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STEADY STATE ANALYSIS FOR IMPROVING MANUFACTURING PRODUCTIVITY

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ABSTRACT

This paper describes techniques that simulate a number of statistical distribution models in order to understand the behavior of manufacturing system processes and to identify irregularities. These simulation techniques provide top management with clear understanding of the flow of manufacturing activities. Manufacturing productivity can dramatically be improved by setting an efficient management plan. A management plan is the process of assessing an organization's goals and creating a realistic, detailed plan of action for meeting the organization's goals. A management plan takes into consideration short- and long-term corporate strategies. The basic steps in the management planning process involve creating a road map that outlines each task the company must accomplish to meet its overall objectives. To achieve an effective and productive plan one need to study and investigate bottleneck problems associated with manufacturing processes. One approach that could identify and detect bottleneck is the understanding of the steady state of a manufacturing system. A steady state implies that the System State is independent of its initial start-up conditions. The steady state provides top managements with clear picture of how to make their production line more effective. A steady state is essentially required in order to show any inconsistencies in the environment of manufacturing process. For example, steady state furnishes 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 of production lines. The steady state confirms that the better trained employees the better productivity and effectiveness be achieved. This step alone could increase the efficiency of production process and make manufacturing plant more profitable. The author has designed, developed, and implemented the simulation models. These simulation models are more flexible, adjustable, robust, and reusable.

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INTRODUCTION

Today's manufacturing companies face variety of challenges and to successfully be competitive, they need to use methodologies such as Lean Manufacturing to reduce waste and Six Sigma to increase quality, in order to improve their productivity. By implementing advanced tools and modern techniques companies bring products to market more quickly, ensure customer satisfaction and maintain their market share. Improving manufacturing productivity involves collecting and analyzing data and making effective decisions. Ensuring the success of these operational excellence initiatives often depends on divisions working together to share data and interpret it appropriately (Yang *et al.*, 2016; Improve productivity, 2016). In order for top managements to be in control of the manufacturing activities, they should be aware

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of the work flow associated with manufacturing your product. This includes the people, processes, administration, and technology required for production as well as the resources, communication and procedures needed throughout the company. Value stream mapping helps business professionals assess, monitor and identify process improvement projects. Then project managers can prioritize and plan to implement new processes to fix known problems. Document the work flow processes on paper, or electronically, using diagramming tools. By reducing product defect rates and eliminating processes that don't add value to the end product, manufacturing productivity can be improved. Project managers can develop manufacturing process improvement plans by sharing comprehensive data with all projects. Improvement can be achieved also by assigning resources to complete the tasks, managing the budgets and determining whether projects met their goals. Establish criteria for standardizing project processes to ensure that all project

managers systematically evaluate performance consistently and interpret changes appropriately. For example, if customer satisfaction falls below 50 percent for any product, trigger distribution of a survey to customers to solicit input on any problems that might be fixed by changing manufacturing processes to make them more productive. Top management can achieve improvement through the creation of a balanced scorecard based on data from a secure repository. Identify financial measures for the scorecard such as monthly sales, customer measures such as the number of product support calls, process measures such as number of products manufactured each month and employee measures such as staff retention. As you implement process improvement changes, note any changes in these operational measures to validate that your interventions were successful (Tao *et al.*, 2015). Monitor information generated from process improvement projects to implement improvements throughout all of your manufacturing operations. Analyze costs and benefits. Create an intranet website to publish reports, balanced scorecards and business case studies. Ensure all employees have access to the information and appropriate training on how to implement the procedures to improve manufacturing productivity. Virtually every manufacturing company that performs steady state or changeover can direct its finite resources in a way that generate the best return. Manufacturing companies should ensure that there is a clear understanding of where productive time is being lost, and that decisions on improvement initiatives are made based on hard data. That means putting a system in place to collect and analyze manufacturing performance data. Reducing changeover time becomes economically possible to have smaller production runs. This provides a number of advantages (SMED, 2016):

- Less capital is tied up in inventory and less warehouse space is needed.
- Less work in progress, reducing costs further.
- The ability to quickly respond to market changes.
- Improved quality and less waste. Defects can be identified and the problem corrected without large quantities of defective product being carried in inventory.
- Product innovations, which provide a competitive advantage, can be brought to the market sooner because inventories of the older product are smaller and will be sold off quicker.

In order to implement an efficient mechanism to improve productivity, a manufacturing company needs a management plan. A management plan is the process of assessing an organization's goals and creating a realistic, detailed plan of action for meeting company goals. Much like writing a business plan, a management plan takes into consideration short- and long-term corporate strategies. The basic steps in the management planning process involve creating a road map that outlines each task the company must accomplish to meet its overall objectives (Planning process, 2016). The first step of the management planning process is to identify the manufacturing company goals. This type of planning process should include a detailed overview of each goal, including the reason for its selection and the anticipated outcomes of goal-related projects. Where possible, objectives should be

described in quantitative or qualitative terms. Each goal should have financial and human resources projections associated with its completion. a management plan may identify how many sales people it will require and how much it will cost to meet the goal of increasing sales, for example, by 25 percent.

Literature Review

In last two decades, manufacturing company's structures and attitude have changed tremendously through the innovations of technology, processes, materials handling, communication and transportation. The major challenge of manufacturing is to produce more products with less material, less energy and less labor involvement. The processes and methods used to transform tangible inputs such as raw materials, semi-finished goods, subassemblies, and intangible inputs, for example ideas, items of information, knowledge, internal structures, and logic into goods or services. Resources are used in this process to create an output that is suitable for use or has exchange value (Li *et al.*, 2010; Production, 2016). Because of the rapid change in market, manufacturing companies should have a strategy and competitive plan in order to compete in a dynamic market (He and Xu, 2015). A manufacturing plan is a set of policies designed to maximize performance among trade-offs and among success criteria to meet the manufacturing task determined by a corporate plan. It is the responsibility of the top management of the company to ensure that there is a coherent manufacturing plan and policies derived from internal and external sources of information to support the whole company's mission (Li *et al.*, 2011; Gao *et al.*, 2011). Strategic planning also has many written definitions but there is a consensus on its purpose. Strategic plans describe where your business is going, how it hopes to get there and how you will measure your progress toward your objectives. This is why strategic plans are often compared to road maps. The company goals are the destination; the taken steps to reach the objective are the highways, streets and avenues; then the methods one will use to measure the progress are the cities, towns, and other checkpoints along the journey (Yang *et al.*, 2016; Strategic Planning, 2016). (Bai and Elhafsi, 2011) presented in their paper an analysis of transient and steady-state of a manufacturing system with setup changes. they confirmed that the optimal scheduling of a one-machine two-product manufacturing system with setup, operating in a continuous time dynamic environment needs a reliable machine. A known constant setup time is incurred when switching over from a part to the other. Each part has specified constant processing time and constant demand rate with sufficient supply of raw material. The global optimal solution, expressed as an optimal feedback control law, provides the optimal production rate and steady state status as a function of the state of the system (backlog and inventory levels). For the steady-state, the optimal cyclic schedule (Limit Cycle) is determined. This is equivalent to solving a one-machine two-product Lot Scheduling Problem. To solve the transient case, the system's state space is partitioned into mutually exclusive regions such that with each region is associated an optimal control policy. (Bai and Elhafsi, 2011) developed an algorithm to obtain the optimal state trajectory. (Damerджи, 1994 and Zimmweman *et al.*, 2011) Studied the variance estimation and model formulation in steady state simulation output analysis and he constructed a confidence

interval for the mean of an output sequence using a consistent estimator of the time-average variance constant of the process. (Damerdji, 1994) Confirmed that a strongly consistent estimator of the variance constant the steady state is required for fixed-width confidence-interval estimation procedures to be asymptotically valid. Damerdji established sufficient conditions to ensure strong consistency of the estimator of the variance constant obtained by several used methods of steady-state simulation output analysis, namely, batch means, overlapping batch means, spaced batch means, and standardized time series. Throughput and utilization rate as productivity metrics are not very helpful for identifying the opportunities for productivity improvement in a manufacturing system. Huang *et al.*, 2003 presented a systematic methodology for productivity measurement and analysis at the factory level. They (Huang *et al.*, 2003) are introduced and developed, metrics of overall equipment effectiveness and overall throughput effectiveness for rigorous and quantitative measurement of equipment and system productivity. These metrics are integrated with computer simulation to facilitate rapid analysis of equipment and manufacturing system productivity, and the investigation of productivity improvement opportunities. One of the major steps to the contribution of improving manufacturing productivity is to find methods that detect bottlenecks in manufacturing systems and how to tackle appropriately these bottlenecks. Bottlenecks include many processes such as steady state associated deficiencies, changeover, set up production line and others. All manufacturing systems are constrained by one or more bottlenecks. Dealing with the bottleneck, and using right mechanisms to reduce their impact, will improve the whole system. However, finding the bottleneck is no straight forward task and need may need the right mechanism to analysis them and to use the appropriate one for improvement. Bottlenecks are dynamic processes and the manufacturing environment may change over time or due to random events, and subsequently the bottleneck may shift from one machine or production line to another machine or line. The shifting bottleneck detection method determines the bottleneck based on the duration a machine is active without interruption. Top management need to search for mechanism that is very robust, easy to apply and able to detect the primary and secondary bottlenecks in a wide range of production systems (Roser *et al.*, 2012). This mechanism allows the use of simulation to predict bottlenecks for both steady state and variable systems. Simulating the steady state and the associated system variables will be developed, investigated, and analyzed in the next section.

Simulation Distribution Models

One of the methods for understanding manufacturing plant environment is to study major bottlenecks of the production lines and the associated activities during the plant design. So what is a steady state? In systems theory, a system or a process is in a steady state if the variables (called state variables) which define the behavior of the system or the process are unchanging in time. In continuous time, this means that for those properties p of the system, the partial derivative with respect to time is zero and remains so:

$$\Delta p / \Delta t = 0 \text{ for all } t.$$

In discrete time, it means that the first difference of each property is zero and remains so:

$$p_t - p_{t-1} = 0 \text{ for all } t.$$

The concept of a steady state has relevance in many fields, in particular thermodynamics, manufacturing, economics, and engineering. If a system is in a steady state, then the recently observed behavior of the system will continue into the future. In stochastic systems, the probabilities that various states will be repeated will remain constant. In many systems, a steady state is not achieved until sometime after the system is started or initiated. This initial situation is often identified as a transient state, start-up or warm-up period (Patterson, 1990). A steady state implies that the System State is independent of its initial start-up conditions. The discussion of the steady state 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 provides 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 is essentially needed to show any inconsistencies in the environment of manufacturing process. For example, steady state furnishes 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 confirms that the better trained employees the better productively and effectively. This step alone could increase the efficiency of production process and make manufacturing plant more profitable. A number of distributions have been coded in C++ in order to simulate activities of manufacturing variables. The advantages of simulation models are that they enable managers run the simulation models thousands of times in order to reach a steady state conditions. For example, if collected data from the manufacturing environment and fit the small sample collected data into one of the distribution then we can use the distribution to generate thousands or millions of data from the distribution. This will helps manager to have a clear insight into the behavior of the manufacturing environment variables.

Weibel Distribution Model

Weibull models are used to describe various types of observed failures of components and phenomena. They are widely used in reliability and survival analysis. In addition to the traditional two-parameter and three-parameter Weibull distributions in the reliability or statistics literature, many other Weibull-related distributions are available. The purpose is to give a brief introduction to those models, with the emphasis on models that have the potential for further applications. Many extensions and generalizations of the basic Weibull distributions are then summarized. Various applications in the reliability context and some Weibull analysis can be found in (Lai *et al.*, 2006). The probability density function of a Weibull random variable is:

$$f(x; \lambda, k) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k} \quad x \geq 0;$$

$$= 0 \quad \text{Otherwise}$$

where $k > 0$ is the *shape parameter* and $\lambda > 0$ is the *scale parameter* of the distribution. Its complementary cumulative distribution function is a stretched exponential function. The Weibull distribution is related to a number of other probability distributions; in particular, it interpolates between the exponential distribution ($k=1$) and the Rayleigh distribution ($k=2$ and $\lambda = \sqrt{2}\sigma$).

Figure 1 shows the family shapes of Weibull probability function.

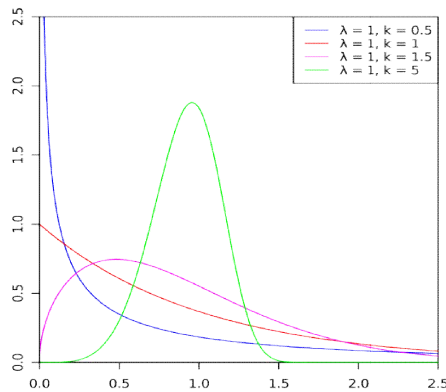


Figure 1. Weibull probability function

Implementation Simulation Weibull Model in C++

```
#include <iostream.h>
#include <math.h>
#include <conio.h>
#include <values.h>
#include <stdlib.h>
double Weibull( double, double);

main ()
{
    double Alpha, Beta, Webeil;
    long int Iter, Lower, Size, Upper, IntervalsNo, freq[1000]=
    {0};
    cout <<"Enter Alpha, Beta, Size, IntervalsNo, and Iterations:
    ";
    cin >>Alpha >>Beta >>Size >>IntervalsNo >>Iter;
    cout <<endl;

    for (int j =0; j <Iter; j++) {
        Webeil = 5 * Weibull(Alpha, Beta);
        if ( Webeil < Size) freq[1]++;
        else {
            Lower = Size;
            for ( int j = 2; j< IntervalsNo; j++)
            { Upper = j * Size;
                if ( Webeil >= Lower && Webeil < Upper) freq[j]++;
                Lower = Upper;
            }
        }
    }
}
```

```
}
if (Webeil > Lower) freq[int(IntervalsNo)]++;
}

cout <<endl <<" Seq\tFrequencies\n=====\t=====\n";
for (int j =1; j <1000; j++) if( freq[j] !=
0)cout <<j <<"\t" <<freq[j] <<endl;
getch();
}

double Weibull( double Alpha, double Beta)
{
    double temp = 0;
    while ( temp <= 0)
    {
        double r = rand()/double(RAND_MAX);
        temp = exp( log(Beta) + (1.0/Alpha)*log(-log(r)));
    }
    return temp;
}
}
```

The above program is an implementation of the weibull distribution function. The program is written by the author to simulate the weibull distribution. It has a flexibility of providing sufficient information regarding the structure of the generated frequencies that satisfy steady state conditions.

Erlang Distribution Model

The Erlang distribution is a two parameter family of continuous probability distributions with support $x \in [0, \infty)$. The two parameters are: a positive integer 'shape' k and a positive real 'rate' μ ; sometimes the scale μ , the inverse of the rate is used. The Erlang distribution with shape parameter k equal to 1 simplifies to the exponential distribution. It is a special case of the Gamma distribution. It is the distribution of a sum of k independent exponential variables with mean μ each. The Erlang distribution examines the number of customer's order which might be made at the same time with other orders. The work of Erlang distribution expanded to consider waiting times in queuing systems in general. The distribution is now used in the fields of stochastic processes and of biomathematics. Figure 2 shows the family shapes of Erlang probability function.

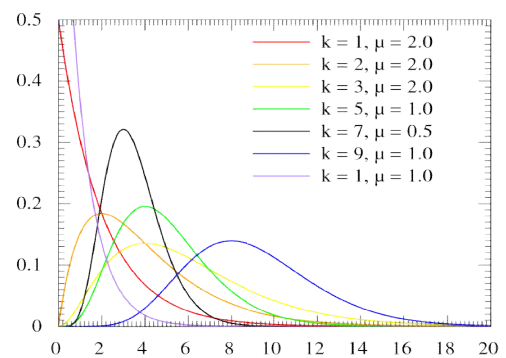


Figure 2. Erlang probability function

Implementation Simulation Erlang Model in C++

```

#include <iostream.h>
#include <math.h>
#include <conio.h>
#include <values.h>
#include <stdlib.h>
double Negexp( double);
double Erlang( int, double);

main ()
{
    double Alpha; int k;
    cout <<"Enter Alpha and k: "; cin>>Alpha>>k;
    cout<<endl;
    for (int j =0; j <2; j++)
        cout << Erlang(k, Alpha)<<endl;
    getch();
}

double Negexp( double Mean)
{
    double r = rand()/double(RAND_MAX);
    return -log(r)*Mean;
}

double Erlang( int k, double Alpha)
{
    double e = 0 ;
    Alpha = Alpha/ k;
    for (int i = 0; i < k; i++)
        e += Negexp( Alpha);
    return e;
}

```

The above piece of code is an implementation of the webeil distribution function. The program is written by the author to simulate the Erlang statistical distribution. It has the flexibility of providing sufficient information regarding the structure of the generated frequencies that satisfy steady state conditions.

Negative Binomial Model

In probability theory and statistics, the negative binomial distribution is a discrete probability distribution of the number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified (non-random) number of failures (denoted r) occurs. For example, if we define a "1" as failure, all non-"1"s as successes, and we throw a die repeatedly until the third time "1" appears ($r =$ three failures), then the probability distribution of the number of non-"1"s that had appeared will be a negative binomial. The Pascal distributions are special cases of the negative binomial. There is a convention among engineers, climatologists, and others to reserve "negative binomial" in a strict sense or "Pascal" for the case of an integer-valued stopping-time parameter r , and use "Polya" for the real-valued case. Figure 3 shows the shape of Binomial probability mass function.

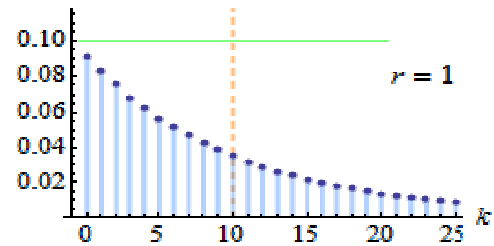


Figure 3. Binomial Probability mass function Implementation Simulation Binomial Model in C++

```

#include <iostream.h>
#include <math.h>
#include <conio.h>
#include <values.h>
#include <stdlib.h>
main ()
{
    double r, p, px, fx, u, gx;
    long int Iter, x, Freq[100] = {0};

    cout <<"Enter Iterations: "; cin>> Iter;
    cout<<endl;
    cout <<"Successful Probability p and Successful Number r: ";
    cin>> p>> r;
    cout<<endl;
    for (int j =0; j <Iter; j++)
    {
        randomize();
        x = r; px = pow( p, r); fx = px ;
        u = rand()/float(RAND_MAX);

        while ( u > fx)
        {
            gx = x * ( 1-p)/( x-r + 1);
            px = gx * px; fx = fx + px;
            x = x + 1;
        }
        ++Freq[x];
    }
    for(int i = 0; i <100; i++)
        if (Freq[i] != 0) cout <<"\n\t"<< i <<"\t"<< Freq[i];
    cout<<endl;

    getch();
}

```

The above piece of code is an implementation of the Negative Binomial distribution function. The program is written by the author to simulate the Negative Binomial statistical distribution. It has the flexibility of providing sufficient information regarding the structure of the generated frequencies that satisfy steady state conditions.

Poisson Distribution Model

In probability theory and statistics, the Poisson distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time and/or space if these events occur with a known average rate and independently of the time since the last event. The

Poisson distribution can also be used for the number of events in other specified intervals such as distance, area or volume. For instance, an individual keeping track of the amount of email they receive each day may notice that they receive an average number of 6 messages per day. If receiving any particular piece of email doesn't affect the arrival times of future pieces of email, i.e., if pieces of email from a wide range of sources arrive independently of one another, then a reasonable assumption is that the number of pieces of email received per day obeys a Poisson distribution. Other examples that may follow a Poisson: the number of product orders received by an order department, the number of decay events per second from a radioactive source, or the number of pedicabs in queue in a particular street in a given hour of a day. Figure 4 shows the shape of Binomial probability mass function.

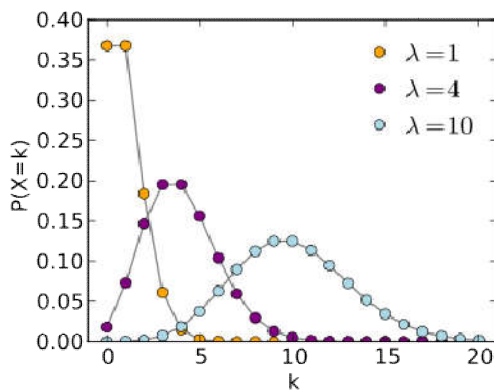


Figure 4. shows the shape of Poisson probability mass function.

Implementation Simulation Poisson Model in C++

```
#include <iostream.h>
#include <math.h>
#include <conio.h>
#include <values.h>
#include <stdlib.h>

double Poisson( double);

main ()
{
    double Mean, Ave = 0, sum = 0;
    long int Iter, k,freq[100]={0};
    cout <<"Enter the Mean: "; cin>> Mean;
    cout <<"Enter the Iterations: "; cin>> Iter;
    cout<<endl;
    for (int j =0; j <Iter; j++)
    { k = int(Poisson(Mean));
      ++freq[k];
      Ave +=k;
    }
    cout <<endl<<" Seq\tFrequencies\n=====\t=====\n";
    for (int j =0; j <100; j++) sum +=freq[j]*j;
    for (int j =0; j <100; j++) if( freq[j] !=
0)cout<<j<<"\t"<<freq[j]<<endl;
    cout <<"\nAverage = "<<Ave/Iter<<"\tFrequency Average
="<<sum/Iter;
    getch();
}
```

```
}
double Poisson( double Mean)
{
    double x = 1, p = 0;
    do {
        x *= rand()/double(RAND_MAX);
        p = p + 1;
    } while ( x >= exp(- Mean));
    return p-1;
}
```

The above piece of code is an implementation of the Poisson distribution function. The program is written by the author to simulate the Poisson statistical distribution. It has the flexibility of providing sufficient information regarding the structure of the generated frequencies that satisfy steady state conditions

Exponential Distribution Model

In probability theory and statistics, the exponential distribution or negative exponential distribution is the probability distribution that describes the time between events in a Poisson process, i.e. a process in which events occur continuously and independently at a constant average rate. It is a particular case of the gamma distribution. It is the continuous analogue of the geometric distribution, and it has the key property of being memory less. In addition to being used for the analysis of Poisson processes, it is found in various other contexts. The exponential distribution is not the same as the class of exponential families of distributions, which is a large class of probability distributions that includes the exponential distribution as one of its members, but also includes the normal distribution, binomial distribution, gamma distribution, Poisson, and many others. Figure 5 shows the shape of Exponential probability density function.

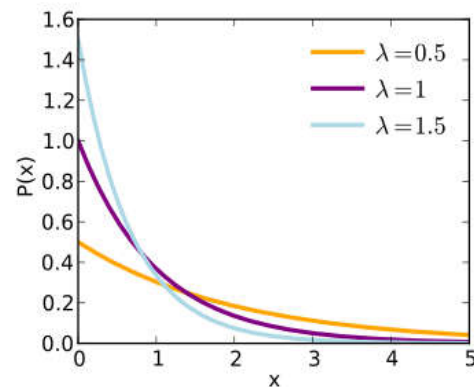


Figure 5. Probability density function

Implementation Simulation Exponential Model in C++

```
#include <iostream.h>
#include <stdlib.h>
#include <conio.h>
#include <values.h>
#include <math.h>
#include <fstream.h>
#include <iomanip.h>
const N = 100;
```


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 7.

Experiment 2. We run the program a number of times with 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 8.

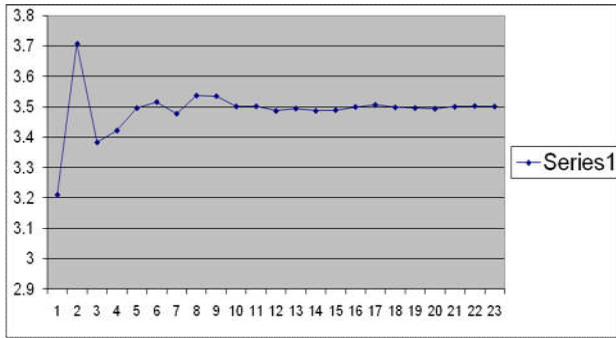


Figure 7. Output of Experiment 1.

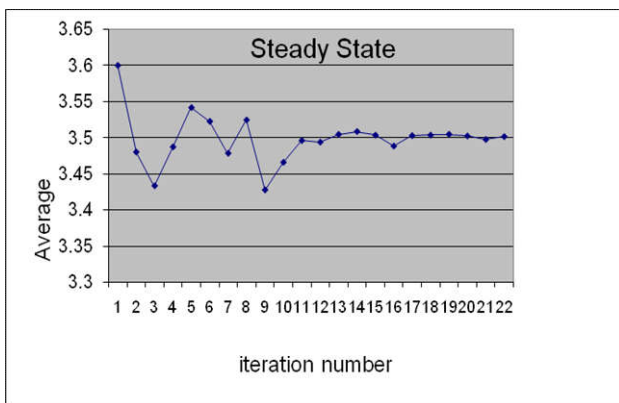


Figure 8. Graph of experiment 2 output

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 9.

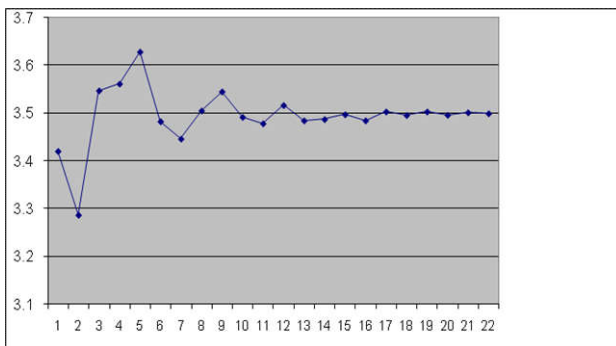


Figure 9. Graph of experiment 3

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 model is developed to analyze parts queuing on the conveyor. The model can be deemed verified when it reflects the following conditions.

- Parts arrive at a desired rate.
- Parts serviced at a desired rate.
- 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.

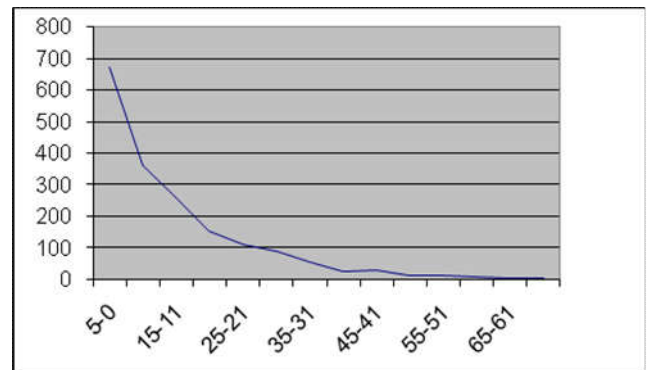


Figure 10. Fitted Negative Exponential distribution

Table 1. Observed changeover time interval

18	13	3	40	9	29	10	3	8	10
1	17	29	2	22	1	22	1	4	32
20	5	8	6	10	3	1	11	13	2
15	8	1	23	29	9	34	17	10	4
15	2	1	1	40	8	6	6	8	1
3	24	14	24	8	14	28	12	18	7
1	5	6	10	54	12	13	1	22	45
5	12	2	14	12	1	33	23	7	5
12	5	46	18	2	2	6	2	39	7
4	4	2	19	1	25	12	3	5	1

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.

needs a management plan. A management plan is the process of assessing an organization's goals and creating a realistic, detailed plan of action for meeting company goals. Much like writing a business plan, a management plan takes into consideration short- and long-term corporate strategies. The basic steps in the management planning process involve creating a road map that outlines each task the company must accomplish to meet its overall objectives.

Table 2. Frequencies and probability distribution calculations

Seq	Class	UppClass	Freq	Prob.	$P(X \leq \text{Upper}) - P(X \leq \text{Lower})$	Expected	Chi-Squared
1	0-5	5	36	0.36	0.331622	33.16217	0.242846
2	6-10	10	21	0.21	0.221649	22.16487	0.06122
3	11-15	15	15	0.15	0.148145	14.81452	0.002322
4	16-20	20	7	0.07	0.099017	9.901705	0.850348
5	21-25	25	8	0.08	0.066181	6.618085	0.288556
6	26-30	30	4	0.04	0.044234	4.423385	0.040524
7	31-35	35	3	0.03	0.029565	2.956495	0.00064
8	36-40	40	3	0.03	0.019761	1.976057	0.530582
9	41-45	45	1	0.01	0.013208	1.320754	0.077897
10	46-50	50	1	0.01	0.008828	0.882763	0.01557
11	>50	55	1	0.01	0.017792	1.779186	0.34124
	Total		100		1		2.451745

Such simulation techniques can reduce subjective decisions and increases the potential for real-time automation (Shin *et al.*, 2013). 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 (Graul *et al.*, 2003). The number in the table represents 100 observations of change over products until steady state condition is met. The number has been studied and chi-square distribution is calculated and we find that the data fit into negative exponential distribution with mean $\mu=12.41$. Table 2. shows the detail of the computation of probability density function and the frequency distribution. The negative exponential distribution is simulated for thousands of times we can make an accurate estimate of changover period in minutes as in figure 10. The diagram in figure 10 shows the output of running the Negative exponential distribution function model. The program is written by the author and it has the flexibility of providing sufficient information regarding the structure of the generated frequencies that satisfy the steady state conditions.

Conclusion

The paper discussed the problems and obstacles face the process of improving manufacturing productivity. Because of the rapid change in market, manufacturing firms should have a strategy and competitive plan in order to compete in a dynamic market. A manufacturing plan is a set of policies designed to maximize performance among trade-offs and among success criteria to meet the manufacturing task determined by a corporate plan. It is the responsibility of the top management of the company to ensure that there is a coherent manufacturing plan and policies derived from internal and external sources of information to support the whole company's mission. In order to implement an efficient mechanism to improve productivity, a manufacturing company

The discussion of the steady state supports our work by providing a clear understanding of costs associated with manufacturing plant through the practical understanding of warm up period. The steady state provides top managements with clear picture of how to make their production line more efficient. Steady state experiments help making production line more efficient by removing any processes that are overly complicated. The author has developed the simulation models. These simulation models are more flexible, adjustable, robust, and reusable. A steady state is essentially needed to show any inconsistencies in the environment of manufacturing process. For example, steady state furnishes 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 confirms that the better trained employees the better productively and effectively. This step alone could increase the efficiency of production process and make manufacturing plant more profitable.

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