Thus, nondeterministic part routing is facilitated. In addition, interfaces between the simulation model and shop-floor control systems were represented as triggering events and decision flows, whereby the framework was equipped with capabilities to plug in arbitrary shop-floor control systems.

This paper suggests for future works to discuss some key issues in implementing agent-based manufacturing systems such as agent encapsulation, agent organization, agent coordination and negotiation, system dynamics, learning, optimization, security and privacy, tools and standards**.**

References

[1]. R. Driessel & L. Monch, (2007). Simulation framework for complex manufacturing systems with automated material handling, Proceedings of the 39th conference on Winter Simulation WSC'07, pp 1713-1721, IEEE Press Piscataway, NJ, USA ©2007.

[2]. B. Ornella and T. Benny, (2008). "Towards an improved tool to facilitate simulation modeling of complex manufacturing systems". *The International Journal of Advanced Manufacturing Technology* 43 (1-2): 191–199.

[3]. E. Turban and J. E. Aronson, (2001). “Decision Support Systems and Intelligent Systems”, Prentice-Hall, third edition.

[4]. J. S. Smith, (2003). Survey on the use of simulation for manufacturing system design and operation, Journal of Manufacturing Systems, Volume 22, Issue 2, 2003, Pages 157-171.

[5]. W. Shen, Q. Hao H. J. Yoon and D. H. Norrie, (2006), Applications of agent-based systems in intelligent manufacturing: An updated review, Advanced Engineering Informatics Volume 20, Issue 4, October, Pages 415–431.

[6]. E. E. Velazco, (2016). "Simulation of manufacturing systems". *International Journal of Continuing Engineering Education and Life Long Learning* 4 (1-2): 80–92, Retrieved June 2016, https://en.wikipedia.org/wiki/Simulation_in_manufacturing_systems

[7]. C. Bowswell, (1999). “Process Simulation Software Offers Efficiency and Savings”, Chemical Market Reporter, Vol. 256, No. 13, September 1999.

[8]. D. Nakagiri and S. Kuriyama, (1994). "A Study on Production Planning for CIM", Proceedings of the 16th International Conference on Computers and Industrial Engineering, March 7-9, pp654-657, JAPAN.

[9]. G. Sharma, R. G. S Asthana, and S. Goel, (1994). "A knowledge-Based Simulation Approach (K-SIM) for Train Operation and Planning", Simulation Vol. 62, No. 6, pp381-391, June 1994.

[10]. A. M. Wildberger, (1995). "AI & SIMULATION", Simulation, Vol. 64, No. 2, Feb 1995.

[11]. S. Robinson,(2014). *Simulation: The Practice of Model Development and Use*. Palgrave Macmillan.

[12]. R. B. Detty; R. B, J. C. Yingling, (2000). "Quantifying benefits of conversion to lean manufacturing with discrete event simulation: A case study". *International Journal of Production Research* 38 (2): 429–445.

[13]. N. C. Weida, R. Richardson, A. Vazsonyi, (2001). "Operations Analysis Using Microsoft Excel", Duxbury.

[14]. D. Lim and M. Seo. (2014). A Generic Simulation Framework for Efficient Simulation Analyses for Semiconductor Manufacturing: A Case Study, International Journal of Control and Automation Vol.7, No.2, pp.75-84.

[15]. S. Benjaafar, (1992). "Intelligent Simulation for Flexible Manufacturing Systems: An Integrated Approach", Computers and Industrial Engineering", Vol. 22, No. 3, pp297-311.

[16]. D. W. Patterson, (1990). "Introduction to Artificial Intelligence and Expert Systems", Prentice-Hall International, Inc.

[17]. M. Shin, J. Lim, S. Bae and B. Park, (2013), Simulation Framework for Performance Assessment of TFT-LCD fab, Proceedings of the 41st International Conference on Computers & Industrial Engineering.

[18]. M. Graul, F. Boydstun, M. Harris, R. Mayer, O. Bagaturova, (2003). "Integrated Framework for Modeling & Simulation of Complex Production Systems", Knowledge Based Systems, Inc.

[19]. W. Terkaj and M. Urgo (2014). A Virtual Factory Data Model as a Support Tool for the Simulation of Manufacturing Systems, 3rd CIRP Global Web Conference - Production Engineering Research – Advancement beyond state of the art (CIRPe2014).

[20]. B. P. Zeigler and J. J. Nutaro (2016). Towards a framework for more robust validation and verification of simulation models for systems of systems, The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology January 2016.

[21]. E. Hosang and G. A. Wainer (2016). Architecture to Facilitate Interoperability of Discrete Event System Specification and Coalition Battle Management Language simulation models, The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology January 2016.

[22]. S. D. Snyder and J. M. Taylor 2015). Novel Approaches to Defense and Military Modeling and Simulation, Journal of Defense Modeling and Simulation: Applications, Methodology, Technology 11:3 (2014), pp. 203–204.

[23]. A. Muñoz-Villamiza, J. R. Montoya-Torres, A. A. Juan, and J. Caceres-Crus, (2013. A simulation-based algorithm for the integrated location and routing problem in urban logistics, Proceeding WSC '13 Proceedings of the 2013 Winter Simulation Conference: Simulation: Making Decisions in a Complex World Pages 2032-2041

[24]. Manufacturing plant, (2016). https://en.wikipedia.org/wiki/Factory, Retrieved in June 2016.

[25]. J. E, Beasley (2016). http://people.brunel.ac.uk/~mastjjb/jeb/or/invent.html, Retrieved June 2016.

[26]. Simulation in Manufacturing (2016), Retrieved in June 2016, https://en.wikipedia.org/wiki/Simulation_in_manufacturing_systems - cite_note-8.