ABSTRACT

An Application of Neural Networks to Statistical Process Control

by

Asterios Papaikonomou

Recent changes in the past World War II economy have produced a more educated, value driven customer. A global economy has emerged to technological advances which has made competition fierce as well as proximate. As a result, manufacturing companies are required to provide consumers with quality products at a reasonable cost. A quality product is defined as one that fulfills the needs and expectations of the consumer and provides him with a sense of value.

Since all companies want to provide quality products, the reason why poor quality is sometimes the result is not the outcome of actions for that purpose but is due to variability which is inherent in manufacturing processess. A technique which avoids products that don't meet specifications to be shipped out is that 100% inspection is not required and thus the system is inexpensive to implement.

The purpose of this thesis is to emphasize the importance of quality, to analyze various aspects of Statistical Process Control and stochastically reproduce some of the nonrandom behavior that often are observed in the industry. Finally, this thesis will explain the development of these expert systems who recognize nonrandom behavior, and recommend methods to continue the research.

An Application of Neural Networks
to Statistical Process Control

by

Asterios Papaikonomou

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This thesis is dedicated
to my parents, Theologos and Evangelia
Papaikonomou and to my fiance
Daria LoConte

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IMPORTANCE OF QUALITY

CHAPTER SYNOPSIS

This chapter describes the current trends in manufacturing while it also stretches the importance of quality in today's manufacturing world. The chapter also provides a definition of Quality and describes the current practices intended to improve quality.

1.1 Current Trends in Manufacturing

Major changes in the world of manufacturing climate have produced an extremely competitive environment in which survival is solely determined by the ability of manufacturers to provide their customers with quality products at the right price. As a result, manufacturers have been paying more attention to competition worldwide since technological advancements in communications and infrastructures have produced a global economy. The marketing department in every company has been of increasing importance while on the other hand, the research and development department has been forced to redefine its role. Moreover, new methods have to be found to make quality feasible. It is well known that to produce parts with tighter tolerances more resources have to be spent on either higher quality materials, state-of-the-art machinery or closer inspection. Therefore, efficiency is sought in every activity a company is involved in.

As a result, during the last decade almost every company is restructuring. While the traditional pyramid of managerial levels consisted of a CEO and a board of directors at the top, while the number of layers was ever-growing, recently the pyramid has been getting wider at the bottom and shorter. Less levels of management exist and at the same time, each manager is responsible for more subordinates. Bureaucracies have been proven to be inefficient and since with the use of computers, communication has been made easier, less administrative staff is needed.

Furthermore, due to the fact that each manager is responsible for more employees, the opinion of subordinates is greatly valued. It has been realized that machine operators are often more knowledgeable about production problems. A current trend has been to involve employees from all levels of a manufacturing organization in decision making. Lower level employees might not be able to vote but, nevertheless their input is considered.

Furthermore, to further make an organization run more efficiently, manufacturers are forcing their suppliers to do the same. It is often the case that materials that are not up to specification or are not delivered promptly can cause the manufacturer to spend a great amount of money and effort to either inspect the incoming material or keep abundant amounts of it in stock. In either case, unnecessary costs are incurred which subsequently are transferred to the customer in the form of higher price or delayed deliveries. Supply arrangements then, have changed rapidly in order to make competition feasible. Japanese techniques are often studied and copied since they have been proven to be most efficient. For example, suppliers are now delivering components instead to parts mainly to overcome the problem of fitting parts together from different suppliers. As a result, there are fewer suppliers for each project involved. At the same time, supplier performance is measured and plays a great role in supplier selection. Even though, however, strides have been noticeable in the North American industry, there is still room for improvement. Figure 1.1.1 provides a comparison of suppliers in Japan, Europe and North America in the automotive industry.

Averages for Each Region	*Japanese Japan*	*Japanese America*	*American America*	*All Europe*
Supplier Performance: (1)				
Die change times (minutes)	7.9	21.4	114.3	123.7
Lead time for new dies (weeks)	11.1	19.3	34.5	40.0
Job classifications	2.9	3.4	9.5	5.1
Machines per worker	7.4	4.1	2.5	2.7
Inventory levels (days)	1.5	4.0	8.1	16.3
No. of daily JIT deliveries	7.9	1.6	1.6	0.7
Parts defects (per car) (2)	.24	na	.33	.62
Supplier Involvement in Design: (3)				
Engineering carried out by suppliers (% total hours)	51	na	14	35
Supplier propriety parts (%)	8	na	3	7
Black box parts (%)	62	na	16	39
Assembler designed parts (%)	30	na	81	54
Supplier/Assembler Relations: (4)				
Number of suppliers per assembly plant	170	238	509	442
Inventory level (days, for 8 parts)	0.2	1.6	2.9	2.0
Proportion of parts delivered just-in-time (%)	45.0	35.4	14.8	7.9
Proportion of parts single sourced (%)	12.1	98.0	69.3	32.9

Notes and sources:

(1) From a matched sample of fifty-four supplier plants in Japan (eighteen), America (ten American-owned and eight Japanese-owned), and Europe (eighteen). T. Nishiguchi, *Strategic Dualism: An Alternative in Industrial Societies*, Ph.D. Thesis, Nuffield College, Oxford, 1989, Chapter 7, pages 313 to 347.

(2) Calculated from the 1988 J. D. Power Initial Quality Survey.

(3) From the survey of twenty-nine product development projects by Clark and Fujimoto. K. B. Clark, T. Fujimoto, and W. B. Chew, "Product Development in the World Auto Industry," *Brookings Papers on Economic Activity*, No. 3, 1987, page 741; T. Fujimoto, *Organizations for Effective Product Development: The Case of the Global Motor Industry*, Ph.D. Thesis, Harvard University, 1989, Table 7.1

(4) From the IMVP *World Assembly Plant Survey*, 1990.

Figure 1.1.1 Cross-Regional Comparison of Suppliers

However, running a lean enterprise will not automatically guarantee quality products as an outcome.

1.2 Importance of Quality

Major changes in the world of manufacturing climate have greatly increased the importance that the American industry places on quality. There are several reasons for these changes. Changes in the past World War II economy while information technology has advanced rapidly and search for new markets have produced a global economy and therefore, a worldwide competition. Today's consumer is more educated, demanding, provided with a great variety of choices on how to spend his resources and equipped with a sense of value. Furthermore, the consumer of the nineties is not loyal to the American industry. The demand of more sophisticated products caused mainly by a continuously increased consumer income, has brought up an awareness that products consumers want are not always manufactured in the United States. As a result, the American industry has been losing market share both worldwide and in the domestic market. Table 1.2.1 illustrates the decline of market share of the American Industry.

Table 1.2.1 Decline of American Industry's Market Share

1950-1970	1970-1985
U.S. productivity up 3% per year.	Decreased to 0.4% per year
U.S. accounts for 25% of world manufacturing.	Slipped to 17%
In U.S. market, companies produce 95% of autos, steel, and electronics.	Dropped to: 70% of autos 86% of steel 50% of electronics

Japanese manufacturers are most frequently cited as the one that have mastered the techniques that provide quality products at a reasonable price, hence value. The quality level of Japanese versus American products during the years 1950 to 1980 is illustrated in figure 1.2.1.

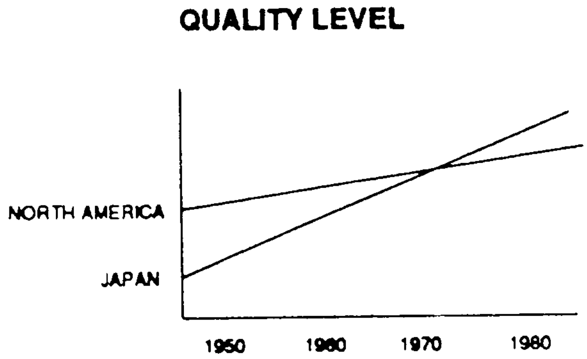


Figure 1.2.1 Quality of American vs. Japanese Products

While quality has been defined differently and a lot of times, the most often definition is simple: quality products are the ones that satisfy customer's needs and expectations at a reasonable cost. To achieve this objective, manufacturers must continually improve the performance and consistency of their products. Quality can be broken down into several attributes:

1. Functionality - The ability of a product to perform the needed function
2. Usability - The ability of the product to execute the function simply and quickly.
3. Reliability - The product's conformance to specification along with the length of time to failure.
4. Performance - The level at which the product executes the function.
5. Serviceability- The restoration of the product once it has failed.
6. Availability - The continuity of the product and the support in the form of parts, service, etc.
7. Price - The cost of function to the customer.

Every manufacturer wishes to produce quality products. Rejects are not an intentional outcome but rather an outcome of several factors. A main factor is that variability is inherent in all manufacturing processes. Variability should be controlled, however, since it cannot be avoided. Furthermore, quality is costly and once the full price is not paid defective products are almost always to be proven the most important cost a manufacturing facility can incur. This is called the Quality Failure Cost (QFC) and it consists of internal factors (during production) or external (to the customer). Internal QFC costs included scrap, rework, higher inspection cost, downtime and costs incurred due to defective products sold at a discount. External QFC costs are mainly warranty costs, returns and losses due to lost customers either from dissatisfaction of bad reputation. On the other hand, these costs can easily be converted to benefits once high quality is achieved. For example, improved product quality often leads to a better market reputation, increased market share which allows for higher prices and economies of sale. Also, production costs are lowered since productivity increases, there is no scrap or rework costs and warranty costs are limited. (See Figure 1.2.2)

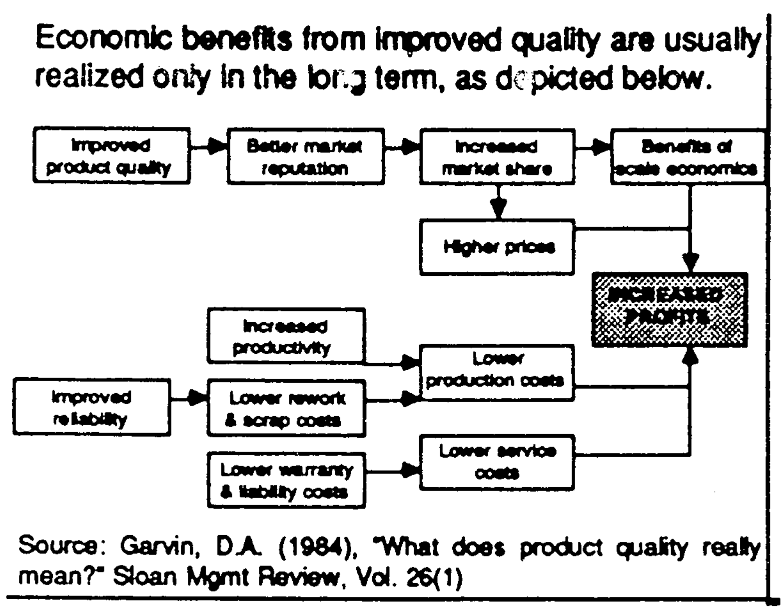


Figure 1.2.2 Benefits of Quality

It is concluded then that quality is free! Higher quality levels are economically justified. Besides, it is evident that traditional efforts to improve quality are no longer effective. It has been realized that proactive rather than reactive measures are required. Traditional quality improvement methods focused on reducing waste, scrap, downtime, rework, etc. Even though important, those methods failed to recognize the importance of the customer's sense of value. Consequently, the customer is the source of both the design of the product and its manufactureability. Research and development departments do not operate in isolation. Customer's needs and expectations cannot be second-guessed but have to be researched. Even though a design, however, might depict closely what the customer wants, the manufacturability of the designed product is not just the next step. As mentioned before, variability is inherent in all manufacturing processes. The industry recognizes this variability so a devised minimum is to built products within specifications. So the designer has taken variability into consideration, has included tolerances in the blueprints and the product was to be dimensionally correct with the designer's target values. The traditional operating philosophy has created a view of quality control which relies heavily in inspection, a reactive method. A widespread use of go/no-go inspection equipment has been in effect which, unfortunately cannot determine how close the dimensions are to the target value. Sources of variation have no way of being discovered by machine operators and therefore, corrected. Besides, communication between operators and quality control personnel are practically non-existent.

A strategy for improvement has been suggested by Dr. W. Edwards Deming which has been proven effective. This strategy consists of 14 points for management applicable to all kinds of organizations. Briefly, Dr. W. Edwards Deming advises for commitment to continuous improvement, adoption of a new philosophy which doesn't accept the same levels of mistakes, defects, etc., requirement of statistical evidence that quality is built into the process and dependence on meaningful measures of quality along with price. Furthermore, management has to adopt modern methods of training, supervision, communication, planning and motivation. Dr. Deming also stresses the importance of top management's commitment to quality at all aspects that the organization is involved with.

1.3 Current Practices for Improving Quality

Several programs are quality oriented. By far the most widespread and successful if implemented properly is Total Quality Management (TQM). Total Quality Management is an overall program to manage quality. It should be formally introduced and effectively managed. The program is defined as an approach to continuously improve the quality of goods and services by involving the participation of people at all levels and functions in the organization, while focusing on all sources and types of defects. By definition then, TQM can be described as a general philosophy of the organization, while on the other hand, can serve as an umbrella of other technologies through the various departments of the organization. Some of these technologies are emphasizing or are oriented towards the human factor. Others are technologically oriented. An example of a human-oriented technology are the quality circles which are independent teams of employees making sure that quality products will only be shipped out of the factory.

For a quality control program to be implemented successfully it has to cover all functions of the organization. Therefore, the main checkpoints of such a program are the following.

A. Supplier management. Defects often are produced due to poor supplier performance. The wrong material at the wrong time can be proven very costly for a manufacturing facility. Several manufacturers have come up with their own supplier performance evaluation on which supplier selection is based upon. A method which has been proven effective is once again found among Japanese supply systems. It is called Just-in Time (JIT). JIT is a production management system that has been designed to provide the right material at the right place and at the right time. Such a system once implemented does not allow any room for mistakes. Production has to be smooth and since no inventory is allowed by definition, all problems have to be exposed and solved and Quality and Performance have to be improved. JIT is not is not always the most desirable supply system. When, however, there is a production rate that is almost uniform, quick and inexpensive setups and preventive maintenance, it can prove to cut costs dramatically. Since quality has to be built into the system, lead-time is reduced, system uncertainty is reduced, set-up time is reduced, and inventory costs are almost eliminated.

B. Quality Assurance. Once targets for quality products have been set, it must be assured that the available technology and processes are able to produce those products. To assure that the design is feasible, Taguchi methods are often used. Professor Genichi Taguchi of Japan employed statistical methods for improving the quality of products and processes. An important concept is the use of experiments to make products that are robust to environmental factors. For problems of this kind designs are employed by manipulation of an 'inner array' and an 'outer array'. For each experimental run in the design (inner array) where the primary design factors of runs is conducted varying several environmental factors that might effect the products performance. Dr. Taguchi also emphasized the idea that the more a quality characteristic deviates from its target value, the greater the cost. Therefore, he designed experiments based on statistics to minimize variation about a target value.

Other aspects for quality assurance include skills training, supervisor training, team problem solving, scheduling for quality vs. quantity and quality incentives.

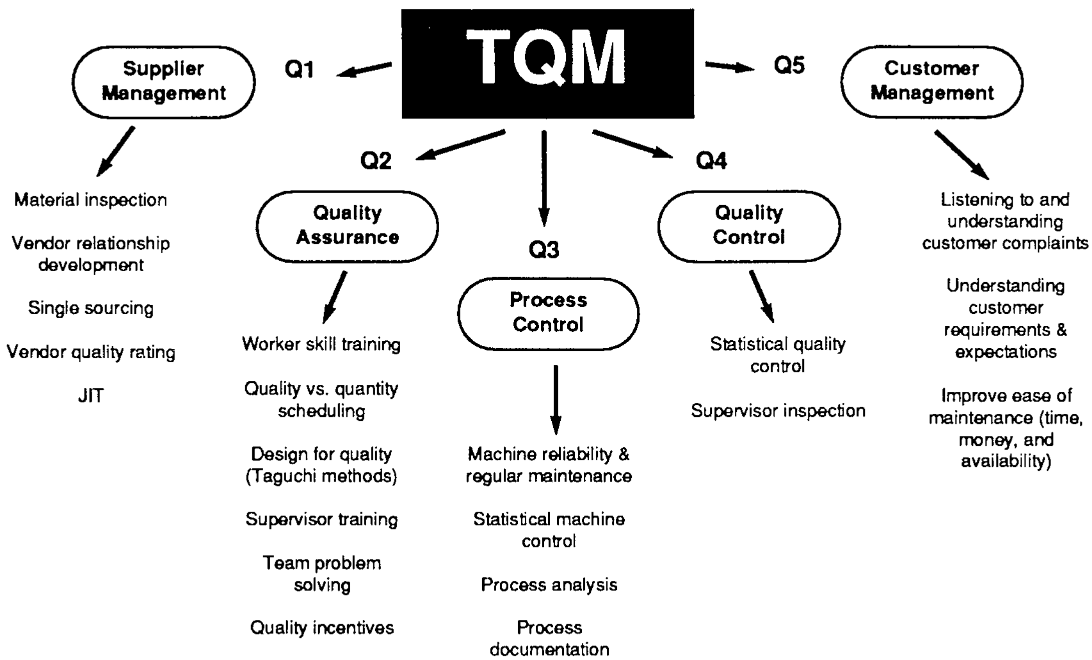
C. Process Control is concerned with detecting the cause of variation of a process and eliminating it. A process analysis is required along with a process documentation and machine reliability and regular maintenance is stressed. Automation is a trend that many manufacturing facilities have been following during the past few years. Even though automation is not always desirable, as for small batch production, Computer Process Control, Computer-aided manufacturing, Computer-aided Process planning and other technologies are frequently the solution to quality problems. A company considering to restructure, however, should consider the huge costs incurred for new machinery and retraining of employees.

D. Quality Control. Even though a management program can be extremely effective, defects are inevitable to be produced. The main objective is to detect these defects, alert the system and correct the source of variation as soon as possible. Inspection has been the traditional method of achieving this objective. In principle, the only way to achieve 100% good quality, is to implement 100% inspection, which is a task that can escalate costs greatly. Firstly, manual 100% inspection is associated with human error and consequently, not full-proof. Automated inspection seems to offer a good alternative. Human error is eliminated. The full potential of automated inspection is realized when it is integrated with the manufacturing process. Once parts are produced by a machine and are presented to an automated inspection system such as machine vision system or a coordinate measuring machine, a feedback loop can provide the preceding manufacturing process with valuable data. The purpose of data is to allow compensating adjustments to be made to the process for quality improvement. Sortation of parts can also be made possible. After inspection parts can be sorted according to their quality level either as acceptable or unacceptable.

A technology which is constantly gaining popularity is Statistical Quality Control (SQC), Statistical Quality Control is less expensive since only samples are inspected (measured) and fairly easy to implement. A detailed discussion on Statistical Quality Control and Statistical Process Control is provided in chapters 2 and 3 of this thesis, since this the focus of the research involved.

E. Finally Customer Management is the most important assessment of the products quality since it is the one that is given by the customer. Customer Management is involved with listening and understanding customer complaints, understanding customer's needs and expectations and improving the ease of maintenance.

Table 1.3.1 Activities of Total Quality Management



Chapter 2

AN INTRODUCTION TO STATISTICAL QUALITY-PROCESS CONTROL

CHAPTER SYNOPSIS

This chapter intends to introduce the theory behind Statistical Quality Control. A brief discussion of the history of SQC will be provided in the first section while in subsequent sections, the importance of SQC will be discussed along with the benefits realized by the use of this method. Also guidelines will be provided on the interpretation of the results of SQC and their relevance to manufacturing processes.

2.1 History of Statistical Quality Control

Manufacturers have been concerned with quality since manufacturing of products began. During the early stages of manufacturing, however, quality problems were easy to handle since the manufacturer-craftsman had contact with each and every product that came out of his shop. During the middle ages, machinery was almost non-existent, apprentices had to be trained for long periods of time. In order for these apprentices to become master craftsman, they had to provide their mentors with evidence of their ability to produce a top quality product.

During craft production most products were hand-made. This fact of course doesn't guarantee quality, but rather eliminates the need for quality control. It was known exactly what had to be done to turn a defective part into a quality product. Furthermore, since there was contact with each and every part produced no defects could escape the shop floor.

Mass production, however, soon became the effective way to manufacture products due to its innovations. With Henry Ford's Model T came the achievement of two objectives that would change the world. First, there was a car that was designed for manufacture and second, in today's terms, it was user friendly. This key to mass production was the complete and consistent interchangability of parts and the simplicity of attaching them to each other. And these were the innovations that made the assembly line possible. To achieve consistent interchangability of parts, however, the dimensions of each past has to be 'exactly' the same. Ford insisted that the same gauging system was used throughout the whole manufacturing process.

Soon after the creation of mass production by Henry Ford, craft production came to an end and the industry adopted the new manufacturing method. It was realized that control of the production process was a critical factor to the success of mass production. Several quantitative methods to ensure quality were developed during the first half of this century and they were applied through the 1980's. Due to fierce competition during the past two decades, the use of these new quantitative approaches to monitor manufacturing process became a necessity. Statistical Process Control (SPC) is one of these methods, which once put into effect, provides the manufacturing industry with ways to improve product quality while at the same time decrease product cost.

Western Electric Co. was the manufacturer of telephones during the 1920's. Since large numbers of identical telephones had to be manufactured and 100% insection drove product cost to rise, new ways of monitoring quality had to be developed. The company (WEC) was required to sample and consequently, pioneered much of the early work in applying statistics to quality control. The major breakthrough in Statistical Quality Control came when Dr. Walter A. Shewhart presented his initial research on quality control during the manufacturing process and later, when Harold F. Dodge and Harry G. Romig formulated their sampling inspection theory. In 1931 Dr. Shewhart published his book on SQC titled as the 'Economic Control of Quality of Manufactured Product.'

During the 1930's the industry's response to Statistical Quality Control was slow and sporadic. The slow response was ascribed mainly to two factors. Firstly, American Engineers were committed to develop or improve technical methods so variations in a manufacturing process are minimized. Secondly, statistical methods were not considered to be 'scientific' and therefore, had no place among production methods. Among the first reviewers of Dr. Shewhart's work on SQC was Dr. W. Edwards Deming who was involved in a SQC program conducted at Stanford University in July of 1942. Dr. Deming proceeded to an educational campaign in 1950 to promote the quality concept to Japanese manufacturers. As a result, many of the Japanese products today are perceived as top quality products. A mail survey conducted by the International Motor Vehicle Program (IMVP) showed that 93% of American suppliers involved in the automotive industry used SPC on all their operations in 1988 an increase by 74% from 1983. The Japanese on the other hand, had diffused SPC to heir suppliers about 30 years ago, during the 1950's.

2.2 The Importance and Theory of SPC

Statistical Process Control is a method which helps monitor and understand the behavior of a manufacturing process. Even though it is desirable for every manufacturer to produce products whose dimensions are as accurate as possible, all manufacturing processes have certain abilities and limitations. SPC provides the operators with feedback about the process so the sources of variation can be examined and decisions can be made about the capability of a process to produce a certain part. To control a process means to direct it as to behave as desired. Statistics is a science involved in using measurements of samples from a population, manipulating these measurements and finally, making inferences about the populations.

To apply statistics in order to understand the behavior of a process the following steps have to be followed:

1. Data Collection: Once the problem is defined, data has to be collected in numerical form. The quality of the data will determine the quality of the result. Thus, data must be relevant, accurate and timely.

2. Presentation and Analysis: Once the data is collected it has to be transformed from its raw form to a form which is summarized, organized and presented properly. Several charts, graphs and measures are used for the organization of data.

3. Inference and Action: Once the data has been presented and analyzed, specific procedures and rules are followed to reach conclusions about the process. When the results deviate from the ones desired, corrective action has to be taken. Statistical process control is a preventive system rather than a detection system.

Once a SPC program goes into effect, a planning session for data collection provides an opportunity for communication between everyone involved. Besides, during this session, decisions involving what is to be measured, how is it going to be measured and who will do the measuring are made. Finally, considerations about the possibility of measurement error are made. Measurement error is usually caused by differences in measuring devices, differences in people making the measurements or differences between the way one person measures a unit from one time to the next.

Several methods exist for the collection of data. Check sheets are the easiest way and there have been several check sheets developed. The most widespread ones are:

- Check sheets for process distribution
- Check sheets for defective items

- Check sheets for location of defects
- Check sheets for cause and effect

Part No. & Name	Char. Measured
Operation No. & Desc.	Date

SAMPLE DATA

No.	Value	No.	Value	No.	Value	No.	Value	No.	Value
1		21		41		61		81	
2		22		42		62		82	
3		23		43		63		83	
4		24		44		64		84	
5		25		45		65		85	
6		26		46		66		86	
7		27		47		67		87	
8		28		48		68		88	
9		29		49		69		89	
10		30		50		70		90	
11		31		51		71		91	
12		32		52		72		92	
13		33		53		73		93	
14		34		54		74		94	
15		35		55		75		95	
16		36		56		76		96	
17		37		57		77		97	
18		38		58		78		98	
19		39		59		79		99	
20		40		60		80		100	

Remarks

TALLY SHEET

VALUE															
TALLY															
FREQUENCY															

Figure 2.2.1 Check Sheet for Capability

To evaluate a process, the shape of the distribution and the relationship of the measured dimension to the specification limits must be determined. As seen in Figure

2.2.1 a check sheet used for this reason is called the Data Collection for Capability Analysis form. The form is preferred for it s simplicity. of use. The operator needs only to make checkmarks in the tally column of the form and the frequency distribution is developed as the data is collected.

Most of the industrial processes behave truly randomly. The distribution shape which most distributions assume, is the normal distribution curve or bell-curve (see Figure 2.2.2).

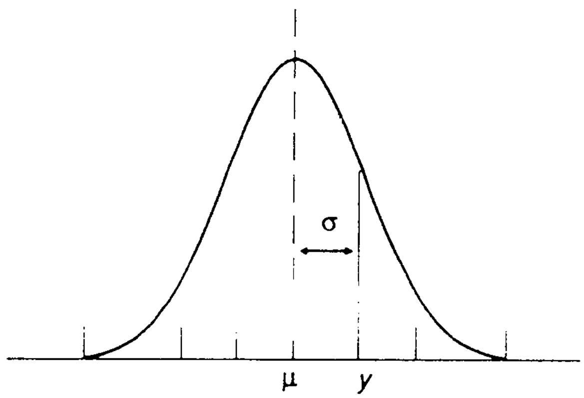


Figure 2.2.2 Normal Distribution

The normal distribution curve is completely described by two characteristics: the mean and the standard deviation. The areas of either side of the curve are equal. About 68.26% of the total area in included within a distance of $\pm\ \sigma$ from the mean while 95.44% of the total area is included within a distance of $\pm\ 2\ \sigma$ of the mean. Virtually the whole area (99.73%) is included within $\pm\ 3\ \sigma$ from the mean. Along with the mean and standard deviation, the range is the only other measurement of deprecion of data which will be needed to construct the control charts. Control charts are plots of those measures which help analyze data. But let's describe the step-by-step procedure followed to construct an SPC chart and then describe its use in signaling the presence of variations in a process.

A. Finding the mean. Among other central measures such as the median and the mode, the mean is the most commonly used central measure. Conventionally, it is represented by a bar over the symbol of the variable, such as $\bar{x}$ (called "x bar"). Once the distribution of a variable has been determined by measuring the same dimension of several parts manufactured, the numerical values are recorded. The mean is the sum of all these numerical values divided by the total number of values in the distribution.

B. Finding the range. The range is a measure of dispersion of the data. It is denoted by the letter R and it is simply the difference between the highest value and the lowest value of the data in hand. The range (R) is fairly easy to compute since only two values are needed to determine it. It is perfect for determining the dispersion of data among small samples, but since all values in between are ignored, a more efficient measure is needed. This measure of depersion is called the root-mean-square deviation (RMS) or simply the standard deviation.

C. Finding the standard deviation. The standard deviation is usually represented by the letter s. For any sample, the calculation for the standard deviation involves finding the average (mean) of the numerical values at hard. Once the mean has been calculated, it is subtracted from each value and the results are squared. The next step is to sum the squares and divide this sum by the total number of values minus one i.e., (n- 1) and determine the square root. The formula for the calculation of the standard deviation is:

$$s = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}}$$

Example: Suppose we are measuring the diameter of a cylindrical shaft. The sample at hand is 10 shafts and the following values for the diameter are recorded:

2.010 in.
2.035 in.
1.982 in.

1.995 in.
2.025 in.
2.046 in.
1.978 in.
1.969 in.
1.988 in.
2.037 in.

Range = 2.046 - 1.969 = 0.077 in

Mean = (2.010 =+ 2.035 + 1.982 + 1.995 + 2.025 + 2.046 + 1.978 + 1.969 + 1.988 + 2.037) / 10 = 2.0065 in.

$(x_i - \bar{x})$	$(x_i - \bar{x})^2$
2.010 - 2.0065 = 0.0035	1.23×10^{-5}
2.035 - 2.0065 = 0.0285	8.123×10^{-4}
1.982 - 2.0065 = -0.0245	6.003×10^{-4}
1.995 - 2.0065 = -0.0115	1.323×10^{-4}
2.025 - 2.0065 = 0.0185	3.423×10^{-4}
2.046-2.0065=0.0395	15.603×10^{-4}
1.978-2.0065=-0.0285	8.123×10^{-4}
1.969-2.0065=-0.0375	$14.063\ x^{-4}$
1.988 - 2.0065 = -0.0185	3.423×10^{-4}
9.037 - 2.0065 = 0.0305	9.303×10^{-4}

$\Sigma(x - x)^2 = 6.951 \times 10^{-3}$

Standard Deviation = $.\sqrt{.\frac{\Sigma(x - x)^2}{n - 1}} = .\sqrt{\frac{6.95x10^{-3}}{9}}$ = 0.0278 in.

Before mentioning the method of constructing control charts, their importance and their meaning, reference must be made on the Statistical Error. A Statistical Inference is a prediction of how a population will behave based on a study on samples from that population. A risk of error is always involved in making such a prediction and this error is of two types: Type I error is rejecting a true hypothesis with a certain probability alpha, while Type II error is accepting a false hypothesis with probability beta. The odds of such risks are minimized when the sample size is large enough compared to the population. Since it is most desirable to use the minimal amount of samples while at the time minimizing error, one can use statistical techniques to determine the appropriate sample size. Sampling frequencies is concerned with how often sampling should occur. For a process which is proven to be well under control, sampling can occur only once or twice a day. When, however, the control is poor, sampling should occur more often. A method then which is often followed to determine the sampling frequency is to sample often in the beginning of implementing Statistical Process Control and gradually decrease sampling once the sources of variations has been found and removed.

While constructing the control charts, the two kinds of sources of variation have to be kept in mind: Common causes refer to causes of variation of a process. The process is still under control and the measured values are normally distributed with the bulk of measurements concentrated around the mean. Special causes on the other hand, are factors causing variation in a process which cannot be properly explained by any single distribution. The process, therefore, is not in statistical control and before the normal behavior of a process can be studied, the special causes have to be removed otherwise they will affect the process output in unpredictable ways.

Control charts are divided into two categories: Control charts for attributes which are plots of simply judgments as to whether the part is good or bad. Control charts for variables are plots of specific measurements of a product characteristic among a continuous scale, such as measurements for dimension, weight etc. We will only be concerned about control charts for variables. The control charts can be constructed for variables such as the mean, range, standard deviation, the median or the individual measurements. The ones used more widely are the first three and their significance is described below.

No matter which control chart is to be constructed the steps for preparation are the same.

1. Gather the data and plot on the chart. Once the process has produced a number of parts and measurements of samples have been taken, the data is converted to a form which can be plotted on a graph.

2. Control. This step involves calculating the control limits (Upper and Lower) of the variation that is expected to be caused only when common causes of variation are present. These limits are not to be confused with the specification limits for a product since they only represent the natural variation of the process which could be significantly larger or smaller than the specifications.

3. Interpretation for Process Control. Once the data has been plotted and compared to the control limits it studied to determine if special causes of variation exist. Any uncommon points near or further than the limits could indicate special causes of variation. Only until these special causes have been discovered and removed which might take several runs and recalculations of the control limits, can we determine the capability of a process.

4. Interpretation for Process Capability. With all special causes of variation removed, the process is investigated about its capability to produce the required products. The process is said to be in statistical control. If the variation is still excessive, the process itself or the design of the product has to be changed.

The methods of constructing an $\bar{x}$ chart (mean chart) and an R chart are identical and will be described together seen in Figure 2.2.3, which depicts an average and range chart. These charts are also constructed together.

ASI **AVERAGE & RANGE CHART** | Plot Area | Chart Area

Part Name (Product) ADJUSTER | Operation FORMING | Spectrum .10 - .18

Operator Ms. Q. Control | Characteristic DIM. "B" | Gage DIAL INDICATOR | Units of Measure .01 mm | Frequency 5/2 Hrs

Date

Time	4:00	9:00	11:00	1:30	3:30	7:00	9:00	11:00	1:30	3:30	7:00	9:00	11:00
1	.15	.12	.13	.15	.14	.13	.13	.16	.12	.13	.13	.13	.15
2	.16	.14	.14	.17	.15	.14	.12	.13	.16	.11	.12	.13	.14
3	.16	.14	.13	.15	.13	.14	.13	.15	.13	.13	.12	.17	.12
4	.15	.13	.17	.13	.16	.13	.14	.13	.15	.16	.13	.14	.12
5	.14	.15	.13	.17	.17	.12	.12	.13	.13	.14	.12	.13	.14
Sum	.75	.86	.78	.77	.75	.66	.64	.70	.66	.86	.82	.78	.87
Ave.	.152	.136	.146	.154	.150	.132	.126	.140	.136	.132	.124	.143	.134
R	.02	.03	.04	.04	.04	.02	.02	.03	.04	.06	.01	.04	.03

Time	1:30	3:30	7:00	9:00	11:00	1:30	3:30	7:00	9:00	11:00	1:30	3:30
1	.15	.15	.16	.13	.15	.15	.16	.12	.16	.14	.16	.15
2	.14	.16	.15	.14	.14	.18	.15	.14	.13	.12	.15	.15
3	.17	.13	.15	.15	.15	.17	3.18	.12	.17	.16	.15	.12
4	.16	.13	.15	.12	.14	.14	.16	.13	.17	.15	.14	.17
5	.14	.16	.17	.17	.14	.13	.16	.16	.15	.15	.13	.14
Sum	.76	.75	.81	71	.72	.76	.75	.87	.76	.72	.73	.73
Ave.	.152	.150	.142	.142	.144	.152	.150	.134	.136	.144	.146	.165
R	.03	.03	.03	.05	.01	.04	.03	.04	.04	.04	.03	.05

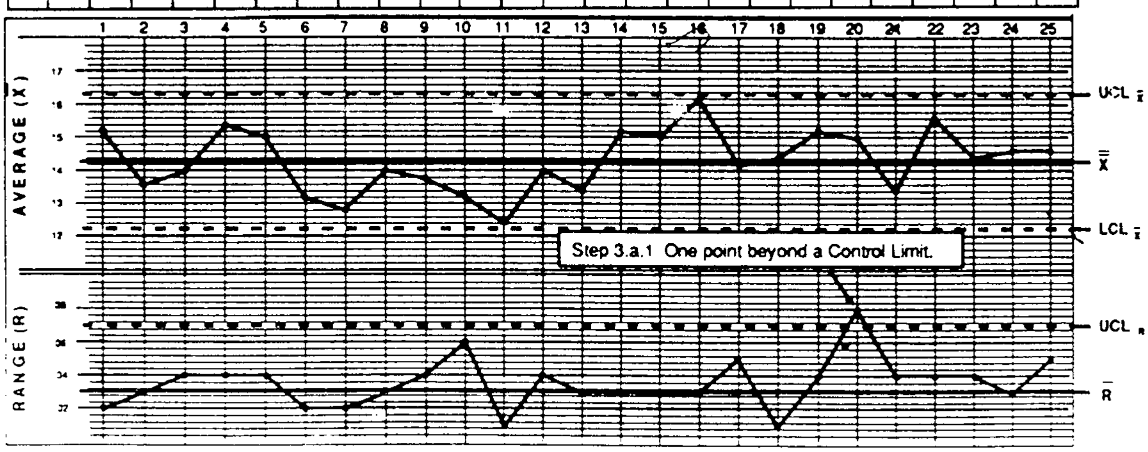


Figure 2.2.3 Control Chart ($\bar{x}$ and R)

In Figure 2.2.3 the sample size chosen is five measurements. The sample size is an important consideration. It must be chosen carefully in a manner that ensures all major sources of variation will be evident. The intervals of sampling should also depict major potential sources of variation such as different operators, different batches of raw material and others. As a guideline from a statistical point of view 25 or more subgroups containing 100 more readings will indicate safely if the process is stable. As a reminder, when the process is first tested, the maximum number of samples should be taken. Subsequently, the number of samples can gradually decrease once the process is in statistical control.

The first step is to gather and record raw data for each sample (subgroup). Once this data is gathered, the average of each sample and its range are calculated and plotted on the chart. While the vertical coordinate is the measured dimension (average or mean) with the Lower Control Limit (initial values) at the bottom and the Upper Control Limit at the top the horizontal coordinate represents time since sampling occurs in certain time intervals. Once the values for all patterns have been plotted connecting them by a solid line could help visualize any patterns created by the process. For the preliminary calculation of the control limits the following formulas are used:

$$UCL_R = D_4\overline{R}$$

$$LCL_R = D_3\overline{R}$$

$$UCL\bar{x} = \bar{\bar{x}} + A_2\overline{R}$$

$$LCL\bar{x} = \bar{\bar{x}} - A_2R$$

$$\text{Where } R = .\frac{R_1 + R_2 + \ldots + R_n}{n}$$

$$\bar{x} = .\frac{\bar{x}_1 + \bar{x}_2 + \ldots + \bar{x}_n}{n}$$

with n being the number of subgroups and $\bar{x}_1$, $\bar{x}_2$... and R_1, R_2 being the average and range of each subgroup. The values for the constants A_2, D_3, D_4 are shown partially in Table 2.2.1.

Table 2.2.1 Constant for Calculation of Control Limits ($\bar{x}$-R)

n	**2**	**3**	**4**	**5**	**6**
D_4	3.267	2.574	2.282	2.114	2.004
D_3	*	*	*	*	*
A_2	1.880	1.023	0.729	0.577	0.483

n	**7**	**8**	**9**	**10**
D_4	1.924	1.864	1.816	1.777
D_3	0.076	0.136	0.184	0.223
A_2	0.419	0.373	0.337	0.308

$\bar{x}$ and S charts are constructed similar to the $\bar{x}$ and R charts. It should be noted that control charts are always used as a pair. As larger sample sizes are used standard deviation is a more efficient measure of dispersion since the values in between the highest and lowest are not ignored. So the use of s charts becomes more desirable when sample sizes are large and the data is recorded and plotted by a computer so the standard deviation is routinely calculated.

Figure 2.2.4 shows an $\bar{x}$ and s chart with the values plotted.

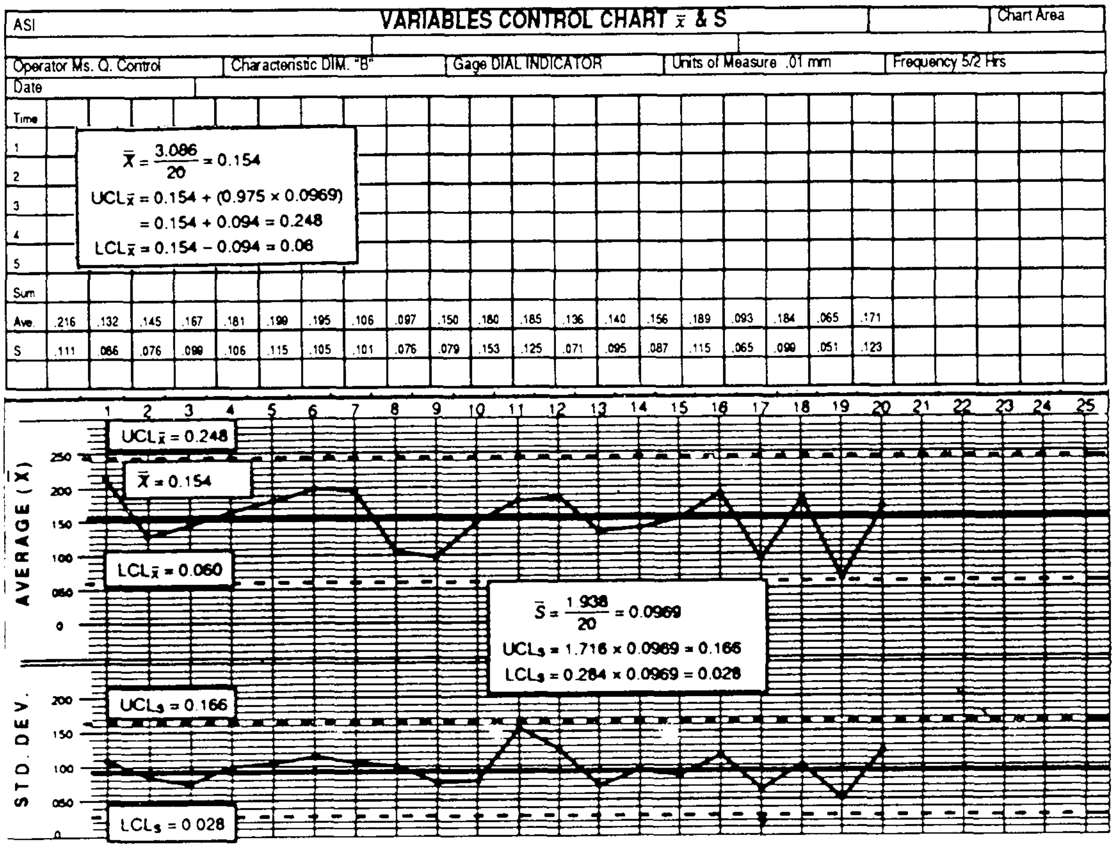


Figure 2.2.4 Control Chart ($\bar{x}$ and S)

Once the raw data for each sample is recorded, the average is calculated at the same manner it was calculated for the $\bar{x}$ and R chart. The standard deviation for each sample is calculated by the following formula: $S = \sqrt{\frac{\sum(xi - \bar{x})^2}{n-1}}$ where xi, $\bar{x}$ and n represent the sample's individual value, average and size respectively. The next step in constructing the $\bar{x}$ and s chart involves plotting the values for each sample on the chart. Once again it is advised connecting these values with a solid line so any unusual patterns are revealed. Finally, the preliminary calculation of the control limits takes place from the following formulas:

$UCLs = B4\bar{s}$

$LCLs = B3\bar{s}$

$UCL\bar{x} = \bar{\bar{x}} + A3\bar{s}$

$LCLx\bar{x} = -A3\bar{s}$

Where $\bar{s}$ is the average of the individual group of sample standard deviations, $\bar{\bar{x}}$ is calculated the same way as for the $\bar{x}$ and R chart and constants A3, B3 and B4 are shown in Table 2.2.2 varying with sample size for sample sizes between 2 and 10.

Table 2.2.2 Constants for Calculation of Control Limits ($\bar{x}$-S)

n	**2**	**3**	**4**	**5**	**6**
B_4	3.267	2.568	2.266	2.089	1.970
B_3	*	*	*	*	0.030
A_3	2.659	1.954	1.628	1.427	1.287

n	**7**	**8**	**9**	**10**
B_4	1.882	1.815	1.761	1.716
B_3	0.118	0.185	0.239	0.284
A_3	1.182	1.099	1.032	0.975

With the construction of the Control Charts completed, the interpretation for process capability is the next step.

2.3. Interpretation of the Control Charts.

The main objective of the control charts is to identify any special causes of variation. If the process is under statistical control only 0.27% of the plotted points should be beyond the control limits (or ±3 standard deviations). The operator of the specific process investigated should be warned for special causes of variation if there are any points outside the control limits, if there is a consecutive run of the 7 or more points above the mean or if there is a consecutive run of 7 or more points increasing or decreasing. A point outside the control limits should be marked and analyzed. If no special causes are evident, the point can be interpreted to represent a miscalculation, a change in the variability or a change in measuring system. If, however, a special cause is discovered, it should be removed before any further study is possible. Even when all the plotted points in the $\bar{x}$ and R chart or the $\bar{x}$ and s chart lie between the limits, the presence of any unusual trends or patterns should alarm the operator for any noncontrol factors affecting the process on a change in the process during the investigated run.

To elaborate, a stable process will provide a control chart whose values are normally distributed and span the control limits. However, several unnatural patterns can exist. For example a sudden shift in level can occur during the run and the center of the distribution is shifted. A **trend** is a gradual rise or fall of plot points indicating that the process is drifting. Caution should be taken before the process is adjusted since the rise or fall and only 3 or 5 points could be random. At least six or seven point should be taken into account before any adjustments occur. Another frequently observed pattern is cycles. Cycles are patterns that are repeated periodically. In a real-life situation cycles can be caused by rotation of operators, material rotation, temperature variation, etc. Another important pattern, also frequently observed is stratification. It is a pattern which is described with only a few points near the center line while the distribution appears to be equally distanced from the control limits. A situation as such can be caused by samples coming from two different machines which produce parts with distributions with different centers, different operators or different environments (temperature, humidity, etc.).

It is of crucial importance that machine operators are trained to recognize such patterns as they occur. When these patterns occur, it is almost certain that special causes of variation are still present and, therefore should be removed. On the other hand, some of these patterns are favorable - such as a decreasing range or standard deviation - and should be studied. The conditions causing such patterns should be traced and reinforced for possible permanent improvement in the process.

When conducting an initial study on a process, the Upper Control Limit and the Lower Control Limit must be recalculated every time a special cause is removed. Only when the process does not exhibit any points out of limits or any patterns are evident, we can extend the control limits for ongoing control. The final calculation of the control limits takes place as follows: The standard deviation (σ:sigma) is calculated first. $\sigma = \overline{R}/d2$, where $\overline{R}$ is the average range of the sample ranges for a group of samples and d2 is taken from the table below varying by sample size:

Table 2.3.1 Constants for Recalculation of Control Limits

n	**2**	**3**	**4**	**5**	**6**
d_2	1.128	1.693	2.059	2.326	2.534

n	**7**	**8**	**9**	**10**
d_2	2.704	2.847	2.970	3.078

Using the constants d2, D3, D4 and A2 from Tables 2.3.1, 2.2.1 and 2.2.2 the new limits are calculated from the formulas below:

$\overline{R}$ new = $\sigma * d_2$

$UCL_R = D4\overline{R}$ new

$LCL_R = D3\overline{R}$ new

$UCL\bar{x} = \overline{\overline{X}} + A_2 \overline{R}$ new

$LCL\bar{x} = \overline{\overline{X}} - A_2 \overline{R}$ new

The Control Limits for the $\bar{x}$ and s chart are computed as before.

As mentioned before, the fact that the process is under statistical control does not guarantee its ability to produce parts within specification with only 0.27% of the parts being defective. The assessment of the capability of the process doesn't begin until after the control charts have been resolved, there are no more special causes of variation and ongoing control shows evidence that the process is well under statistical control with at least 25 or more groups of samples. The objective once all these criteria have been met is to determine the percentage of all defective parts. The procedure followed is the following! First the process standard deviation s is calculated as before along with the process average. Then, the spread of the process average and the specification limits per standard deviation is calculated as the value z = .\F(specification - average, standard deviation). Then the upper and lower limits of z are calculated as follows:

$$Z_{USL} = .\frac{USL - \bar{x}}{\sigma}$$

$$Z_{LSL} = .\frac{\bar{x} - LSL}{\sigma}$$

where: USL: upper specification limit

LCL: lower specification limit

From table 2.3.2 the numbers P_{ZUSL} and P_{ZLSL} can be found which represent respectively the percentage of parts above the upper specification limit and the percentage of parts below the specification limit. Their sum is the total percentage of defective parts.

Table 2.3.2 Constants for Percentage of Defective Parts

Z	X.X0	X.X1	X.X2	X.X3	X.X4	X.X5	X.X6	X.X7	X.X8	X.X9
4.0	0.00003									
3.9	0.00005	0.00005	0.00004	0.00004	0.00004	0.00004	0.00004	0.00004	0.00003	0.00003
3.8	0.00007	0.00007	0.00007	0.00006	0.00006	0.00006	0.00006	0.00005	0.00005	0.00005
3.7	0.00011	0.00010	0.00010	0.00010	0.00009	0.00009	0.00008	0.00008	0.00008	0.00008
3.6	0.00016	0.00015	0.00015	0.00014	0.00014	0.00013	0.00013	0.00012	0.00012	0.00011
3.5	0.00023	0.00022	0.00022	0.00021	0.00020	0.00019	0.00019	0.00018	0.00017	0.00017
3.4	0.00034	0.00032	0.00031	0.00030	0.00029	0.00028	0.00027	0.00026	0.00025	0.00024
3.3	0.00048	0.00047	0.00045	0.00043	0.00042	0.00040	0.00039	0.00038	0.00036	0.00035
3.2	0.00069	0.00068	0.00064	0.00062	0.00060	0.00058	0.00056	0.00054	0.00052	0.00050
3.1	0.00097	0.00094	0.00090	0.00087	0.00084	0.00082	0.00079	0.00076	0.00074	0.00071
3.0	0.00135	0.00131	0.00126	0.00122	0.00118	0.00114	0.00111	0.00107	0.00104	0.00100
2.9	0.0019	0.0018	0.0018	0.0017	0.0016	0.0016	0.0015	0.0015	0.0014	0.0014
2.8	0.0026	0.0025	0.0024	0.0023	0.0023	0.0022	0.0021	0.0021	0.0020	0.0019
2.7	0.0035	0.0034	0.0033	0.0032	0.0031	0.0030	0.0029	0.0028	0.0027	0.0026
2.6	0.0047	0.0045	0.0044	0.0043	0.0041	0.0040	0.0039	0.0038	0.0037	0.0036
2.5	0.0062	0.0060	0.0059	0.0057	0.0055	0.0054	0.0052	0.0051	0.0049	0.0048
2.4	0.0082	0.0080	0.0078	0.0075	0.0073	0.0071	0.0069	0.0068	0.0066	0.0064
2.3	0.0107	0.0104	0.0102	0.0099	0.0096	0.0094	0.0091	0.0089	0.0087	0.0084
2.2	0.0139	0.0136	0.0132	0.0129	0.0125	0.0122	0.0119	0.0116	0.0113	0.0110
2.1	0.0179	0.0174	0.0170	0.0166	0.0162	0.0158	0.0154	0.0150	0.0146	0.0143
2.0	0.0228	0.0222	0.0217	0.0212	0.0207	0.0202	0.0197	0.0192	0.0188	0.0183
1.9	0.0287	0.0281	0.0274	0.0268	0.0262	0.0256	0.0250	0.0244	0.0239	0.233
1.8	0.0359	0.0351	0.0344	0.0336	0.0329	0.0322	0.0314	0.0307	0.0301	0.0294
1.7	0.0446	0.0436	0.0427	0.0418	0.0409	0.0401	0.0392	0.0384	0.0375	0.0367
1.6	0.0548	0.0537	0.0526	0.0516	0.0505	0.0495	0.0485	0.0475	0.0465	0.0455
1.5	0.0668	0.0655	0.0643	0.0630	0.0618	0.0606	0.0594	0.0582	0.0571	0.0559
1.4	0.0808	0.0793	0.0778	0.0754	0.0749	0.0735	0.0721	0.0708	0.0694	0.0681
1.3	0.0968	0.0951	0.0934	0.0918	0.0901	0.0885	0.0869	0.0853	0.0838	0.0823
1.2	0.1151	0.1131	0.1112	0.1093	0.1075	0.1056	0.1038	0.1020	0.1003	0.0985
1.1	0.1357	0.1335	0.1314	0.1292	0.1271	0.1251	0.1230	0.1210	0.1190	0.1170
1.0	0.1587	0.1562	0.1539	0.1515	0.1492	0.1469	0.1446	0.1423	0.1401	0.1379
0.9	0.1841	0.1814	0.1788	0.1762	0.1736	0.1711	0.1685	0.1660	0.1635	0.1611
0.8	0.2119	0.2090	0.2061	0.2033	0.2005	0.1977	0.1949	0.1922	0.1894	0.1867
0.7	0.2420	0.2389	0.2358	0.2327	0.2297	0.2266	0.2236	0.2206	0.2177	0.2148
0.6	0.2743	0.2709	0.2676	0.2643	0.2611	0.2578	0.2546	0.2514	0.2483	0.2451
0.5	0.3085	0.3050	0.3015	0.2981	0.2946	0.2912	0.2877	0.2843	0.2810	0.2776
0.4	0.3446	0.3409	0.3372	0.3336	0.3300	0.3264	0.3228	0.3192	0.3156	0.3121
0.3	0.3821	0.3783	0.3745	0.3707	0.3669	0.3632	0.3594	0.3557	0.3520	0.3483
0.2	0.4207	0.4168	0.4129	0.4090	0.4052	0.4013	0.3974	0.3936	0.3897	0.3859
0.1	0.4602	0.4562	0.4522	0.4483	0.4443	0.4404	0.4364	0.4325	0.4286	0.4247
0.0	0.5000	0.4960	0.4920	0.4880	0.4840	0.4801	0.4761	0.4721	0.4681	0.4641

Other methods to access the capability of a process include the calculation of capability indices (C_p and C_{pk}) which again are calculated from a control chart but are more efficient since they provide a more generalized method and simplify the process' ability to hold specs with simple numbers.

Once the capability of a process has been determined it can be improved regardless of the fact if it is capable or not. Several machine adjustments can reduce the variability and consequently, increase the part quality. Adjusting the process mean for example involves shifting the process so that the average coincides with the specification center. Furthermore, common-cause variability can be analyzed and reduced. Consistent materials, the operation of a process or tooling can improve product quality. As a last resort, since it is only a temporary measure, the specification tolerance can be increased so as to reduce product cost by reducing scrap and rework costs.

2.4 Role of SPC and Its Results.

The implementation of a Statistical Process Control program is sensitive to the specific company's environment. The issues to be confronted differ from company to company and there are several tools which, once applied properly can identify the decisions to be made in order for the program to be successful.

One of those decisions is where to begin implementing a Statistical Quality-Process Control Program. It is not economically feasible to implement such a program in every activity a manufacturing facility is involved in. A Pareto analysis can help identify the most vital areas were SPC is needed. The Pareto principle basically states that only 20% of the causes account for about 80% of the problem (also known as the "80/20 rule"). Translated to manufacturing terms, this would mean that only 20% of the processes involved to produce a product are accountable for 80% of the defects. The problem then, is redefined as to identify those processes. By listing each process and next to it listing its contribution to the total defects, the results are the solution. Furthermore, the cumulative percentage of the defects can be listed and a graph can be constructed (see Fig. 2.4.1) with the left vertical axis showing the number of defects from each operation, the right horizontal axis showing the percent contribution of defects from each operation while the horizontal axis is just the list of operations needed to produce the part. The operations are listed with the most frequent at the left and in a descending order.

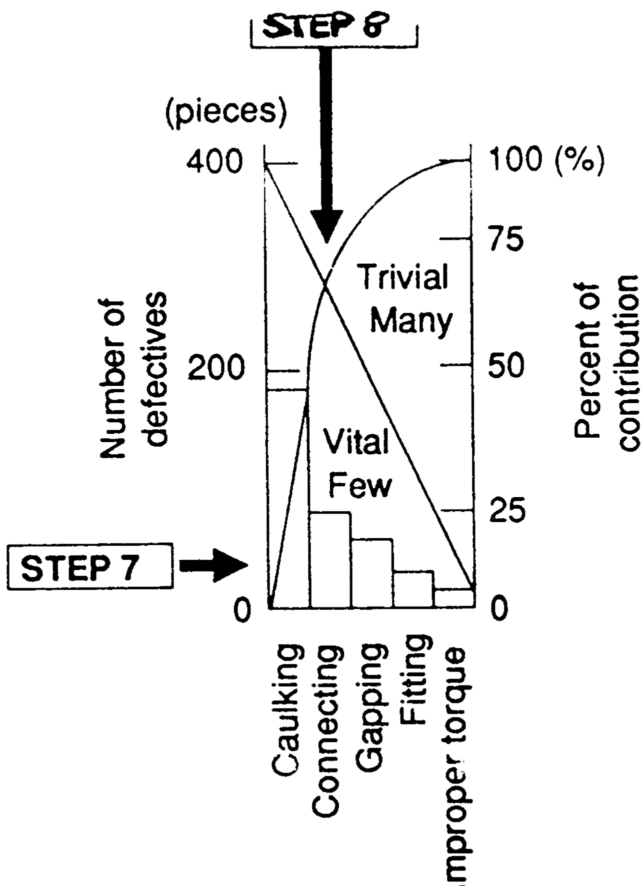


Figure 2.4.1 Pareto Diagram

As seen in the pareto diagram in Figure 2.4.1 the intersection of the line from the 100% point on the left vertical axis to the last point on the horizontal axis with the line for the cumulative averages will determine on which processes the effort should be concentrated.

Another question frequently asked once the problems have been identified is what are the causes for these problems. A cause-and-effect diagram (also referred to as a fishbone diagram) can provide with useful insight. To construct such a diagram, the quality characteristic to be analyzed is determined first. Then the process to be analyzed is drawn as a horizontal arrow pointing to the box with the quality characteristic under study. The major causes effecting such a process are represented with boxes which are parallel to the main arrow and minor causes are concentrated around the major causes (see figure 2.4.2). By consensus, the causes are identified as important sources of the effect, they are improved and reviewed regularly.

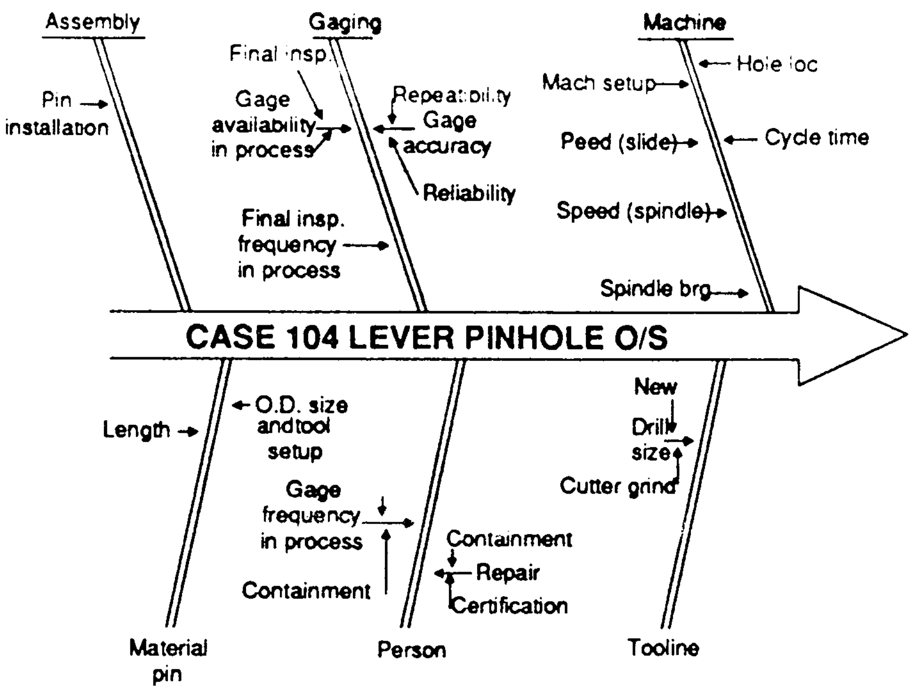


Figure 2.4.2 Fishbone Diagram Example

Once the SPC program goes into effect, its success depends on several factors. Unless top management is committed and actively involved in the program, success becomes trivial. Delegating authority is not enough. A deep understanding of the methods and principles is required first to motivate subordinates and second to plan effectively for the introduction of the program and its monitoring. A common philosophy has to be developed and communicated across the board. It is easier to implement quality control when common standards and measurement methods are used. Furthermore, teamwork is required so people from different disciplines can be involved. Consequently, extensive training must be provided for everyone involved. The individual responsible for coordinating the program should have a vast knowledge on statistical quality control, while every employee from quality control to operators should be trained, even though less extensive for long-term results to be evident.

A SPC program is designed to replace continuous inspection with a company-wide effort for continuous improvement in quality. The information obtained by quality assurance is to be used by all the departments in the company. Purchasing, marketing, production will all concentrate their efforts for a common objective in such a way as to guarantee the success of a quality control program. Besides, the suppliers of raw materials, parts and components should also be involved. Once the quality of incoming materials is guaranteed, multiple sourcing becomes obsolete. By dealing with less suppliers, higher quality due to uniformity of parts is achieved while the cost is minimized. Going one step further, the suppliers can get their subsuppliers involved into using the same methodologies. A chain is then created with each link committed to providing quality products to their customers.

Another key step for the success of an SPC program is the development of a pilot program. This can be a study which takes place in a critical area. Every step for the success of the program has to be followed as mentioned above, and based on the results obtained from the pilot program the methods can be modified to suit each particular area where the SPC principles will be applied on.

Statistical Process Control will be a major source of feedback to the Designing Engineers. The information obtained from the control charts can give useful insight for better designs. Planning for manufacturing, quality targets and production rates becomes more efficient.

The American economy has been based on manufacturing through the 1970's. During the past 2 decades, however, a rapid shift brought up changes. The economy is now based on an information and service industry. It is estimated that about 70% of the workforce is occupied by the service industry and the percentage constantly increases. It is vital, therefore, that statistical thinking in manufacturing has to be implemented. Every product is accompanied with information. Everyone has to be aware of statistical methods so production rates increase along with the quality of the product while at the same time the cost decreases. These are the key concepts that will bring the American industry back to the top of the manufacturing world.

This study will attempt to create stochastically data from measured dimensions of a process, recreate several patterns which are common in manufacturing processes and finally develop expert systems that will not only recognize that the process is going out of control, but also give a warning with an explanation on what the problem exactly is. This can help avoid extensive training of machine operators on statistical quality control program. Further research might be able to create systems that will not only identify the problem but also provide the operators with a solution.

Chapter 3

STOCHASTIC GENERATION OF PROCESSES

CHAPTER SYNOPSIS

This chapter describes the methods used to generate a capable process stochastically. The software used to analyze the process statistically is later explained. Furthermore, the generation of processes which are statistically out of control is described. Many of the incapable processes generated posses the patterns described in chapter 2.

3.1 The Monte-Carlo Method of Simulating a Process.

This experiment involves generating a capable manufacturing process. The simulation of manufacturing cylindrical shafts of diameter d=2.0 inches is attempted. The specifications for this dimension dictate a tolerance of ± 3 standard deviations. The specified tolerance is ±0.06 inches. The standard deviation for the process can be calculated as follows:

Tolerance = (t) = ±3 standard deviations (σ) = ±0.06 inches

$$\sigma = \frac{0.06''}{3} = 0.02 \text{ inches}$$

A statistically controlled process is described as a process whose output is randomly distributed. As a result, the exact dimension of the output can be found once the area under the curve (the probability of this dimension) is known. This number is denoted by **z**. The formula which gives the exact dimension (**x**) of the part generated is:

$$x = \mu + \sigma\,(z) \qquad (1)$$

where μ is the average of the process. In the case of the cylindrical shaft produced, the average is equal to 2.0 inches while the standard deviation is equal to 0.02 inches. A table of Random Normal Numbers is used to obtain z and it is shown below:

Table 3.1.1 Table of Random Normal Numbers

$\mu = 0,\ \sigma = 1$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	0.464	0.137	2.455	−0.323	−0.068	0.296	−0.288
2	0.060	−2.526	−0.531	−1.940	0.543	−1.558	0.187
3	1.486	−0.354	−0.634	0.697	0.926	1.375	0.785
4	1.022	−0.472	1.279	3.521	0.571	−1.851	0.194
5	1.394	−0.555	0.046	0.321	2.945	1.974	−0.258
6	0.906	−0.513	−0.525	0.595	0.881	−0.934	1.579
7	1.179	−1.055	0.007	0.769	0.971	0.712	1.090
8	−1.501	−0.488	−0.162	−0.136	1.033	0.203	0.448
9	−0.690	0.756	−1.618	−0.445	−0.511	−2.051	−0.457
10	1.372	0.225	0.378	0.761	0.181	−0.736	0.960
11	−0.482	1.677	−0.057	−1.229	−0.486	0.856	−0.491
12	−1.376	−0.150	1.356	−0.561	−0.256	0.212	0.219
13	−1.010	0.598	−0.918	1.598	0.065	0.415	−0.169
14	−0.005	−0.899	0.012	−0.725	1.147	−0.121	−0.096
15	1.393	−1.163	−0.911	1.231	−0.199	−0.246	1.239
16	−1.787	−0.261	1.237	1.046	−0.508	−1.630	−0.146
17	−0.105	−0.357	−1.384	0.360	−0.992	−0.116	−1.698
18	−1.339	1.827	−0.959	0.424	0.969	−1.141	−1.041
19	1.041	0.535	0.731	1.377	0.983	−1.330	1.620
20	0.279	−2.056	0.717	−0.873	−1.096	−1.396	1.047
21	−1.805	−2.008	−1.633	0.542	0.250	0.166	0.032
22	−1.186	1.180	1.114	0.882	1.265	−0.202	0.151
23	0.658	−1.141	1.151	−1.210	−0.927	0.425	0.290
24	−0.439	0.358	−1.939	0.891	−0.227	0.602	0.973
25	1.398	−0.230	0.385	−0.649	−0.577	0.237	−0.289
26	0.199	0.208	−1.083	−0.219	−0.291	1.221	1.119
27	0.159	0.272	−0.313	0.084	−2.828	−0.439	−0.792
28	2.273	0.606	0.606	0.747	0.247	1.291	0.063
29	0.041	−0.307	0.121	0.790	−0.584	0.541	0.484
30	−1.132	−2.098	0.921	0.145	0.446	−2.661	1.045
31	0.768	0.079	−1.473	0.034	−2.127	0.665	0.084
32	0.375	−1.658	−0.851	0.234	−0.656	0.340	−0.086
33	−0.513	−0.344	0.210	−0.736	1.041	0.008	0.427
34	0.292	−0.521	1.266	−1.206	−0.899	0.110	−0.528
35	1.026	2.990	−0.574	−0.491	−1.114	1.297	−1.433
36	−1.334	1.278	−0.568	−0.109	−0.515	−0.566	2.923
37	−0.287	−0.144	−0.254	0.574	−0.451	−1.181	−1.190
38	0.161	−0.886	−0.921	−0.509	1.410	−0.518	0.192
39	−1.346	0.193	−1.202	0.394	−1.045	0.843	0.942
40	1.250	−0.199	−0.288	1.810	1.378	0.584	1.216

The objective is to generate a hundred cylindrical shafts. Since the process is assumed to be capable, only 0.27 percent of the parts should be beyond the specification limits. To generate the shafts, the first 100 numbers from Table 3.1.1 are used to obtain z and each shaft diameter is calculated by (1). For example the first shaft would have a diameter of $x_1 = 2.0 + (0.02)(0.464) = 2.0093$ inches.

3.2 The SPC Module of STORM

To investigate whether or not the generated process is truly capable it is subjected to SPC. The software package used is the STORM QUANTITATIVE MODELING FOR DECISION SUPPORT. The control charts that are generated by STORM reflect the behavior of the process. These control charts are the x-bar chart, the RANGE chart and the S chart. Control charts can be designed based on either history or standards. When no historical data is available from the past standard values may be used for the Upper and Lower Control Limits. Such values may be based on the manufacturer's specifications or the machines operator's estimates of the process capability. The advantage of using historical data is that the control limits computed are real. It is known if the process is capable if the plotted values stay within the limits since they have in the past. For the simulation of the manufacturing of cylindrical shafts, historical data is used to design the control charts. Samples consist of 5 shafts each. Since we have already simulated the production of 100 shafts by the Monte-Carlo method, 20 samples are available to be used as historical data.

Several criteria have been suggested to determine whether or not a process is under statistical control. STORM provides the user with a variety of such criteria from which selection is available. These criteria are:

0. A point outside control limits. This criterion is always on since it automatically signals nonrandom behavior of the process. STORM uses the conventional three standard deviation limits to design the charts.

1. A run of two or more points outside two standard deviation limits. This criterion is underlined by the concept that it should be realized that the process is degrading before it actually is out of control. The probability of a point being outside two standard deviation limits is 4.56%. For two consecutive points to be outside two standard deviation limits, the probability greatly reduces. Even though the process is randomly distributed, when only a small amount of data is available this criterion should be selected. Furthermore, this criterion should only be used only when the samples are submitted in their exact order of production, as in our case.

2. A run of three or more points outside one standard deviation limits. This criterion is analogous to criterion 1. Once again, the process is to be corrected before it actually degrades. As in criterion 1, the same logic operates. The probability of a point being out of one standard deviation limit is 31.74%. For three consecutive points to be outside one standard deviation limits, the probability reduces greatly. Once again, this criterion should be used only when the samples are submitted to their exact order of production to truly depict the behavior of the process.

3. A run of seven or more points above/below the centerline. This criterion depicts the famous engineering 'rule of seven.' When there is a large amount of data available, this criterion might not be meaningful. It should only be used when the samples are submitted in their exact order of production.

4. The fourth criterion is analogous to criterion 3. A run of seven or more consecutive points increasing or decreasing might signal that the process is not

behaving randomly since the probability of such a pattern is small. Only when the samples are submitted in their exact order of production and a small amount of data is available as in our case, is this criterion meaningful.

5. The number of runs above/below the centerline. When this criterion flags a sample in a run, nonrandom behavior is suspected. The probability of the number of runs occurring by random chance is less than 5 percent.

6. The length of the longest run above/below the centerline. When the number of samples in a run increase, the longer a run below or above the centerline can occur without suspicion raised. When, however, a sample has been flagged by criterion 6, the probability of such an event occurring randomly is less than 1 percent and non random behavior is suspected. Criteria 7 and 8 operate under the same logic and instead of comparing samples above/below the centerline, they compare samples increasing or decreasing.

Caution should be used in selecting the above criteria. A false out-of-control signal is more likely to be received when more criteria are selected. That means that even when the process is statistically controlled, some criterion will be flagged. These criteria are based both on rules of thumb and on statistical theory which are considered appropriate.

Data entry in the Statistical Process Control Module of STORM is going to be explained in terms of an example. The data used is the 100 cylindrical shafts generated by the Monte-Carlo method and the variable which will be used to create the control charts is the diameter. The STORM editor with the data entered is shown in figure 3.2.1. First the title is entered as "SPC example"

```
STORM EDITOR : Statistical Process Control Module
Title : Statistical Quality Control Project
Number of samples          :     20  Number of variables         :    1
Number of attributes       :      0  Raw or Summarized data      :  RAW
Sample size (variables)    :      5  Sample size (attributes)    :    0

R1   : C1       VAR  1 VR  1/OB 1 VR  1/OB 2 VR  1/OB 3 VR  1/OB 4 VR  1/OB 5
SAMPLE    1       XXXX     2.0093     2.0012     2.0297     2.0204     2.0279
SAMPLE    2       XXXX     2.0181     2.0236       1.97     1.9862     2.0274
SAMPLE    3       XXXX     1.9904     1.9725     1.9798     1.9999     2.0279
SAMPLE    4       XXXX     1.9643     1.9979     1.9732     2.0208     2.0056
SAMPLE    5       XXXX     1.9639     1.9763     2.0132     1.9912      2.028
SAMPLE    6       XXXX      2.004     2.0032     2.0455     2.0008     1.9774
SAMPLE    7       XXXX     2.0155     2.0075     1.9897     2.0058     2.0205
SAMPLE    8       XXXX     1.9733     1.9943     2.0032     1.9731      2.025
SAMPLE    9       XXXX     2.0027     1.9495     1.9929     1.9906     1.9989
SAMPLE   10       XXXX     1.9897     1.9789     1.9902     2.0151     2.0045
SAMPLE   11       XXXX     2.0335      1.997      2.012      1.982     1.9767
SAMPLE   12       XXXX     1.9948     1.9929     2.0365     2.0107     1.9589
SAMPLE   13       XXXX     1.9598     2.0236     1.9772     2.0072     1.9954
SAMPLE   14       XXXX     2.0042     2.0054     2.0121     1.9939      1.958
SAMPLE   15       XXXX     2.0016     1.9668     1.9931     1.9896     2.0598
No entry
F1 Block  F2 GoTo  F3 InsR  F4 DelR  F5 InsC  F6 DelC  F7 Done  F8 Help KB: N
```

Figure 3.2.1 The SPC Module of STORM (Data Entry)

Then, the number of samples, 20 in the shaft example, is entered and the number of variables is entered next. Since the only variable used is the diameter of the shaft, number 1 is entered. No attribute data is used in our analysis and therefore, number 0 is entered as the number of attributes. The data is raw and the sample size is 5. STORM editor asks the user next if he is ready to go into detailed variable data entry. Typing 'y' will prompt the cursor to the first row of the detailed data area. Each row represents a sample and a total of 20 samples provide the user with 20 rows for data entry. Once all the data points have been entered, execution of the module is available. Some choices have to be made first, however. Selection of the charts is made first. The charts selected for the shaft experiment are the x-bar chart, the RANGE chart and the S chart. These are control charts for the average, the range and the standard deviation respectively.

Besides, the selection of historical data or standard values is made. By typing 'h' the module will be executed with the data entered in the editor and the control limits are going to be calculated from that. The final step is selecting the out-of-control criteria for each chart generated. Figure 3.2.2 shows the X-BAR chart for the shaft example. The column labeled as 'Value' is the average diameter of each sample. The Lower Control Limit (LCL) and the Upper Control Limit (UCL) are shown at the top of the chart as calculated by the module. No sample have been flagged by the criteria selected (all) and no patterns are evident so the process is assumed to be in statistical control and capable of producing the part within specification limits.

```
          STOCHASTIC GENERATION OF PROCESSES  (CAPABLE)
                       VAR   1 : S CHART
     LCL = 0.0000       Center = 0.0217      UCL = 0.0453

Sample            Value   LCL             C              UCL 012345

-----------------------------------------------------------------------
SAMPLE    1      0.0122    :   .   *      :         .     :
SAMPLE    2      0.0255    :   .          : *       .     :
SAMPLE    3      0.0216    :   .          *         .     :
SAMPLE    4      0.0233    :   .          :*        .     :
SAMPLE    5      0.0262    :   .          :  *      .     :
SAMPLE    6      0.0246    :   .          : *       .     :
SAMPLE    7      0.0117    :   .   *      :         .     :
SAMPLE    8      0.0219    :   .          *         .     :
SAMPLE    9      0.0205    :   .         *:         .     :
SAMPLE    10     0.0142    :   .    *     :         .     :
SAMPLE    11     0.0231    :   .          :*        .     :
SAMPLE    12     0.0283    :   .          :   *     .     :
SAMPLE    13     0.0250    :   .          : *       .     :
SAMPLE    14     0.0215    :   .          *         .     :
SAMPLE    15     0.0347    :   .          :        *.     :
SAMPLE    16     0.0158    :   .     *    :         .     :
SAMPLE    17     0.0264    :   .          :  *      .     :
SAMPLE    18     0.0152    :   .     *    :         .     :
SAMPLE    19     0.0186    :   .       *  :         .     :
SAMPLE    20     0.0232    :   .          :*        .     :
-----------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 3 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

Figure 3.2.2 X-BAR chart

The RANGE chart is analyzed next. The column labeled as 'Value' is the difference between the largest and smallest diameter within the sample. Next, each of the sample ranges are plotted. The process average range (center), the LCL and UCL are shown in the top of the chart (Figure 3.2.3). Since the samples were submitted in the exact order of production, the vertical axis represents the time. Since no out-of-control criteria are triggered, the process operates under statistical control.

```
          STOCHASTIC GENERATION OF PROCESSES  (CAPABLE)
                            VAR   1 : RANGE CHART
     LCL = 0.0000          Center = 0.0545       UCL = 0.1153

Sample            Value  LCL           C                    UCL 012345

---------------------------------------------------------------------
SAMPLE   1      0.0285   :   .  *     :        .     :
SAMPLE   2      0.0575   :   .        :*       .     :
SAMPLE   3      0.0554   :   .        *        .     :
SAMPLE   4      0.0566   :   .        *        .     :
SAMPLE   5      0.0641   :   .        : *      .     :
SAMPLE   6      0.0681   :   .        :  *     .     :
SAMPLE   7      0.0308   :   .  *     :        .     :
SAMPLE   8      0.0519   :   .       *:        .     :
SAMPLE   9      0.0533   :   .        *        .     :
SAMPLE  10      0.0362   :   .    *   :        .     :
SAMPLE  11      0.0568   :   .        :*       .     :
SAMPLE  12      0.0777   :   .        :     *  .     :
SAMPLE  13      0.0638   :   .        : *      .     :
SAMPLE  14      0.0541   :   .        *        .     :
SAMPLE  15      0.0930   :   .        :        *     :
SAMPLE  16      0.0433   :   .     *  :        .     :
SAMPLE  17      0.0618   :   .        : *      .     :
SAMPLE  18      0.0399   :   .     *  :        .     :
SAMPLE  19      0.0455   :   .      * :        .     :
SAMPLE  20      0.0524   :   .       *:        .     :
---------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

Figure 3.2.3 RANGE Chart

The analysis of the standard deviation chart is analogous to the analysis of the RANGE chart. As shown in Figure 3.2.4 the S chart is constructed by calculating the standard deviation of each sample and then plotting it against time. The process standard deviation (center), the LCL and UCL are automatically calculated by the module. Since the standard deviation cannot by negative, the Lower Control Limit is zero. Once again, the process is capable of producing cylindrical shafts within the tolerance limits since no criteria have been triggered.

```
            STOCHASTIC GENERATION OF PROCESSES   (CAPABLE)
                              VAR   1 : X-BAR CHART
     LCL = 1.9677              Center = 1.9992        UCL = 2.0306

Sample              Value  LCL              C             UCL 012345
--------------------------------------------------------------------------
SAMPLE    1         2.0177   :     .         :        *.     :
SAMPLE    2         2.0051   :     .         :   *      .    :
SAMPLE    3         1.9941   :     .       * :          .    :
SAMPLE    4         1.9924   :     .      *  :          .    :
SAMPLE    5         1.9945   :     .       * :          .    :
SAMPLE    6         2.0062   :     .         :   *      .    :
SAMPLE    7         2.0078   :     .         :    *     .    :
SAMPLE    8         1.9938   :     .       * :          .    :
SAMPLE    9         1.9849   :     .  *      :          .    :
SAMPLE   10         1.9957   :     .       * :          .    :
SAMPLE   11         2.0003   :     .         *          .    :
SAMPLE   12         1.9988   :     .         *          .    :
SAMPLE   13         1.9926   :     .      *  :          .    :
SAMPLE   14         1.9947   :     .       * :          .    :
SAMPLE   15         2.0022   :     .         :*         .    :
SAMPLE   16         2.0010   :     .         :*         .    :
SAMPLE   17         2.0105   :     .         :     *    .    :
SAMPLE   18         1.9923   :     .      *  :          .    :
SAMPLE   19         1.9979   :     .        *:          .    :
SAMPLE   20         2.0014   :     .         :*         .    :
--------------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE    1 to SAMPLE   20

 0    Points outside control limits
 1    Run of 2 or more points outside two sigma limits
 2    Run of 3 or more points outside one sigma limits
 3    Run of 7 or more above/below the centerline
 4    Run of 7 or more up or down
 5    Number of runs above/below the centerline

 A    Assignable cause
 M    Missing value
```

Figure 3.2.4 S Chart

It is worthwhile to mention at this point that all three charts should be analyzed in order to determine the capability and rondom behavior of the process. As it will become evident in the next section, while one chart might not show any signs of process behaving nonrandomly, the others might signal that the process is going out of statistical control.

3.3 Stochastic Generation of Nonrandom Processes.

The patterns generated are the following: A trend of increasing average, a trend of increasing standard deviation, sampling from two different machines with different averages (stratification), a shift in stratification and finally a cycles pattern.

A. The method of generating an increasing average trend is based on the Monte-Carlo method and is very similar to the generation of a capable process. For the first sample, the values of the diameter of each shaft are identical in both cases. Formula (1) is used and the number z comes from the first five numbers on table 3.1.1. The second sample is generated the exact same way but instead of using an average $\mu = 2.0$ inches the mean is increased by 0.005 inches. Each subsequent sample is drawn by a population whose mean keeps increasing by 0.005 from its initial value. By using the first 100 numbers from table 3.1.1 20 samples are generated which are then subjected to SPC. The results from STORM SPC module are shown in Appendix A. The title of the report is 'Stochastic generation of process (rising avg)' and it contains the data file along with the X-BAR, RANGE and S charts. It should be noted that while it is obvious from the X-BAR chart that the process is moving out of control, the RANGE and S charts show no evidence of nonrandom behavior of the process. A situation as this process could arise in a real manufacturing environment by tool wear. The X-BAR chart is flagged from criteria 0,1,2,3,5 and any subsequent samples should signal the process is out of control.

B. The generation of this trend involves samples taken from populations of increasing standard deviation. It is similar to the generation of the rising average trend. The first sample is drawn from a population with a mean $\mu = 2.0$ inches and a standard deviation $\sigma = 0.02$ inches. The first five numbers are used from table 3.1.1 for z and the calculation of the shaft diameters is performed by formula (1). The second sample is generated the exact same way by the next five numbers for z but this time the standard deviation (σ) is equal to 0.025. Each subsequent sample is drawn from a population with mean $\mu = 2.0$ inches and a standard deviation that increases by 0.005 inches from its initial value. The data obtained is entered in the Statistical Process Control module of STORM and the results are shown in Appendix A. The title of the report is 'Stochastic Generation of Processes (Rising Standard Deviation). The number of samples is 20 and the sample size of 5. As seen from X-BAR chart, even though the center (mean) of the process is considerably lower than 2.0 inches (center = 1.9957), the process and all sample averages are well within the control limits. A glance in the RANGE and S charts, however, reveals an obvious trend. Criteria 2,3 and 5 are triggered mainly because as the process standard deviation increases (and eventually goes beyond the Upper Control Limit) the ranges keep getting larger and larger. Any additional samples will also be flagged by criteria 2,3 and 5 and the process should be stopped and adjusted at this point. In a real-life situation this trend can be caused by gradual loosening of the fixtures that hold the part on the machine table or increased oscillation of the machine base itself.

C. The generation of a stratified process takes place next. This situation can exist in real life when samples are taken from two machines and the mixed together before they are subjected to SPC. For the simulation of such a process, the Monte-Carlo method is used. This time, however, samples are taken from two different populations. The population from which sample 1 is drawn has a mean (μ) equal to 2.02 inches and a standard deviation (σ) of 0.02 inches. Once again, the first five numbers from table 3.1.1 are used to obtain z and the shaft diameters are calculated from formula (1). The second sample (sample 2) is drawn from a population whose mean is 1.98 inches and same standard deviation of 0.02 inches. Shaft diameters are calculated from formula (1) and the z's are the next five numbers from table 3.1.1. The next samples are drawn from population with mean of 2.02 inches if the sample number is odd and from a population with a mean of 1.98 inches if the sample number is even. The standard deviation remains constant until 20 samples of size 5 are generated. The sample number is then entered in the SPC module of STORM and can be seen in Appendix A. The data listing is titled as 'Stochastic Generation of Processes (Two Machines)' and so are the control charts. While the process mean is the same as the mean for the capable process (center = 1.9992) and doesn't raise any suspicion of nonrandom behavior, when the plotted values are viewed stratification becomes obvious. The plotted averages seem to "hug" the centerline without actually being close to it. Criteria 1 and 2 are triggered signaling that the values are not centered as they should be. It should be noted at this time that the RANGE and S charts show no evidence of nonrandom behavior and are in fact identical to the respective charts for the capable process. In any case, the process should be stopped and analyzed at this point. Samples should be drawn from each machine and analyzed separately so the mean can be adjusted. Once both machines a behave similarly samples could be mixed again even though such practice is not achieved since the behavior could change over time.

D. The first nine samples for the next pattern are identical to the samples of the capable process since they are generated exactly the same. The next two samples come from a population with mean of 2.01 inches and samples 12 through 20 come from a population with a mean of 2.02 inches. The standard deviation remains constant at 0.02 inches for all 20 samples of size 5. The resulting shaft diameters are then entered in the SPC module of STORM and are shown in Appendix A as the data listing titled as 'Stochastic Generation of Processes (Stratification).' The control charts are also shown in Appendix Aand are titled the same. As seen the process mean has increased by 0.01 inches from the capable process mean (1.9992). The plotted results (X-BAR chart) show that the process average has suddenly shifted towards the upper control limit. Furthermore, by looking at the RANGE chart and the S chart, it is obvious that it is the average shifting and not the standard deviation . There is no evidence of any nonrandom behavior in these control charts and no out-of-control criteria have been triggered. The process at his point should be should be stopped and analyzed. The cause of such a shift can be the change of operators or use of a different batch of raw material. As a remark, a shift in the process standard deviation can be generated by leaving the mean the same while increasing the standard deviation of the samples 12 through 20 by a constant. The X-BAR chart would show no evidence of a trend, while the RANGE and S chart would signal nonrandom behavior of the process.

E. Another common pattern observed in real-life processes is the cyclical one. Cycles are consistent patterns of repeated high and low points that recur periodically. They are usually caused by rotation of operators, shipping schedules, operator fatigue, roller eccentricity, temperature variation during different shifts, voltage fluctuation etc. To simulate such a pattern by the Monte-Carlo method, the following procedure was used: The first sample is drawn from a population whose mean is 2.005 inches and standard deviation of 0.02 inches. The first five numbers from table 3.1.1 are used to obtain z and the first sample consists of shaft diameters calculated from formula (1). The next sample up to sample 5 come from populations of averages that increase by a step of 0.005 inches for each sample. Sample G is drawn from a population with the same mean as sample 5 (2.025) and subsequent samples up to sample 10 come from population of decreasing average by the same step (0.005 inches) for each sample. The same procedure is followed for samples 11 through 20. The resulting shaft diameters are shown in Appendix A in detailed data listing is the SPC module of STORM and are titled as 'Stochastic Generation of Processes (Cycles).' The module is executed and the control charts that are titled the same are obtained (see Appendix A). A first that glance in the X-BAR chart does not reveal anything nonrandom about the process. Even though out-of-control criterion 2 is triggered, such occurrence can result for a random process. The limits are well within specification an the RANGE and S charts show no evidence of any nonrandom pattern. When, however, the plotted values are joined by a solid line the cyclical behavior of the process becomes obvious. As a matter of fact, joining the plotted values on every chart is strongly recommended.

3.4. Important Results-Conclusions

The results obtained from the control charts truly depict patterns that occur in manufacturing. The study of these results can help gain a useful insight in the theory of Statistical Process Control. What is really important however, is that the process is generated stochastically. Therefore, the methods used might by able to educate-train employees who do not have a hands-on experience in the machinery of products. The Monte-Carlo method of simulating a process has been effective while it was a basic tool of generating processes that behave in a nonrandom fashion. The procedure was lengthy since there were many calculations involved which had to be performed manually due to the fact that the values for z had to be obtained from the tables also imposed a limitation to the procedure since 280 parts could be produced. To overcome these obstacles, a program was written in PASCAL programming language. As seen in the following program titled as Sosto, a great number of variables can be generated which represent an array of measurements coming from a population with a certain mean and a standard deviation. In the first part of the program, function RAND randomly generates a number which comes from a normal distribution with a desired mean and a desired standard deviation. The formula used to generate such a number is the following

$$x = \mu + \sigma \frac{\sum_{i=1}^{n} ri - \frac{n}{2}}{\sqrt{n/12}}$$

where ri is the number randomly generated by function rand and n is any constant that is chosen to be used. The value for n equal to 12 is often used with this formula and this is the value chosen for our case due to the simplicity of the calculation (the denominator reduces to 1). The whole procedure is based on the Central Limit Theory which states that irrespective of how the universe distribution is shaped, average values of the variable computed of samples of size N drawn from that universe will tend toward a normal distribution as the sample size N increases. By creating a loop around the generation of each x, as many x's as desired can be created (1500 in this case). Furthermore, by creating more loops, variation of program Sosto can create x's that come from populations with increasing average or standard deviation as each x (or a number of x's) is generated. The output of the program can serve as the input to the Statistical Process Control Module of STORM software package. Following is Program Sosto:

```
This program will generate randomly 1500 numbers with a mean M=2.0 and a standard
deviation SIG=0.02 }

FUNCTION RAND(VAR X:INTEGER):REAL;
VAR Y,Z:INTEGER;
BEGIN
        Z:=259*X;
        IF Z>=0   THEN Y:=Z
                  ELSE BEGIN Y:=Z+32767; Y:=Y+l END;
                  RAND:=0.3051757E-4*Y; X : =Y END;

PROCEDURE FINDXI;
        VAR
                XI,M,SIG,SUMl,SUM:REAL; X,I,J:INTEGER;
                BEGIN

                WRITE('INPUT YOUR VALUE OF M    ');
                READLN(M);
                WRITE('INPUT YOUR VALUE FOR SIG   ');
                READLN(SIG);
                FOR I:=l TO 1500 DO

                SUMl:=O;
                SUM:=O;
                BEGIN
```

```
            FOR J:=l TO 12 DO BEGIN
            SUMl:=RAND(X)+SUM;
            SUM:=SUMl;

        END; XI:=M+SIG*(SUM-6);

        WRITELN('XI IS ',XI:8:4);

        END;
    END;

BEGIN {Sosto}
    FINDXI;

END. {Sosto}
```

Important conclusions are drawn from the stochastic generation of nonrandom processes. Care should be taken so that pairs of control charts are analyzed. As seen in Appendix A, while some charts do not reveal anything suspicious about the process, the others reveal its nonrandom behavior. It is also observed that in every case the RANGE chart exhibited an identical pattern with the s chart. Unless then the behavior of the ranges must be individually analyzed, the X-BAR chart along with the S chart can be sufficient. Time is saved since the R chart requires a third of the total time it takes to create the control charts.

It is also strongly recommended to join the individual plotted values by a solid line. As it was the case with the cyclical pattern, non random behavior is not always obvious. The patterns was better visualized by the solid line. Such a practice might reveal pattern which were never suspected to be present. Stratification of a small degree for example would be close to impossible to be discovered. Since continuos improvement is our goal, even patterns of a small degree have to be detected. As a reminder Dr. Genici Taguchi's philosophy is mentioned: A product which is within specifications but close to the limits is not as good as a product which is within specification but close to the center.

Chapter 4

APPLICATION OF NEURAL NETWORKS TO SQC

CHAPTER SYNOPSIS

This chapter provides the reader with a brief introduction to neural networks. The history of the field is described along with an explanation on what exactly an artificial neural network is. The abilities of neural networks are described and the specific software package used for this application is introduced. Next the creation of the expert systems to diagnose on out-of-control process is analyzed step-by-step.

4.1 A Brief History of Neural Networks.

Historically, neural networks have been under study for centuries. As a matter of fact, a great deal was known about the nervous human system by the time of Galen in ancient Greece (200 B.C.) The focus of this knowledge of course was the relationship between mind and brain. The first formal studies on sensory processing didn't begin until the late 1800's, however, when the human nervous system was viewed as analogous to a switching network. During the 1940's the science of "cybernetics" was born due to the works of Warren McCulloch and Walter Pitts who proposed new models of neural nets. The most influential neural net model was the "Perceptron," proposed by Frank Rosenblatt in 1957. The limitations of this model, however, were soon realized by Minsky and Papert who in 1968, published the "Perceptions" a book which played a huge role into the shift of funding from neural networks to the new field of Artificial Intelligence. It was not until the early eighties that researchers regained interest in neural networks. Actually the period following the early eighties was a period of explosive growth for neural networks. The neurobiological breakthroughs that took place during the years from mid-1950's to the early 1970's played a major role to that growth. For example, Hubel and Weisel were rewarded with the Nobel Prize for their research on the operation of mammalian visual system. During the same period, Hartline and Ratliffe shed new light on the low-level operation of a crustacean visual system. Besides, several models of cortex and cerebellum were proposed by Eccles, Marr and Szentagothai.

Recently, research on neural networks and their development has gained federal funding. DARPA, which is a federal agency is largely responsible for this shift in funding. Disciplines such as psychology, neurobiology and engineering have contributed through their representatives to broad advances in biological and artificial network theory. The future of artificial neural networks looks very promising since new applications are discovered continuously.

4.2 The Biological Background

The theory of artificial neural networks (or ANN's as they will be referred to from now on), has been based on the current understanding of the human nervous system. Even though this understanding is far from complete, the basic neural functions have been studied in detail. We will begin our discussion with the neuron. The neuron is an electrically active cell. Neural networks are groups of neurons interacting with each other through the flow of small electrical currents. These ionic currents are caused by a voltage differential across the cell's membrane. To maintain this differential, a set of biochemical pumps are located in the membrane and the voltage is of magnitude -60 millivolts. This voltage is also called the membrane resting potential. A nerve can be thought of as a fiber consisting by a magnitude of neurons. They way an electrical impulse travels through nerves is often thought of a burning fuse. The impulse is initiated at one side of the fuse and propagates along the adjacent areas of the fiber. Once, however, the impulse has traveled through a cell's membrane, the membrane's biochemical pumps work to restore its resting potential. Until this is achieved, another impulse cannot propagate through the same cells. Consequently, the number of ionic impulses produced by neurons are limited to a thousand per second. The fibers which link cell bodies together and are the means of impulse propogation are called dendrites (input fibers) and axons (output fibers). Impulses through these fibers can only travel through one direction on any dendrite or axon so impulses are fired in definite directions.

The ways that each neuron combines impulses arriving from other neurons are several. The most important ones are the temporal summation and the spatial summation (figure 4.2.1) Temporal summation is based on the frequency of the arriving impulse train. The cell membrane acts as a capacitor that stores the electric charge. If this charge exceeds the membrane's threshold, the cell will fire. Otherwise, when for example the incoming impulse frequency is low, the membrane's potential decays to zero. Spatial summation, on the other hand, involves input impulses arriving from several cells at the same time. Once again, the cell membrane acts as a leaky capacitor. When a simultaneous input from many cells is large enough to exceed the threshold value the receiving cell will fire. What makes neural networks so amazing is that a tremendous amount of such operations can take place simultaneously, while all controlled and monitored by one center, the brain.

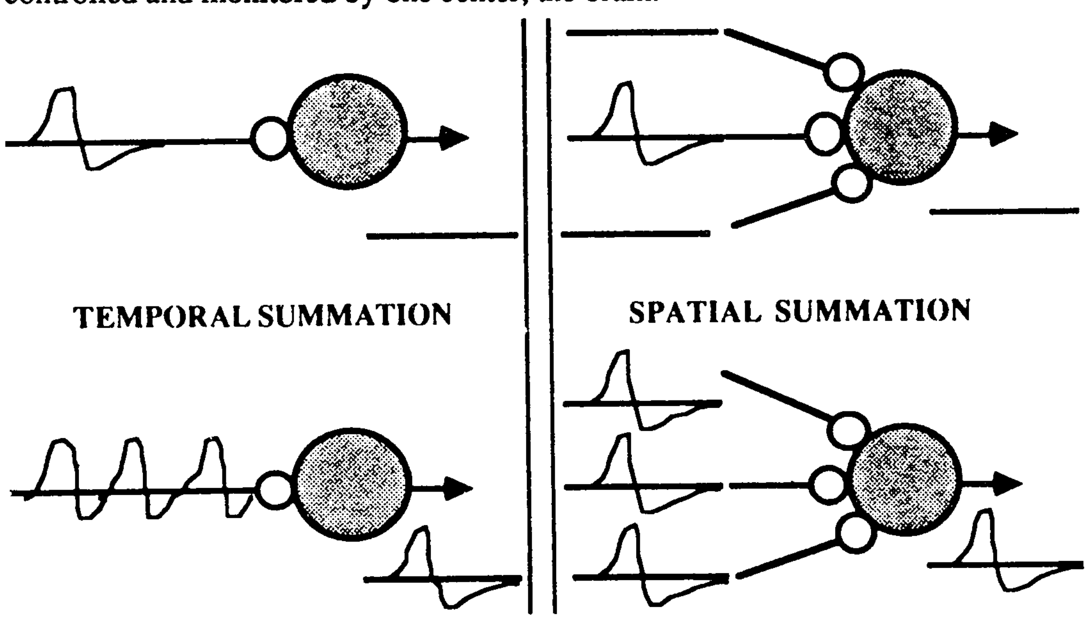


Figure 4.2.1 Temporal-Spatial Summation of ANN's

4.3 Artificial Neural Networks (ANN's)

By distilling the same neurobiological operations to a formal model we can construct artificial neural networks. The cell bodies (neurons) are replaced by nodes in ANN's while the paths between nodes are replaced by links. Communication within ANNs is local in a sense that electrical impulses and, therefore, information flows between nodes along links in a unidirectional fashion. ANNs also posses the capacity to execute several pieces of information simultaneously. ANNs don't operate in a pattern processing mode. Each node has an activation level (usually in the range between 0 and 1). Once an event arrives to the node, which can be any piece of information, the activation level of the node changes. As a result, the network's immediate response to an input is dictated by the current activation level of every node of the network. This temporal behavior of neural network is what makes them dynamic systems and gives them the ability to learn. The basic pattern-processing functions that neural networks usually perform are the following:

1. Pattern production. This is the case when an occurrence of a pattern causes the activation of another pattern.

2. Pattern storage. In this case the occurrence of a pattern which is stored in the network's short-term memory causes a change in the networks processing characteristics (contained in the long-term memory). This function is only possible in adaptive networks.

3. Pattern recognition. This is the function that will activate a specific node when the pattern represented by the node occurs.

To perform these functions, neural networks use several mechanisms. Nodes sum the weighted activation levels arriving from other nodes through links. Usually, a threshold is subtracted from this sum and the result serves as the input to an activation function. The function's output is the node's output activation level. The activation function can either be linear or non-linear. An example of a non-linear function is the sigmoid form where the function rises slowly from 0 then passes through a region of a steeper increase and then approaches its maximum value asymptotically (see figure 4.3.1)

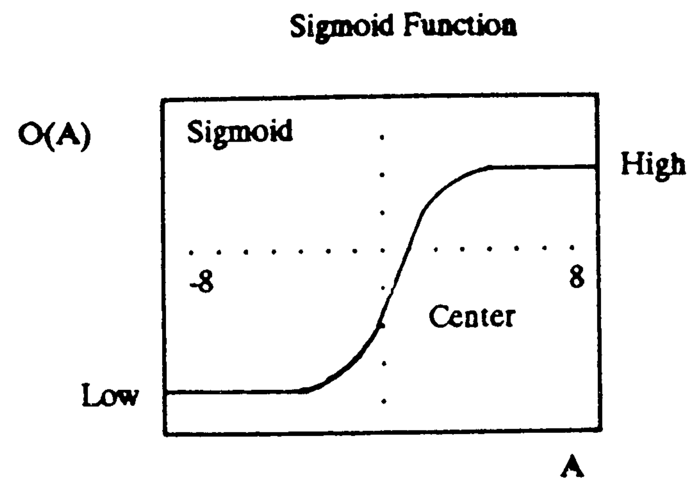


Figure 4.3.1 Sigmoid Function

While the current activation level of all nodes flows over the links it is weighed by the link-weight of that particular link. A source node then, can affect each sink node at a different degree. Such mechanisms make many learning models possible. The link-weight of each link is not a constant value but is usually modified through the learning phase of a network. Furthermore, the firing threshold of each node can be varied through the learning models.

The importance of neural networks is realized through the capabilities they posses. While standard computing processes each piece of information sequentially, ANNs due to their parallelism, are capable of performing several functions at the same time. Consequently, they gain a speed advantage and they can solve problems with simultaneous large sets of constraints. Besides, their asychronous nature makes them attractive for real-time applications. Input events that may occur simultaneously can easily be handled by ANNs while each event can trigger different outputs. Furthermore, some neural networks are adaptive. The operating characteristics of the net can change during the course of processing. The network's response may be different at the same input at different times. It is this last capability which is responsible for the growing interest in neural networks.

4.4 The Brain Maker

The software used to design, built, train and test the neural network which recognizes the problem with a process going out of statistical control, is the Brain Maker. No programming was required to run the Brain Maker. The basic neuron used in this software package looks like the one in Figure 4.4.1. The double line box represents a

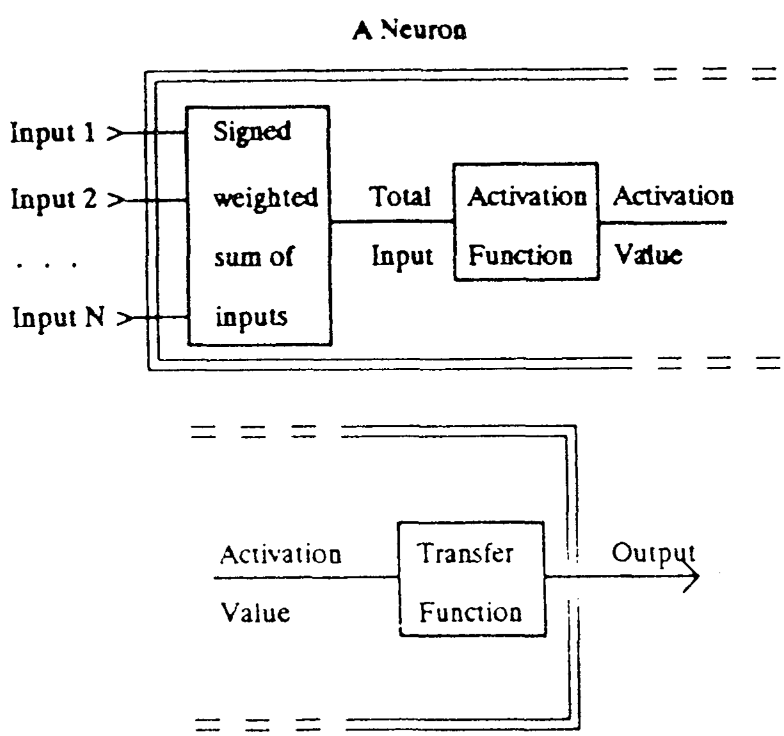


Figure 4.4.1 A Single Neuron of the Brain Maker

single neuron. It receives N inputs from other neurons. The neuron sends a single output to the rest of the network and it is represented by the outgoing line labeled Output. The inputs that the neuron receives may be excitatory (tending to increase the neuron's activation level), or inhibitory (creating to decrease the neuron's activation). Somehow the inputs are combined into a single value in the box labeled signed Weighted Sum of Inputs. The result is the Total Input. This Total Input is run through the Activation Function. In the case of the Brainmaker, the Activation Function is nothing else but the Identity matrix which leaves the Total Input unchanged. Next, the activation value goes through the Transfer Function which produces the neuron's output. The basis of the behavior of neural networks is their Transfer Function. The types of transfer function supported by the Brainmaker can be linear, linear threshold, step sigmoid and guassian. The software recommends (and uses it as its default value) the Sigmoid function. The Sigmoid transfer function also known as S-Shaped, is one which the output is a continuous along with its derivatives and it approaches the low and high values asymptotically. This function is recommended for the Brainmaker because it works well with the back propagation algorithm which the software uses.

Back propagation is a supervised learning scheme by which a layered feedforward network is trained to become a pattern matching engine. For the network's implementation, the neurons in every layer are not interconnected. Furthermore, the inputs go through each layer in the same direction and through every layer. In other words, a layer receives information from its immediate previous layer and sends output to its immediate subsequent layer. The output from one layer to the other is weighed by a real-valued matrix.

When there are a number of input-output pairs that we need to teach the network with, we can index them with the latter t, which designates t runs from 1 to N, where N is the number of input-output pairs. Training the network to recognize the input pattern and subsequently associate it with an output pattern is a problem of minimizing the total error on all patterns. The method used to solve such a problem is known as a gradient descent. Even though it is not a great algorithm, it is acceptable. The gradient descent algorithm involves moving down by small steps to local gradient of the scalar field. The drawback of this method is that a local minimum can be found which is different from the global minimum and then the algorithm is stuck. To avoid such a situation, some noise is added to the weights, thereby "shaking" the algorithm out of the fake minimum.

The architecture of back propogation networks is based in essence in "mapping" the input patterns to produce desired output patterns. It thus provides a method of recognizing the input patterns and then producing a desired output. A "hidden" layer of nodes is required for this scheme to work. Such a network is capable of constructing an internal representation of the input patterns via the hidden layers and therefore is enabled to achieve other than direct connection between inputs and outputs. Figure 4.4.2 shows the architecture of a network which uses back propogation methods.

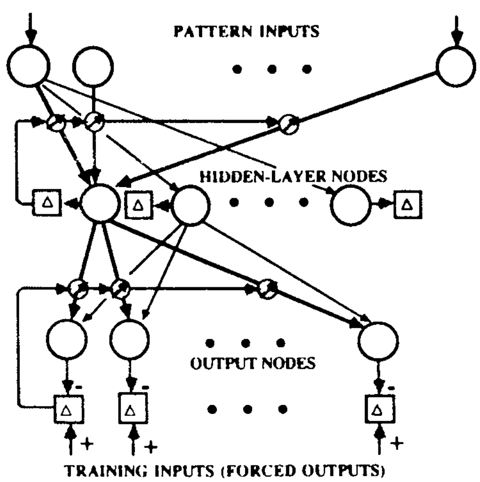


Figure 4.4.2 A Back Propogation Network

The back propogation network has two modes of operation:

1. The training mode during which the output patterns are associated with sets of "training" input patterns.

2. The performance mode during which the network presents an output (learned) pattern each time an input pattern is presented to it. During this mode, the user can present input patterns to the network for which the responses are known and test the network.

4.5 Creating Expert Systems to Recognize Out-of-Control Processes.

A. The first expert system will use Brainmaker's back propogation feedforward network to compare between patterns which represent control charts from manufacturing processes. This network will be represented with an input pattern representing the average values of samples which are subjected to Statistical Process Control. This input will be compared to the pattern of a capable process and a pattern of a process whose average is continuously rising. An output of 1 will signal success and an output of 0 will warn the operator that the process average is rising and therefore, has to be adjusted.

The first decision to be made is the format of the training files. The training facts consist of input patterns to be learned followed by a corresponding desired output. To develop the input facts, the number of facts required for training the network has to be decided first. For the particular network, 20 patterns coming from a capable process and 20 patterns coming from a process whose average is increasing were sufficient to train the network. To generate those patterns, program 'Sosto' was used. The program will generate 1500 numbers coming from a normally distributed population with mean equaling 2.0 inches and standard deviation equaling 0.02 inches. These 1500 numbers were used to create the samples of a capable process. As in chapter 3, the samples represent the measured diameters of cylindrical shafts. Each sample is of size 5 and each input fact is made up by 15 samples. To construct 1 input fact then, 75 shaft diameters must be available. Since 20 input facts are required, the total number of shafts required is 1500. Each set of 75 shaft diameters is entered into STORM's Statistical

Process Control module and the X-BAR chart is developed. The 15 averages obtained are the input fact of a capable process. When 20 of these facts are made, they are used to make a training file for the networks. Each fact is entered as a row of the 15 averages followed by a row with the desired output. In this case the desired output is the number 1 and signals success. The network will be trained to compare the patterns of the successful process with patterns from a process whose average is increasing. Therefore, 20 more input facts have to be developed. Once again program Sosto generated 1500 shaft diameters. The program is modified to increase the mean for every sample of size 5. Once the mean increases 15 times for the 15 samples required, it returns to its original value and starts increasing again. This procedure generates 20 input facts of 15 samples each. Those input facts however, have to serve as data for the SPC module of STORM so that the averages are computed. The results obtained are entered to the network as rows. Each row represents 15 averages of samples drawn from an incapable process. It is followed by a row which only contains the number 0. This is the desired output and it signals the operator that the process has to be adjusted. For better results, the facts have to be entered in the training file in a random order. Lotus 1-2-3 was used to mix the facts via its sorting function. The procedure involved generating numbers 1 to 40 randomly by a program in PASCAL, and using them as a guideline for Lotus to sort the files. On the top of the training file the desired format is entered. The "input number" is 1 to 15 since each pattern consists of 15 averages. The hidden layers were chosen to be 30. The larger the number of hidden layer, the more efficient the training of the network is going to be. This is mainly due to the fact that an increasing number of hidden layers increases the number of connections between the input-output layers. Next, the output format is specified. In this case the output is either 1 (a capable process) or a 0 (process whose average is rising). Finally we have to specify the minima and maxima of the input files so that the neurons will go through all the data without getting stuck to a local minimum. A training (definition) file is shown in Appendix B.

The definition file is now ready to be used to train the network. When training begins, the input portion of the fact is presented to the input layer of the network. After the network has run, the values of the output neurons are decoded into the same format of the fact's training pattern so it is possible to compare the two directly. If the output is correct, no learning takes place. If, however, there is an error, the connection strengths between the neurons are modified to reduce that error. Several runs are usually necessary to train the network. Training stops when the networks produces outputs that match the training pattern. At this point the network can be tested.

A test file is developed the exact same way as the training file with exception that the desired output is not entered below each fact. In this expert network the test file consisted by the averages shown in Figure 4.5.1. These averages are taken from a process which is

Facts

2.0177	2.0101	2.0074	2.0145	2.0312	2.0378	2.0288
2.0249	2.0407	2.0503	2.0526	2.0597	2.0722	

Figure 4.5.1 Test File #1

known to go out of control due to an increasing average. When the network was tested, the output was 0 which was the desired output. This should signal the machine operator that a process is slowly moving out of control and should be adjusted. As a matter of fact, it is recommended that the network should be trained to recognize inputs of less samples so that the process is adjusted as soon as possible. The famous rule of seven is a good rule of thumb. When seven consecutive points seem to form an increasing pattern, the process is very likely to be out of statistical control.

B. The second expert system is designed to compare pattern from a capable process versus pattern of stratification (see Chapter 3). Stratified patterns are formed when samples subjected to Statistical Process Control come from two processes (machines) with different averages and mixed. When these averages are plotted they seem to "hug" the centerline of the X-Bar control chart without actually being close to the center. The network will be trained to recognize such a pattern and display a zero (0) thus signaling that the process should be adjusted. The same exact method of constructing the training file of the first expert system is a followed. The diameters of shafts of a capable machining process are the same as before. The generate the diameters of shafts of two processes with different averages program 'Sosto' is modified. It produces a number x coming from a population of mean μ = 1.28 inches and a standard deviation σ=0.02 inches. The next number comes from a population of mean μ = 2.02 inches and the same standard deviation. That way 1500 numbers are generated and every other one comes from different populations.

Once these numbers have been generated, they are entered in STORM to construct the X-BAR charts. Each file contains 15 samples of 5 shaft diameters each. Since 20 such files are required to train the network, 1500 shaft diameters were used. The averages computed by the SPC module of STORM for each sample are used to train the network. They are entered as rows. Each row contains 15 averages representing a stratified pattern and is followed by the desired output which is 0. Once again the input number is 15 and the number of hidden layers is 30. The output is either a 0 or 1. Then, the minima and maxima are entered. Before actually training the network, the facts (pairs) are mixed as required by the software. Finally, the network is trained. (The actual training file is shown in Appendix C).

The training ceases when the error is minimized. The network at this point can be tested. The file used to test the network is shown in Figure 4.5.2

Facts

2.0477	1.9751	2.0241	1.9624	2.0245	1.9762	2.0378	1.9638
2.0149	1.9657	2.0303	1.9688	2.0226	1.9647	2.0322	

Figure 4.5.2 Test File #2

These sample averages are known to form a stratified pattern (simulated by the Monte-Carlo method and table 3.1.1) and the desired output is 0. The output is 0 indeed when the process is run and the network's success in evident. The operator is warned to adjust both processes so that the mean is the same for both of them. It is recommended that SPC is applied to each process separately so that this nonrandom behavior ceases to exist.

C. The third and last expert system differs from the other two in the respect that instead of the sample averages forming the patterns and used as input, the standard deviations are used. A mentioned in Chapter 3, when a pattern of increasing standard deviation was simulated and subjected to Statistical Process Control, the X-BAR chart showed no evidence of a nonrandom behavior. The RANGE and S charts, however, showed that the process was moving to a state of being statistically out of control. Therefore, the standard deviations should be compared of a capable versus an incapable process.

The facts of the capable process standard deviation are readily available from the SPC module of STORM. Each sample's standard deviation is in the S chart. 20 charts of 15 samples each are used to construct the network's training file. For the process whose standard deviation is constantly increasing, program 'Sosto' is modified so the standard deviation increases by $\Delta\sigma = 0.005$ for every 5 shafts produced. Instead of printing the diameter, the standard deviation is computed for every 5 diameters produced and printed. Every time 75 shaft diameters are generate, the standard deviation returns to its original value and starts increasing again. The process is repeated 20 times and consequently, the 20 facts of the incapable process are available.

These facts are randomly mixed before training the network, and are always a pair with number '0' which is the desired output. The minima and maxima along with the number of input numbers at each row and the hidden layers are entered at the top of the file. The complete training (definition) file is shown in Appendix C.

The network is trained with the facts in the training file until every input matched with the desired output. Once trained, the network can be tested. The test file consists of a pattern which is developed by a process whose standard deviation is constantly increasing. (See figure 4.5.3)

Facts

0.0122	0.0139	0.0323	0.0408	0.0524	0.0553	0.0293	
0.0601	0.0616	0.046	0.081	0.1062	0.0978	0.0915	0.156

Figure 4.5.3 Test File #3

The network displayed a '0' when tested with these facts which is the desired output. Therefore, the network was successful as to warn the machine operator to stop the process and adjust it.

4.6 Results and Conclusions

The great benefit of these expert systems is that machine operators are not required to have any knowledge in Statistics or the theory of Statistical Quality Control to realize that the process behaves nonrandomly. Once the averages of sample are computed, along with the standard deviations they can be entered to each of the expert systems. If all three expert systems display a '1', the process is still capable of producing the part. If, however, any one (or even 2) networks display a '0' then the process is out of control. Furthermore, depending on which system picked up the nonrandom behavior, the operator knows what exactly is wrong with the process. If for example, the first neural network gives a warning, it is known that the average is rising, and the most probable cause is tool wear. By inspecting the tool, the process can be adjusted. When two expert systems pick up a nonrandom pattern is signals that there is more than one thing causing defective parts. A process for example, can be both of constantly increasing average and of increasing standard deviation.

It should be noted at this point that the expert systems display just a number showing that the process is either capable or incapable. The exact patterns formed are not shown. Thus, control charts are still useful for supervisors and management for an in-depth study of the process. The next chapter will discuss how continued research can develop expert systems that incorporate the statistical knowledge of managers and the experience of operators as to provide not only with of correcting the problem.

Finally, it is recommended that the neural networks developed use patterns of smaller size to train the network. 15 samples were used in this case. However, after 15 samples were taken the process might be way out of control limits and to avoid such a situation patterns of 7 samples are a good rule of thumb (the famous engineering rule of 7).

Chapter 5

UPGRADING OF THE NEURAL NETWORKS

(THE NEXT STEP)

CHAPTER SYNOPSIS

This chapter describes in brief the theory behind expert systems of artificial intelligence, while providing the interested reader with ideas on how to continue the research. The process of detecting nonrandom processes can be integrated with a system that will not only provide a list with possible causes but also with solution for each cause.

5.1 Artificial Intelligence and Expert Systems

The technological changes along with the complexity of social and technological systems dictate more powerful control upon these systems. Artificial Intelligence is a field developed recently. The word intelligence implies that such a system can learn and change its response accordingly. One has to keep in mind that real-life problems are characterized by their high degree of uncertainty and their computational complexity. To solve such problems a high degree of expertise is required. People who have dealt with similar problems successfully are often called upon for their advice. Artificial Intelligence expert systems make it possible to incorporate the expert's knowledge by gradually learning the characteristics of the environment. Such systems are able to learn also from their own experience which gives them a quality of robustness. They are an excellent means of controlling a process' behavior so that its output is within certain specifications. Once such s system is integrated with Statistical Process Control, it can not only detect what cause the process to be out of control but to make decision on how to correct the process too. The three functions that intelligence control systems perform are the following:

1. Identification function. This function involves determining the current performance by the system. Feedback data from the process is provided and compared to the values that the expert system has learned to identify. An example of such a comparison is the current performance quality with some desired optimal performance.
2. Decision function. Once the performance of the process to be controlled has been determined, the expert system has to decide how the control mechanism should be adjusted to improve this performance. If the performance is satisfactory of course, no adjustment should be made. This function can be performed by means of a preprogrammed logic provided by the system designer. So the system has to be designed as to incorporate all possibilities. Depending on the programming and the degree of automation of the facility, the expert system's decision may be able to change one or more of the controllable inputs to the process.
3. Modification function. This function is to actually implement the decision taken. The modification function is more concerned with a physical or mechanical change in the system and therefore, is not a logic function. It greatly depends on the available hardware. The process can be driven towards a state of optimal performance automatically or via information provided to the machine operator which manually changes the input variables. As an example, if the process is detected to be out-of-control and the probable cause has been identified by the system to be tool wear, the system can either advice the operator to change the tool or give a command to an automated tool changer to do that. Figure 5.1.1 shows the general configuration of such a system.

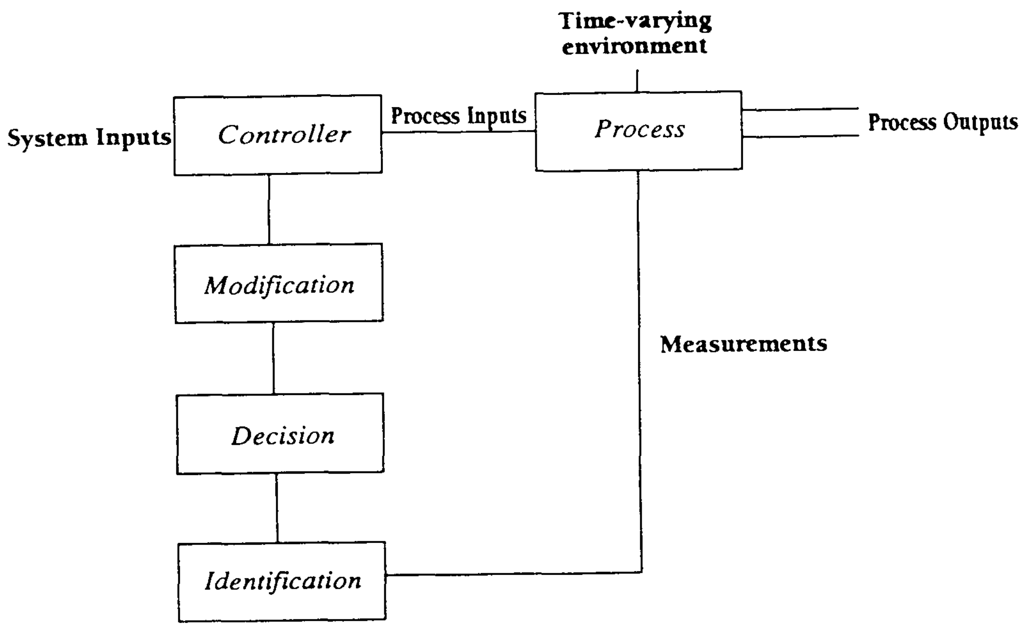


Figure 5.1.1: General Configuration of an "Intelligent" Control System

Some systems posses the capability of reinforcement learning. Reinforcement learning is based on the idea that when an adjustment is followed by satisfactory performance then the tendency to make such an adjustment is reinforced. While for example, the neural network of the Brainmaker uses supervisory learning an expert system using reinforcement learning would be more powerful but more complicated.

5.2 Conclusions

As it is made obvious by the preceding section, adaptive control would greatly enhance the capability of our experts systems designed. Once the neural networks identify a process as being out of control and also identify what is going wrong, this information can be used to find the cause and implement a solution. Such a system would fall in the category of adaptive controls. Nevertheless, such systems have some difficulties associated with their use.

Such difficulties are:

1. Complexity of the system. Adding an adaptive loop of control increases the complexity of the analysis problem. Often linear systems which are relatively simple turn to nonlinear systems of great complexity.
2. Difficulty of the identification function. The performance of the system depends on the measure used to evaluate performance. By characterizing the overall performance of the system with a simple index may simplify the implementation of adaptive control but unless this index is truly representative, the measure is going to lead to erroneous results. Even when the index is representative of the performance, however, reliable and accurate measures are a must. State-of -the-art sensors are required to measure process variables. Finally, the identification function should be performed under normal operating conditions. The benefits of adaptive control then must more than compensate for the costs of the search techniques to be used when seeking the optimum performance.
3. System stability. Consequently, because of the difficulties with the identification function, the system might tend to go out of control and self-destruct.
4. System cost. A cost analysis should be carried out to justify implementation of an adaptive, "intelligent" control system. The improvement on the performance of the process might not be so great in value as the cost associated with the implementation of such a system.

The problems mentioned above are solvable. Manufacturing is heading towards a direction of total automation. The future factory is going to be a computer-integrated manufacturing factory, where controls and process are going to be integrated and computers are going to run the factory. Cells that are totally automated exist already but are not interconnected yet. Nevertheless, it is obvious that manufacturers who will not be able to follow the trend of automation are not going to be able to compete. Product cost is not going to decrease by itself nor will quality improve magically. These manufacturers are going to be confined then in competing in small markets with different niches. Eventually of course, they will disappear since automation also provides a high degree of flexibility. A flexible factory is able to follow market shifts easy while also producing in small batches. The only way to survive is the constant improvement of quality and the most efficient way yet has been proven to be integrated automation and control.

APPENDIX A

STORM DATA SET LISTING
STATISTICAL PROCESS CONTROL DATA SET

Problem Description Parameters

Title : STOCHASTIC GENERATION OF PROCESSES (RISING AVG)

Number of samples	:	20
Number of variables	:	1
Number of attributes	:	0
Raw or Summarized data	:	RAW
Sample size (variables)	:	5
Sample size (attributes)	:	0

```
              STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)
                              VAR    1 : RANGE CHART
        LCL = 0.0000          Center = 0.1865        UCL = 0.3943

Sample                Value  LCL            C                UCL 012345

--------------------------------------------------------------------------
SAMPLE   1          0.0285   |  * .          |           .      |      23 5
SAMPLE   2          0.0718   |    .*         |           .      |      23 5
SAMPLE   3          0.0831   |    . *        |           .      |      23 5
SAMPLE   4          0.0990   |    .  *       |           .      |      23 5
SAMPLE   5          0.1281   |    .    *     |           .      |       3 5
SAMPLE   6          0.1532   |    .      *   |           .      |       3 5
SAMPLE   7          0.0770   |    .*         |           .      |       3 5
SAMPLE   8          0.1428   |    .     *    |           .      |       3 5
SAMPLE   9          0.1598   |    .      *   |           .      |       3 5
SAMPLE  10          0.1177   |    .   *      |           .      |       3 5
SAMPLE  11          0.1988   |    .          |*          .      |       3 5
SAMPLE  12          0.2912   |    .          |         * .      |       3 5
SAMPLE  13          0.2550   |    .          |       *   .      |       3 5
SAMPLE  14          0.2296   |    .          |   *       .      |       3 5
SAMPLE  15          0.4183   |    .          |           .      +   0   3 5
SAMPLE  16          0.2056   |    .          |*          .      |       3 5
SAMPLE  17          0.3089   |    .          |           *      |       3 5
SAMPLE  18          0.2096   |    .          | *         .      |       3 5
SAMPLE  19          0.2501   |    .          |     *     .      |       3 5
SAMPLE  20          0.3014   |    .          |          *.      |       3 5
--------------------------------------------------------------------------

Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

0    Points outside control limits
1    Run of 2 or more points outside two sigma limits
2    Run of 3 or more points outside one sigma limits
3    Run of 7 or more above/below the centerline
4    Run of 7 or more up or down
5    Number of runs above/below the centerline

A    Assignable cause
M    Missing value
```

```
        STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)
                         VAR   1 : X-BAR CHART
      LCL = 1.8882        Center = 1.9957        UCL = 2.1033

Sample          Value  LCL            C           UCL 012345

------------------------------------------------------------------
SAMPLE   1     2.0177    |    .        |  *     .    |
SAMPLE   2     2.0063    |    .        |*       .    |
SAMPLE   3     1.9911    |    .       *|        .    |
SAMPLE   4     1.9866    |    .       *|        .    |
SAMPLE   5     1.9890    |    .       *|        .    |
SAMPLE   6     2.0139    |    .        | *      .    |
SAMPLE   7     2.0195    |    .        |  *     .    |
SAMPLE   8     1.9829    |    .      * |        .    |
SAMPLE   9     1.9548    |    .   *    |        .    |
SAMPLE  10     1.9860    |    .       *|        .    |
SAMPLE  11     2.0009    |    .        |*       .    |
SAMPLE  12     1.9953    |    .        *        .    |
SAMPLE  13     1.9705    |    .     *  |        .    |
SAMPLE  14     1.9776    |    .      * |        .    |
SAMPLE  15     2.0098    |    .        | *      .    |
SAMPLE  16     2.0046    |    .        |*       .    |
SAMPLE  17     2.0523    |    .        |      * .    |
SAMPLE  18     1.9597    |    .   *    |        .    |
SAMPLE  19     1.9886    |    .       *|        .    |
SAMPLE  20     2.0079    |    .        | *      .    |
------------------------------------------------------------------
```

Plan based on 20 valid samples from SAMPLE 1 to SAMPLE 20

0 Points outside control limits
1 Run of 2 or more points outside two sigma limits
2 Run of 3 or more points outside one sigma limits
3 Run of 7 or more above/below the centerline
4 Run of 7 or more up or down
5 Number of runs above/below the centerline

A Assignable cause
M Missing value

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)

ROW LABEL	VR 1/OB 5	XXXX ASIGN CAUS	OPERATOR	MACHINE
SAMPLE 1	2.02788	XXXX	.	.	.
SAMPLE 2	2.0343	XXXX	.	.	.
SAMPLE 3	2.04179	XXXX	.	.	.
SAMPLE 4	2.00976	XXXX	.	.	.
SAMPLE 5	2.05592	XXXX	.	.	.
SAMPLE 6	1.94906	XXXX	.	.	.
SAMPLE 7	2.0513	XXXX	.	.	.
SAMPLE 8	2.06875	XXXX	.	.	.
SAMPLE 9	1.9667	XXXX	.	.	.
SAMPLE 10	2.01463	XXXX	.	.	.
SAMPLE 11	1.91859	XXXX	.	.	.
SAMPLE 12	1.8458	XXXX	.	.	.
SAMPLE 13	1.9816	XXXX	.	.	.
SAMPLE 14	1.82167	XXXX	.	.	.
SAMPLE 15	2.2691	XXXX	.	.	.
SAMPLE 16	1.98109	XXXX	.	.	.
SAMPLE 17	2.0046	XXXX	.	.	.
SAMPLE 18	2.03969	XXXX	.	.	.
SAMPLE 19	1.89979	XXXX	.	.	.
SAMPLE 20	2.08245	XXXX	.	.	.

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)

ROW LABEL	VAR 1	VR 1/OB 1	VR 1/OB 2	VR 1/OB 3	VR 1/OB 4
SAMPLE 1	XXXX	2.00928	2.0012	2.02972	2.02044
SAMPLE 2	XXXX	2.02265	2.02947	1.96247	1.98275
SAMPLE 3	XXXX	1.98554	1.95872	1.9697	1.99985
SAMPLE 4	XXXX	1.93745	1.99633	1.95314	2.03643
SAMPLE 5	XXXX	1.9278	1.95256	2.02632	1.98244
SAMPLE 6	XXXX	2.00896	2.00715	2.10228	2.00184
SAMPLE 7	XXXX	2.0384	2.01875	1.97435	2.0146
SAMPLE 8	XXXX	1.92663	1.98422	2.00886	1.92597
SAMPLE 9	XXXX	2.00822	1.84844	1.97876	1.97168
SAMPLE 10	XXXX	1.96666	1.93142	1.96828	2.04914
SAMPLE 11	XXXX	2.11739	1.9895	2.04186	1.93707
SAMPLE 12	XXXX	1.98043	1.97322	2.13702	2.04012
SAMPLE 13	XXXX	1.83936	2.0944	1.90872	2.02864
SAMPLE 14	XXXX	2.01768	2.02312	2.05151	1.9739
SAMPLE 15	XXXX	2.00711	1.85078	1.96904	1.95311
SAMPLE 16	XXXX	2.12141	1.98632	1.91583	2.01834
SAMPLE 17	XXXX	2.2455	1.9469	1.9366	2.1279
SAMPLE 18	XXXX	1.94488	2.00074	1.98299	1.83011
SAMPLE 19	XXXX	1.99373	2.14916	1.89902	2.00132
SAMPLE 20	XXXX	2.14226	1.84084	1.88971	2.08406

STORM DATA SET LISTING
STATISTICAL PROCESS CONTROL DATA SET

Problem Description Parameters

Title : STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)

Number of samples	:	20
Number of variables	:	1
Number of attributes	:	0
Raw or Summarized data	:	RAW
Sample size (variables)	:	5
Sample size (attributes)	:	0

```
         STOCHASTIC GENERATION OF PROCESSES (RISING AVG)
                         VAR    1 : S CHART
     LCL = 0.0000       Center = 0.0217       UCL = 0.0453

Sample          Value  LCL           C             UCL 012345

-------------------------------------------------------------------
SAMPLE    1    0.0122   :    .  *     :        .     :
SAMPLE    2    0.0255   :    .        : *      .     :
SAMPLE    3    0.0216   :    .        *        .     :
SAMPLE    4    0.0233   :    .        :*       .     :
SAMPLE    5    0.0262   :    .        :  *     .     :
SAMPLE    6    0.0246   :    .        : *      .     :
SAMPLE    7    0.0117   :    .  *     :        .     :
SAMPLE    8    0.0219   :    .        *        .     :
SAMPLE    9    0.0205   :    .       *:        .     :
SAMPLE   10    0.0142   :    .   *    :        .     :
SAMPLE   11    0.0231   :    .        :*       .     :
SAMPLE   12    0.0283   :    .        :   *    .     :
SAMPLE   13    0.0250   :    .        : *      .     :
SAMPLE   14    0.0215   :    .        *        .     :
SAMPLE   15    0.0347   :    .        :       *.     :
SAMPLE   16    0.0158   :    .   *    :        .     :
SAMPLE   17    0.0264   :    .        :  *     .     :
SAMPLE   18    0.0152   :    .   *    :        .     :
SAMPLE   19    0.0186   :    .     *  :        .     :
SAMPLE   20    0.0232   :    .        :*       .     :
-------------------------------------------------------------------

Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

0   Points outside control limits
1   Run of 2 or more points outside two sigma limits
2   Run of 3 or more points outside one sigma limits
3   Run of 7 or more above/below the centerline
4   Run of 7 or more up or down
5   Number of runs above/below the centerline

A   Assignable cause
M   Missing value
```

```
          STOCHASTIC GENERATION OF PROCESSES (RISING AVG)
                        VAR    1 : RANGE CHART
     LCL = 0.0000        Center = 0.0545       UCL = 0.1153

Sample             Value  LCL              C             UCL 012345

------------------------------------------------------------------------
SAMPLE   1        0.0285   :   .  *        :         .       :
SAMPLE   2        0.0575   :   .           :*        .       :
SAMPLE   3        0.0554   :   .           *         .       :
SAMPLE   4        0.0566   :   .           *         .       :
SAMPLE   5        0.0641   :   .           : *       .       :
SAMPLE   6        0.0681   :   .           :  *      .       :
SAMPLE   7        0.0308   :   .  *        :         .       :
SAMPLE   8        0.0519   :   .          *:         .       :
SAMPLE   9        0.0533   :   .           *         .       :
SAMPLE  10        0.0362   :   .    *      :         .       :
SAMPLE  11        0.0568   :   .           :*        .       :
SAMPLE  12        0.0777   :   .           :     *   .       :
SAMPLE  13        0.0638   :   .           : *       .       :
SAMPLE  14        0.0541   :   .           *         .       :
SAMPLE  15        0.0930   :   .           :         *       :
SAMPLE  16        0.0433   :   .      *    :         .       :
SAMPLE  17        0.0618   :   .           : *       .       :
SAMPLE  18        0.0399   :   .      *    :         .       :
SAMPLE  19        0.0455   :   .       *   :         .       :
SAMPLE  20        0.0524   :   .          *:         .       :
------------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

```
        STOCHASTIC GENERATION OF PROCESSES (RISING AVG)
                      VAR    1 : X-BAR CHART
     LCL = 2.0152       Center = 2.0467       UCL = 2.0781

Sample            Value  LCL              C              UCL 012345

--------------------------------------------------------------------
SAMPLE    1       2.0177  |*    .         |         .    |   123 5
SAMPLE    2       2.0101  +     .         |         .    |  0123 5
SAMPLE    3       2.0041  +     .         |         .    |  0123 5
SAMPLE    4       2.0074  +     .         |         .    |  0123 5
SAMPLE    5       2.0145  +     .         |         .    |  0123 5
SAMPLE    6       2.0312  |     . *       |         .    |    23 5
SAMPLE    7       2.0378  |     .    *    |         .    |     3 5
SAMPLE    8       2.0288  |     .*        |         .    |     3 5
SAMPLE    9       2.0249  |    *.         |         .    |     3 5
SAMPLE   10       2.0407  |     .     *   |         .    |     3 5
SAMPLE   11       2.0503  |     .         | *       .    |     3 5
SAMPLE   12       2.0538  |     .         |  *      .    |     3 5
SAMPLE   13       2.0526  |     .         |  *      .    |     3 5
SAMPLE   14       2.0597  |     .         |     *   .    |    23 5
SAMPLE   15       2.0722  |     .         |         . *  |   123 5
SAMPLE   16       2.0760  |     .         |         .   *|   123 5
SAMPLE   17       2.0905  |     .         |         .    +  0123 5
SAMPLE   18       2.0773  |     .         |         .    *   123 5
SAMPLE   19       2.0879  |     .         |         .    +  0123 5
SAMPLE   20       2.0964  |     .         |         .    +  0123 5
--------------------------------------------------------------------

Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

0    Points outside control limits
1    Run of 2 or more points outside two sigma limits
2    Run of 3 or more points outside one sigma limits
3    Run of 7 or more above/below the centerline
4    Run of 7 or more up or down
5    Number of runs above/below the centerline

A    Assignable cause
M    Missing value
```

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FO..
STOCHASTIC GENERATION OF PROCESSES (RISING AVG)

ROW LABEL	VR 1/OB 5	XXXX ASIGN CAUS	OPERATOR	MACHINE
SAMPLE 1	2.02788	XXXX	.	.
SAMPLE 2	2.03244	XXXX	.	.
SAMPLE 3	2.03786	XXXX	.	.
SAMPLE 4	2.02058	XXXX	.	.
SAMPLE 5	2.04796	XXXX	.	.
SAMPLE 6	2.00236	XXXX	.	.
SAMPLE 7	2.05052	XXXX	.	.
SAMPLE 8	2.06	XXXX	.	.
SAMPLE 9	2.0289	XXXX	.	.
SAMPLE 10	2.0495	XXXX	.	.
SAMPLE 11	2.02674	XXXX	.	.
SAMPLE 12	2.01388	XXXX	.	.
SAMPLE 13	2.0554	XXXX	.	.
SAMPLE 14	2.02304	XXXX	.	.
SAMPLE 15	2.1298	XXXX	.	.
SAMPLE 16	2.07102	XXXX	.	.
SAMPLE 17	2.08092	XXXX	.	.
SAMPLE 18	2.09256	XXXX	.	.
SAMPLE 19	2.07178	XXXX	.	.
SAMPLE 20	2.10934	XXXX	.	.

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (RISING AVG)

ROW LABEL	VAR 1	VR 1/OB 1	VR 1/OB 2	VR 1/OB 3	VR 1/OB 4
SAMPLE 1	XXXX	2.00928	2.0012	2.02972	2.02044
SAMPLE 2	XXXX	2.02312	2.02858	1.97498	1.9912
SAMPLE 3	XXXX	2.00036	1.98248	1.9898	2.0099
SAMPLE 4	XXXX	1.97926	2.0129	1.98822	2.03582
SAMPLE 5	XXXX	1.9839	1.99628	2.03316	2.01122
SAMPLE 6	XXXX	2.02898	2.02818	2.07046	2.02582
SAMPLE 7	XXXX	2.04536	2.0375	2.01974	2.03584
SAMPLE 8	XXXX	2.00832	2.02926	2.03822	2.00808
SAMPLE 9	XXXX	2.04274	1.98948	2.03292	2.03056
SAMPLE 10	XXXX	2.03474	2.0239	2.03524	2.06012
SAMPLE 11	XXXX	2.08354	2.047	2.06196	2.03202
SAMPLE 12	XXXX	2.04978	2.04786	2.09154	2.0657
SAMPLE 13	XXXX	2.01984	2.0836	2.03718	2.06716
SAMPLE 14	XXXX	2.06916	2.07044	2.07712	2.05886
SAMPLE 15	XXXX	2.07158	2.03684	2.06312	2.05958
SAMPLE 16	XXXX	2.10056	2.07212	2.05728	2.07886
SAMPLE 17	XXXX	2.1291	2.06938	2.06732	2.10558
SAMPLE 18	XXXX	2.0745	2.08514	2.08176	2.05264
SAMPLE 19	XXXX	2.08886	2.11712	2.07164	2.09024
SAMPLE 20	XXXX	2.11974	2.06732	2.07582	2.10962

```
      STOCHASTIC GENERATION OF PROCESSES (RISING STD.DEV)
                          VAR    1 : S CHART
    LCL = 0.0000        Center = 0.0740       UCL = 0.1546

Sample              Value  LCL            C             UCL 012345

---------------------------------------------------------------------
SAMPLE    1       0.0122   : * .          :         .     :     23 5
SAMPLE    2       0.0319   :    . *       :         .     :     23 5
SAMPLE    3       0.0323   :    . *       :         .     :     23 5
SAMPLE    4       0.0408   :    .  *      :         .     :     23 5
SAMPLE    5       0.0524   :    .    *    :         .     :      3 5
SAMPLE    6       0.0553   :    .     *   :         .     :      3 5
SAMPLE    7       0.0293   :    .*        :         .     :      3 5
SAMPLE    8       0.0601   :    .      *  :         .     :      3 5
SAMPLE    9       0.0616   :    .      *  :         .     :      3 5
SAMPLE   10       0.0460   :    .   *     :         .     :      3 5
SAMPLE   11       0.0810   :    .         :*        .     :      3 5
SAMPLE   12       0.1062   :    .         :     *   .     :      3 5
SAMPLE   13       0.0998   :    .         :    *    .     :      3 5
SAMPLE   14       0.0915   :    .         :  *      .     :      3 5
SAMPLE   15       0.1560   :    .         :         .     +  0   3 5
SAMPLE   16       0.0752   :    .         *         .     :      3 5
SAMPLE   17       0.1321   :    .         :         .*    :      3 5
SAMPLE   18       0.0801   :    .         :*        .     :      3 5
SAMPLE   19       0.1023   :    .         :    *    .     :      3 5
SAMPLE   20       0.1335   :    .         :         .*    :      3 5
---------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0    Points outside control limits
 1    Run of 2 or more points outside two sigma limits
 2    Run of 3 or more points outside one sigma limits
 3    Run of 7 or more above/below the centerline
 4    Run of 7 or more up or down
 5    Number of runs above/below the centerline

 A    Assignable cause
 M    Missing value
```

STORM DATA SET LISTING
STATISTICAL PROCESS CONTROL DATA SET

Problem Description Parameters

Title : STOCHASTIC GENERATION OF PROCESSES (TWO MACHINES)

Number of samples	:	20
Number of variables	:	1
Number of attributes	:	0
Raw or Summarized data	:	RAW
Sample size (variables)	:	5
Sample size (attributes)	:	0

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (TWO MACHINES)

ROW LABEL	VAR 1	VR 1/OB 1	VR 1/OB 2	VR 1/OB 3	VR 1/OB 4
SAMPLE 1	XXXX	2.02928	2.0212	2.04972	2.04044
SAMPLE 2	XXXX	1.99812	2.00358	1.94998	1.9662
SAMPLE 3	XXXX	2.01036	1.99248	1.9998	2.0199
SAMPLE 4	XXXX	1.94426	1.9779	1.95322	2.00082
SAMPLE 5	XXXX	1.9839	1.99628	2.03316	2.01122
SAMPLE 6	XXXX	1.98398	1.98318	2.02546	1.98082
SAMPLE 7	XXXX	2.03536	2.0275	2.00974	2.02584
SAMPLE 8	XXXX	1.95332	1.97426	1.98322	1.95308
SAMPLE 9	XXXX	2.02274	1.96948	2.01292	2.01056
SAMPLE 10	XXXX	1.96974	1.9589	1.97024	1.99512
SAMPLE 11	XXXX	2.05354	2.017	2.03196	2.00202
SAMPLE 12	XXXX	1.97478	1.97286	2.01654	1.9907
SAMPLE 13	XXXX	1.97984	2.0436	1.99718	2.02716
SAMPLE 14	XXXX	1.98416	1.98544	1.99212	1.97386
SAMPLE 15	XXXX	2.02158	1.98684	2.01312	2.00958
SAMPLE 16	XXXX	2.00556	1.97712	1.96228	1.98386
SAMPLE 17	XXXX	2.0691	2.00938	2.00732	2.04558
SAMPLE 18	XXXX	1.9695	1.98014	1.97676	1.94764
SAMPLE 19	XXXX	2.01886	2.04712	2.00164	2.02024
SAMPLE 20	XXXX	2.00474	1.95232	1.96082	1.99462

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (TWO MACHINES)

ROW LABEL	VR	1/OB 5	XXXX ASIGN CAUS	OPERATOR	MACHINE
SAMPLE	1	2.04788	XXXX	.	.	.
SAMPLE	2	2.00744	XXXX	.	.	.
SAMPLE	3	2.04786	XXXX	.	.	.
SAMPLE	4	1.98558	XXXX	.	.	.
SAMPLE	5	2.04796	XXXX	.	.	.
SAMPLE	6	1.95736	XXXX	.	.	.
SAMPLE	7	2.04052	XXXX	.	.	.
SAMPLE	8	2.005	XXXX	.	.	.
SAMPLE	9	2.0089	XXXX	.	.	.
SAMPLE	10	1.9845	XXXX	.	.	.
SAMPLE	11	1.99674	XXXX	.	.	.
SAMPLE	12	1.93888	XXXX	.	.	.
SAMPLE	13	2.0154	XXXX	.	.	.
SAMPLE	14	1.93804	XXXX	.	.	.
SAMPLE	15	2.0798	XXXX	.	.	.
SAMPLE	16	1.97602	XXXX	.	.	.
SAMPLE	17	2.02092	XXXX	.	.	.
SAMPLE	18	1.98756	XXXX	.	.	.
SAMPLE	19	2.00178	XXXX	.	.	.
SAMPLE	20	1.99434	XXXX	.	.	.

```
          STOCHASTIC GENERATION OF PROCESSES  (TWO MACHINES)
                          VAR   1 : X-BAR CHART
      LCL = 1.9677        Center = 1.9992       UCL = 2.0306

Sample           Value  LCL           C            UCL 012345

---------------------------------------------------------------
SAMPLE    1     2.0377   !    .        !        .    +  O 2
SAMPLE    2     1.9851   !    .  *     !        .    !    2
SAMPLE    3     2.0141   !    .        !      * .    !    2
SAMPLE    4     1.9724   ! *  .        !        .    !    2
SAMPLE    5     2.0145   !    .        !      * .    !    2
SAMPLE    6     1.9862   !    .  *     !        .    !    2
SAMPLE    7     2.0278   !    .        !        .   *!   12
SAMPLE    8     1.9738   !  * .        !        .    !   12
SAMPLE    9     2.0049   !    .        !  *     .    !
SAMPLE   10     1.9757   !   *.        !        .    !   12
SAMPLE   11     2.0203   !    .        !        *    !   12
SAMPLE   12     1.9788   !    *        !        .    !    2
SAMPLE   13     2.0126   !    .        !     *  .    !    2
SAMPLE   14     1.9747   !  * .        !        .    !   12
SAMPLE   15     2.0222   !    .        !        .*   !   12
SAMPLE   16     1.9810   !    .*       !        .    !    2
SAMPLE   17     2.0305   !    .        !        .    *   12
SAMPLE   18     1.9723   ! *  .        !        .    !   12
SAMPLE   19     2.0179   !    .        !       *.    !    2
SAMPLE   20     1.9814   !    .*       !        .    !    2
---------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

```
          STOCHASTIC GENERATION OF PROCESSES   (TWO MACHINES)
                         VAR    1 : RANGE CHART
        LCL = 0.0000       Center = 0.0545       UCL = 0.1153

Sample         Value     LCL          C            UCL 012345
-------------------------------------------------------------------
SAMPLE   1     0.0285    !   .  *     !        .     !
SAMPLE   2     0.0575    !   .        !*       .     !
SAMPLE   3     0.0554    !   .        *        .     !
SAMPLE   4     0.0566    !   .        *        .     !
SAMPLE   5     0.0641    !   .        ! *      .     !
SAMPLE   6     0.0681    !   .        !  *     .     !
SAMPLE   7     0.0308    !   .  *     !        .     !
SAMPLE   8     0.0519    !   .       *!        .     !
SAMPLE   9     0.0533    !   .        *        .     !
SAMPLE  10     0.0362    !   .    *   !        .     !
SAMPLE  11     0.0568    !   .        !*       .     !
SAMPLE  12     0.0777    !   .        !     *  .     !
SAMPLE  13     0.0638    !   .        ! *      .     !
SAMPLE  14     0.0541    !   .        *        .     !
SAMPLE  15     0.0930    !   .        !        *     !
SAMPLE  16     0.0433    !   .     *  !        .     !
SAMPLE  17     0.0618    !   .        ! *      .     !
SAMPLE  18     0.0399    !   .     *  !        .     !
SAMPLE  19     0.0455    !   .      * !        .     !
SAMPLE  20     0.0524    !   .       *!        .     !
-------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

```
           STOCHASTIC GENERATION OF PROCESSES   (TWO MACHINES)
                            VAR    1 : S CHART
         LCL = 0.0000       Center = 0.0217      UCL = 0.0453

Sample          Value  LCL            C            UCL 012345

-----------------------------------------------------------------
SAMPLE   1     0.0122    !   .  *     !        .     !
SAMPLE   2     0.0255    !   .        ! *      .     !
SAMPLE   3     0.0216    !   .        *        .     !
SAMPLE   4     0.0233    !   .        !*       .     !
SAMPLE   5     0.0262    !   .        !  *     .     !
SAMPLE   6     0.0246    !   .        ! *      .     !
SAMPLE   7     0.0117    !   .  *     !        .     !
SAMPLE   8     0.0219    !   .        *        .     !
SAMPLE   9     0.0205    !   .       *!        .     !
SAMPLE  10     0.0142    !   .   *    !        .     !
SAMPLE  11     0.0231    !   .        !*       .     !
SAMPLE  12     0.0283    !   .        !   *    .     !
SAMPLE  13     0.0250    !   .        ! *      .     !
SAMPLE  14     0.0215    !   .        *        .     !
SAMPLE  15     0.0347    !   .        !       *.     !
SAMPLE  16     0.0158    !   .    *   !        .     !
SAMPLE  17     0.0264    !   .        !  *     .     !
SAMPLE  18     0.0152    !   .    *   !        .     !
SAMPLE  19     0.0186    !   .      * !        .     !
SAMPLE  20     0.0232    !   .        !*       .     !
-----------------------------------------------------------------
```

Plan based on 20 valid samples from SAMPLE 1 to SAMPLE 20

0 Points outside control limits
1 Run of 2 or more points outside two sigma limits
2 Run of 3 or more points outside one sigma limits
3 Run of 7 or more above/below the centerline
4 Run of 7 or more up or down
5 Number of runs above/below the centerline

A Assignable cause
M Missing value

STORM DATA SET LISTING
STATISTICAL PROCESS CONTROL DATA SET

Problem Description Parameters

Title : STOCHASTIC GENERATION OF PROCESSES (STRATIFICATION)

Number of samples	:	20
Number of variables	:	1
Number of attributes	:	0
Raw or Summarized data	:	RAW
Sample size (variables)	:	5
Sample size (attributes)	:	0

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (STRATIFICATION)

ROW LABEL	VAR 1 VR	1/OB 1 VR	1/OB 2 VR	1/OB 3 VR	1/OB 4
SAMPLE 1	XXXX	2.00928	2.0012	2.02972	2.02044
SAMPLE 2	XXXX	2.01812	2.02358	1.96998	1.9862
SAMPLE 3	XXXX	1.99036	1.97248	1.9798	1.9999
SAMPLE 4	XXXX	1.96426	1.9979	1.97322	2.02082
SAMPLE 5	XXXX	1.9639	1.97628	2.01316	1.99122
SAMPLE 6	XXXX	2.00398	2.00318	2.04546	2.00082
SAMPLE 7	XXXX	2.01536	2.0075	1.98974	2.00584
SAMPLE 8	XXXX	1.97332	1.99426	2.00322	1.97308
SAMPLE 9	XXXX	2.00274	1.94948	1.99292	1.99056
SAMPLE 10	XXXX	1.99974	1.9889	2.00024	2.02512
SAMPLE 11	XXXX	2.04354	2.007	2.02196	1.99202
SAMPLE 12	XXXX	2.01478	2.01286	2.05654	2.0307
SAMPLE 13	XXXX	1.97984	2.0436	1.99718	2.02716
SAMPLE 14	XXXX	2.02416	2.02544	2.03212	2.01386
SAMPLE 15	XXXX	2.02158	1.98684	2.01312	2.00958
SAMPLE 16	XXXX	2.04556	2.01712	2.00228	2.02386
SAMPLE 17	XXXX	2.0691	2.00938	2.00732	2.04558
SAMPLE 18	XXXX	2.0095	2.02014	2.01676	1.98764
SAMPLE 19	XXXX	2.01886	2.04712	2.00164	2.02024
SAMPLE 20	XXXX	2.04474	1.99232	2.00082	2.03462

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (STRATIFICATION)

ROW LABEL	VR	1/OB 5	XXXX	ASIGN CAUS	OPERATOR	MACHINE
SAMPLE	1	2.02788	XXXX	.	.	.
SAMPLE	2	2.02744	XXXX	.	.	.
SAMPLE	3	2.02786	XXXX	.	.	.
SAMPLE	4	2.00558	XXXX	.	.	.
SAMPLE	5	2.02796	XXXX	.	.	.
SAMPLE	6	1.97736	XXXX	.	.	.
SAMPLE	7	2.02052	XXXX	.	.	.
SAMPLE	8	2.025	XXXX	.	.	.
SAMPLE	9	1.9889	XXXX	.	.	.
SAMPLE	10	2.0145	XXXX	.	.	.
SAMPLE	11	1.98674	XXXX	.	.	.
SAMPLE	12	1.97888	XXXX	.	.	.
SAMPLE	13	2.0154	XXXX	.	.	.
SAMPLE	14	1.97804	XXXX	.	.	.
SAMPLE	15	2.0798	XXXX	.	.	.
SAMPLE	16	2.01602	XXXX	.	.	.
SAMPLE	17	2.02092	XXXX	.	.	.
SAMPLE	18	2.02756	XXXX	.	.	.
SAMPLE	19	2.00178	XXXX	.	.	.
SAMPLE	20	2.03434	XXXX	.	.	.

```
          STOCHASTIC GENERATION OF PROCESSES  (STRATIFICATION)
                          VAR    1 : X-BAR CHART
         LCL = 1.9777       Center = 2.0092      UCL = 2.0406

Sample          Value  LCL            C            UCL 012345

-------------------------------------------------------------------
SAMPLE    1     2.0177   :    .        :   *    .    :       5
SAMPLE    2     2.0051   :    .      * :        .    :     3 5
SAMPLE    3     1.9941   :    . *      :        .    :    23 5
SAMPLE    4     1.9924   :    . *      :        .    :    23 5
SAMPLE    5     1.9945   :    . *      :        .    :    23 5
SAMPLE    6     2.0062   :    .       *:        .    :     3 5
SAMPLE    7     2.0078   :    .       *:        .    :     3 5
SAMPLE    8     1.9938   :    . *      :        .    :     3 5
SAMPLE    9     1.9849   :  * .        :        .    :     3 5
SAMPLE   10     2.0057   :    .      * :        .    :     3 5
SAMPLE   11     2.0103   :    .        *        .    :     3 5
SAMPLE   12     2.0188   :    .        :   *    .    :     3 5
SAMPLE   13     2.0126   :    .        : *      .    :     3 5
SAMPLE   14     2.0147   :    .        : *      .    :     3 5
SAMPLE   15     2.0222   :    .        :     *  .    :    23 5
SAMPLE   16     2.0210   :    .        :    *   .    :    23 5
SAMPLE   17     2.0305   :    .        :        *    :    23 5
SAMPLE   18     2.0123   :    .        :*       .    :     3 5
SAMPLE   19     2.0179   :    .        :   *    .    :     3 5
SAMPLE   20     2.0214   :    .        :    *   .    :     3 5
-------------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

STOCHASTIC GENERATION OF PROCESSES (STRATIFICATION)
VAR 1 : RANGE CHART
LCL = 0.0000 Center = 0.0545 UCL = 0.1153

```
Sample          Value  LCL            C             UCL 012345

-----------------------------------------------------------------
SAMPLE   1     0.0285    |   .  *     |        .     |
SAMPLE   2     0.0575    |   .        |*       .     |
SAMPLE   3     0.0554    |   .        *        .     |
SAMPLE   4     0.0566    |   .        *        .     |
SAMPLE   5     0.0641    |   .        | *      .     |
SAMPLE   6     0.0681    |   .        |  *     .     |
SAMPLE   7     0.0308    |   .  *     |        .     |
SAMPLE   8     0.0519    |   .       *|        .     |
SAMPLE   9     0.0533    |   .        *        .     |
SAMPLE  10     0.0362    |   .    *   |        .     |
SAMPLE  11     0.0568    |   .        |*       .     |
SAMPLE  12     0.0777    |   .        |     *  .     |
SAMPLE  13     0.0638    |   .        | *      .     |
SAMPLE  14     0.0541    |   .        *        .     |
SAMPLE  15     0.0930    |   .        |        *     |
SAMPLE  16     0.0433    |   .     *  |        .     |
SAMPLE  17     0.0618    |   .        | *      .     |
SAMPLE  18     0.0399    |   .     *  |        .     |
SAMPLE  19     0.0455    |   .      * |        .     |
SAMPLE  20     0.0524    |   .       *|        .     |
-----------------------------------------------------------------
```

Plan based on 20 valid samples from SAMPLE 1 to SAMPLE 20

0 Points outside control limits
1 Run of 2 or more points outside two sigma limits
2 Run of 3 or more points outside one sigma limits
3 Run of 7 or more above/below the centerline
4 Run of 7 or more up or down
5 Number of runs above/below the centerline

A Assignable cause
M Missing value

```
        STOCHASTIC GENERATION OF PROCESSES  (STRATIFICATION)
                               VAR   1 : S CHART
       LCL = 0.0000        Center = 0.0217       UCL = 0.0453

Sample          Value  LCL           C             UCL 012345

-----------------------------------------------------------------
SAMPLE   1      0.0122  :   .  *     :        .     :
SAMPLE   2      0.0255  :   .        : *      .     :
SAMPLE   3      0.0216  :   .        *        .     :
SAMPLE   4      0.0233  :   .        :*       .     :
SAMPLE   5      0.0262  :   .        :  *     .     :
SAMPLE   6      0.0246  :   .        : *      .     :
SAMPLE   7      0.0117  :   .  *     :        .     :
SAMPLE   8      0.0219  :   .        *        .     :
SAMPLE   9      0.0205  :   .       *:        .     :
SAMPLE  10      0.0142  :   .   *    :        .     :
SAMPLE  11      0.0231  :   .        :*       .     :
SAMPLE  12      0.0283  :   .        :   *    .     :
SAMPLE  13      0.0250  :   .        : *      .     :
SAMPLE  14      0.0215  :   .        *        .     :
SAMPLE  15      0.0347  :   .        :       *.     :
SAMPLE  16      0.0158  :   .    *   :        .     :
SAMPLE  17      0.0264  :   .        :  *     .     :
SAMPLE  18      0.0152  :   .    *   :        .     :
SAMPLE  19      0.0186  :   .      * :        .     :
SAMPLE  20      0.0232  :   .        :*       .     :
-----------------------------------------------------------------

Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

0   Points outside control limits
1   Run of 2 or more points outside two sigma limits
2   Run of 3 or more points outside one sigma limits
3   Run of 7 or more above/below the centerline
4   Run of 7 or more up or down
5   Number of runs above/below the centerline

A   Assignable cause
M   Missing value
```

STORM DATA SET LISTING
STATISTICAL PROCESS CONTROL DATA SET

Problem Description Parameters

Title : STOCHASTIC GENERATION OF PROCESSES (CYCLES)

Number of samples	:	20
Number of variables	:	1
Number of attributes	:	0
Raw or Summarized data	:	RAW
Sample size (variables)	:	5
Sample size (attributes)	:	0

STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (CYCLES)

ROW LABEL	VAR 1 VR	1/OB 1 VR	1/OB 2 VR	1/OB 3 VR	1/OB 4
SAMPLE 1	XXXX	2.01428	2.0062	2.03472	2.02544
SAMPLE 2	XXXX	2.02812	2.03358	1.97998	1.9962
SAMPLE 3	XXXX	2.00536	1.98748	1.9948	2.0149
SAMPLE 4	XXXX	1.98426	2.0179	1.99322	2.04082
SAMPLE 5	XXXX	1.9889	2.00128	2.03816	2.01622
SAMPLE 6	XXXX	2.02898	2.02818	2.07046	2.02582
SAMPLE 7	XXXX	2.03536	2.0275	2.00974	2.02584
SAMPLE 8	XXXX	1.98832	2.00926	2.01822	1.98808
SAMPLE 9	XXXX	2.01274	1.95948	2.00292	2.00056
SAMPLE 10	XXXX	1.99474	1.9839	1.99524	2.02012
SAMPLE 11	XXXX	2.03854	2.002	2.01696	1.98702
SAMPLE 12	XXXX	2.00478	2.00286	2.04654	2.0207
SAMPLE 13	XXXX	1.97484	2.0386	1.99218	2.02216
SAMPLE 14	XXXX	2.02416	2.02544	2.03212	2.01386
SAMPLE 15	XXXX	2.02658	1.99184	2.01812	2.01458
SAMPLE 16	XXXX	2.05056	2.02212	2.00728	2.02886
SAMPLE 17	XXXX	2.0691	2.00938	2.00732	2.04558
SAMPLE 18	XXXX	2.0045	2.01514	2.01176	1.98264
SAMPLE 19	XXXX	2.00886	2.03712	1.99164	2.01024
SAMPLE 20	XXXX	2.02974	1.97732	1.98582	2.01962

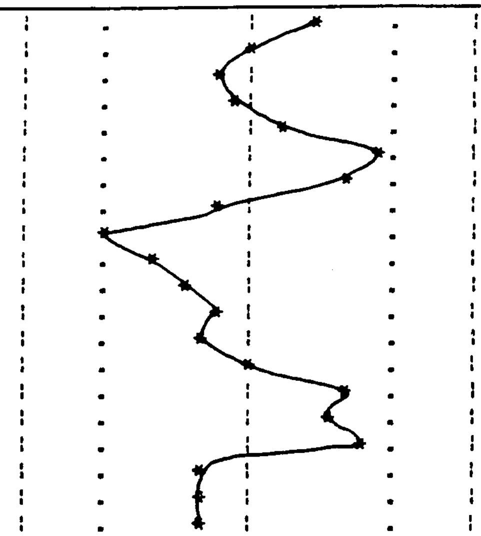
STORM DATA SET LISTING
DETAILED PROBLEM DATA LISTING FOR
STOCHASTIC GENERATION OF PROCESSES (CYCLES)

ROW LABEL	VR 1/OB 5	XXXX	ASIGN CAUS	OPERATOR	MACHINE
SAMPLE 1	2.03288	XXXX	.	.	.
SAMPLE 2	2.03744	XXXX	.	.	.
SAMPLE 3	2.04286	XXXX	.	.	.
SAMPLE 4	2.02558	XXXX	.	.	.
SAMPLE 5	2.05296	XXXX	.	.	.
SAMPLE 6	2.00236	XXXX	.	.	.
SAMPLE 7	2.04052	XXXX	.	.	.
SAMPLE 8	2.04	XXXX	.	.	.
SAMPLE 9	1.9989	XXXX	.	.	.
SAMPLE 10	2.0095	XXXX	.	.	.
SAMPLE 11	1.98174	XXXX	.	.	.
SAMPLE 12	1.96888	XXXX	.	.	.
SAMPLE 13	2.0104	XXXX	.	.	.
SAMPLE 14	1.97804	XXXX	.	.	.
SAMPLE 15	2.0848	XXXX	.	.	.
SAMPLE 16	2.02102	XXXX	.	.	.
SAMPLE 17	2.02092	XXXX	.	.	.
SAMPLE 18	2.02256	XXXX	.	.	.
SAMPLE 19	1.99178	XXXX	.	.	.
SAMPLE 20	2.01934	XXXX	.	.	.

STOCHASTIC GENERATION OF PROCESSES (CYCLES)
VAR 1 : X-BAR CHART
LCL = 1.9827 Center = 2.0142 UCL = 2.0456

Sample Value LCL C UCL 012345

Sample	Value	012345
SAMPLE 1	2.0227	
SAMPLE 2	2.0151	
SAMPLE 3	2.0091	
SAMPLE 4	2.0124	
SAMPLE 5	2.0195	
SAMPLE 6	2.0312	
SAMPLE 7	2.0278	
SAMPLE 8	2.0088	
SAMPLE 9	1.9949	
SAMPLE 10	2.0007	
SAMPLE 11	2.0053	
SAMPLE 12	2.0088	
SAMPLE 13	2.0076	
SAMPLE 14	2.0147	
SAMPLE 15	2.0272	2
SAMPLE 16	2.0260	2
SAMPLE 17	2.0305	2
SAMPLE 18	2.0073	
SAMPLE 19	2.0079	
SAMPLE 20	2.0064	



Plan based on 20 valid samples from SAMPLE 1 to SAMPLE 20

0 Points outside control limits
1 Run of 2 or more points outside two sigma limits
2 Run of 3 or more points outside one sigma limits
3 Run of 7 or more above/below the centerline
4 Run of 7 or more up or down
5 Number of runs above/below the centerline

A Assignable cause
M Missing value

```
          STOCHASTIC GENERATION OF PROCESSES (CYCLES)
                      VAR    1 : RANGE CHART
     LCL = 0.0000        Center = 0.0545       UCL = 0.1153

Sample          Value  LCL           C             UCL 012345

-----------------------------------------------------------------
SAMPLE   1     0.0285    !   .  *     !        .     !
SAMPLE   2     0.0575    !   .        !*       .     !
SAMPLE   3     0.0554    !   .        *        .     !
SAMPLE   4     0.0566    !   .        *        .     !
SAMPLE   5     0.0641    !   .        ! *      .     !
SAMPLE   6     0.0681    !   .        !  *     .     !
SAMPLE   7     0.0308    !   .  *     !        .     !
SAMPLE   8     0.0519    !   .       *!        .     !
SAMPLE   9     0.0533    !   .        *        .     !
SAMPLE  10     0.0362    !   .    *   !        .     !
SAMPLE  11     0.0568    !   .        !*       .     !
SAMPLE  12     0.0777    !   .        !     *  .     !
SAMPLE  13     0.0638    !   .        ! *      .     !
SAMPLE  14     0.0541    !   .        *        .     !
SAMPLE  15     0.0930    !   .        !        *     !
SAMPLE  16     0.0433    !   .     *  !        .     !
SAMPLE  17     0.0618    !   .        ! *      .     !
SAMPLE  18     0.0399    !   .     *  !        .     !
SAMPLE  19     0.0455    !   .      * !        .     !
SAMPLE  20     0.0524    !   .       *!        .     !
-----------------------------------------------------------------

 Plan based on 20 valid samples from SAMPLE   1 to SAMPLE  20

 0   Points outside control limits
 1   Run of 2 or more points outside two sigma limits
 2   Run of 3 or more points outside one sigma limits
 3   Run of 7 or more above/below the centerline
 4   Run of 7 or more up or down
 5   Number of runs above/below the centerline

 A   Assignable cause
 M   Missing value
```

Appendix B

Input number 1 15

hidden 30

output number 1 1

display input number 4 20 21 10

display output number 4 50 16 10

display pattern number 4 60 16 10

display screen 4 33

capable

minimum

1.9719	1.983	1.9882	1.9876	1.9794	1.9719	1.9841	1.965	1.9859
1.9846	1.9861	1.9799	1.9851	1.9825	1.9849			

0

maximum

2.0217	2.027	2.0247	2.0371	2.0331	2.0422	2.0433	2.0467	2.0636
2.063	2.0717	2.0727	2.0776	2.0723	2.092			

facts

1.9719	2.0043	2.0051	1.9984	1.9923	1.9986	2.0055	1.9968	1.9967
2.0010	2.0098	1.9952	2.0050	1.9954	2.0022			

1

2.0075	2.0093	1.9997	2.0105	2.0179	2.0357	2.0141	2.0429	2.0443
2.0501	2.0484	2.0633	2.00506	2.0055	1.9983	2.0117		

1

2.0063 2.0032 2.0085 2.0223 2.0047 2.0195 2.0229 2.0467 2.0471

2.0359 2.0573 2.0471 2.0614 2.0723 2.0636

0

1.9917 2.0071 2.0069 1.9913 2.0121 1.9974 1.9873 1.9896 2.0045

1.9998 2.0117 1.9920 2.0008 1.9942 2.0080

1

2.0005 1.9998 2.0077 1.9960 1.9888 2.0182 1.9960 2.0141 2.0172

1.9966 2.0044 2.0048 2.0176 2.0029 1.9928

1

2.0063 1.9982 1.9985 2.0073 1.9847 1.9945 1.9960 1.9873 2.0104

2.0071 1.9966 2.0044 2.0048 2.0176 2.0024 1.9942 2.0080

1

2.0148 2.0052 2.0120 2.0194 2.0373 2.0136 2.0244 2.0378 2.0636

2.0499 2.0608 2.0521 2.0560 2.0563 2.0572

0

1.9917 2.0121 2.0169 2.0063 2.0321 2.0224 2.0173 2.0246 2.0445

2.0448 2.0617 2.0470 2.0608 2.0592 2.0780

0

2.0108 2.0156 2.0009 1.9988 2.0091 2.0080 2.0035 1.9992 1.9955

2.0163 2.0217 2.0035 2.0059 1.9967 2.0001

1

2.0141 1.9994 2.0013 1.9956 1.9945 2.0058 2.0058 2.0037 1.9900

2.0002 1.9940 2.0164 1.9872 2.0066 1.9984

1

2.0052 1.9880 2.0194 2.0232 2.0196 2.0204 2.0378 2.0278 2.0259

2.0548 2.0361 2.0600 2.0643 2.0692 2.0670

0

2.0019 1.9958 2.0061 1.9930 1.9883 1.9802 1.9834 1.9933 2.0107

2.0005 1.9949 2.0177 1.9851 1.9929 1.9893

1

2.0052 1.9830 2.0094 2.0082 1.9996 1.9954 2.0078 1.9926 1.9859

2.0118 1.9861 2.0050 2.0043 2.0042 1.9970

1

1.9904 2.0142 2.0066 2.0114 2.0246 2.0136 2.0186 2.0409 2.0318

2.0431 2.0630 2.0593 2.0655 2.0633 2.0817

0

2.0075 2.0043 1.9897 1.9955 2.0087 1.9841 2.0079 2.0043

2.0051 1.9984 2.0083 1.9906 1.9935 2.0008

1

2.0148 2.0002 2.0020 2.0044 2.0072 2.0066 1.9944 2.0028 2.0236

2.0049 2.0108 1.9971 1.9960 1.9913 1.9872

1

2.0030 2.0014 1.9882 1.9876 1.9794 1.9918 2.0006 2.0059 1.9958

2.0101 2.0010 1.9843 1.9922 1.9965 2.0093

1

2.0107 2.0035 2.0059 1.9967 2.0001 1.9719 2.0043 2.0051 1.9984

1.9984 1.9923 1.9986 2.0055 1.9968 1.9967

1

2.0005 2.0048 2.0177 2.0110 2.0088 2.0432 2.0260 2.0454 2.0572

2.0416 2.0544 2.0598 2.07766 2.0679 2.0628

0

2.0067 1.9975 2.0129 2.0047 2.0331 20139 2.0433 2.0291 2.0354

2.0503 2.0416 2.0655 2.0618 2.0584 2.0920

0

2.0141 2.0044 2.0113 2.0106 2.0145 2.0567 2.0305 2.0230 2.0468

2.0452 2.0440 2.0714 2.0472 2.0718 2.0684

0

2.067 1.9925 2.0029 1.9897 2.0131 1.9668 2.0133 1.9941 1.9954

2.0053 1.9916 2.0011 2.0018 1.9937 2.0220

1

2.0217 2.0085 2.0159 2.0117 2.0201 1.9969 2.0343 2.0401 2.0384

2,0373 2.0486 2.0605 2.0568 2.0604 2.0722

0

1.9719 2.0093 20151 2.0134 2.0123 2.0236 2.0358 2.0318 2.0367

2.0460 2.0567 2.0502 2.0650 2.0604 2.0722

0

2.0119 2.0037 2.0081 2.0209 2.0143 2.0081 2.0242 2.0213 2.0486

2.0445 2.0568 2.0457 2.0550 2.0568 2.0792

0

2.0023 2.0006 2.0075 1.9988 1.9952 1.9958 1.99892 2.0070 1.9986

1.9974 2.0002 2.0036 1.9914 1.9998 2.0006

1

1.9951 2.0270 2.0233 2.0282 2.0135 2.0273 2.0297 2.0003 2.0519

2.0557 2.0441 2.0409 2.0583 2.0681 2.0664

1

1.9967 1.9970 2.0058 2.0032 1.9890 2.0034 1.9942 2.0056 1.9934

2.0018 2.0026 1.9799 1.9858 1.9881 1.9950

1

2.0019 2.0008 2.0161 2.0080 2.0083 2.0052 2.0145 2.0283 2.0507

2.0455 2.0449 2.0727 2.0451 2.0579 2.0593

0

1.9967 2.0020 2.0158 2.0182 2.0090 2.0284 2.0242 2.0406 2.0334

2.0468 2.0526 2.0526 2.00349 2.0455 2.0593

0

2.0030 2.0064 1.9982 2.0026 1.9994 2.0168 2.0306 2.0409 2.0358

2.0551 2.0510 2.0393 2.0522 2.0615 2.0793

0

2.0015 1.9919 2.0146 2.0221 2.0019 2.0063 2.0031 1.9924 1.9863

1.9846 2.0115 2.0028 1.9947 1.9910 2.0038

1

1.9816 2.0094 1.9898 2.0066 2.0039 1.9938 2.0041 1.9950 1.9903

2.0102 2.0025 1.9953 1.9887 1.9825 1.9849

0

2.0108 2.0206 2.0109 2.0138 2.0291 2.0330 2.0333 2.0342 2.0355

2.0613 2.0717 2.0585 2.0659 2.0617 2.0701

0

2.0023 2.0056 2.0175 2.0138 2.0267 2.0202 2.0258 2.0242 2.0470

2.0424 2.0502 2.0586 2.0514 2.0648 2.0706

0

1.9816 2.0144 1.9998 2.0216 2.0239 2.0188 2.0341 2.0300 2.0303

2.0552 2.0525 2.0503 3.0487 2.0475 2.0549

0

2.0015 1.9969 2.0247 2.0371 2.0219 2.0313 2.0331 2.0274 2.0263

2.0296 2.0615 2.0578 2.0547 2.0560 2.0738

0

Appendix C

input number 1 15

hidden 30

output 1 1

display input number 4 20 21 10

display output number 4 50 16 10

display pattern number 4 60 16 10

display screen 4 33

capable

minimum

1.9719	1.9630	1.9882	1.9676	1.9794	1.9519	1.9841	1.9453	1.9859
1.9646	1.9861	1.9599	1.9851	1.9625	1.9849			

0

maximum

2.0147	2.0220	2.0347	2.0331	2.0182	2.0333	2.0117	2.0436	2.0180
2.0417	2.0177	2.0376	2.0073	2.0420	2.0549			

facts

1.9719	2.0043	2.0051	1.9984	1.9923	1.9983	2.0055	1.9968	1.9967
2.0010	2.0098	1.9952	2.0050	1.9954	2.0022			

1

2.0027	1.9843	2.0097	1.9755	2.0197	1.9887	2.0041	1.9879	2.0243
1.9851	2.0184	1.9883	2.0106	1.9735	2.0208			

0

1.9904 2.0092 1.9966 1.9964 2.0048 1.9938 2.0106 1.9968 2.0031

2.0180 2.0093 2.0052 2.0055 1.9983 2.0117

1

2.0263 1.9782 2.0185 1.9873 2.0047 1.9745 2.0129 1.9917 2.0271

1.9709 2.0273 2.0214 1.9873 2.0138

0

1.9917 2.0071 2.0069 1.9913 2.0121 1.9974 1.9873 1.9898 2.0045

1.9998 2.0117 1.9920 2.0008 1.9942 2.0080

1

2.0005 1.9998 2.0077 1.9960 1.9888 2.0182 1.9960 2.0104 2.0172

1.9966 2.0044 2.0048 2.0176 2.0029 1.9928

1

2.0063 1.9982 1.9985 2.0073 1.9847 1.9945 1.9929 2.0117 2.0071

1.9909 2.0073 1.9921 2.0014 2.0073 1.9936

1

2.0348 1.9802 2.0220 1.9844 2.0272 1.9866 2.0144 1.9828 2.0436

1.9849 2.0308 1.9771 2.0160 1.9713 2.0072

0

2.0117 1.9871 2.0269 1.9713 2.0321 1.9774 2.0073 1.9696 2.0245

1.9798 2.0317 1.9720 2.0208 1.9742 2.0280

0

2.0108 2.0156 2.0009 1.9988 2.0091 2.0080 2.0033 1.9992 1.9955

2.0163 2.0217 2.0035 2.0059 1.9967 2.0001

1

2.0141 1.9994 2.0013 1.9956 1.9945 2.0058 2.0057 1.9900 2 .0068

2.0002 1.9940 2.0164 1.9872 2.0066 1.9984

1

2.0252 1.9630 2.0294 1.9882 2.0196 1.9754 2.0278 1.9726 2.0059

1.9918 2.0061 1.9850 2.0243 1.9842 2.0102

0

2.0019 1.9958 2.0061 1.9930 1.9883 1.9802 1.9843 1.9933 2.0107

2.0005 1.9949 2.0177 1.9851 1.9929 1.9893

1

2.0052 1.9830 2.0094 2.0082 1.9996 1.9954 2.0078 1.9926 1.9859

2.0118 1.9861 2.0050 2.0043 2.0042 1.9970

0

2.0075 2.0043 1.9897 1.9955 1.9979 2.0067 1.9841 2.0079 2.0043

2.0051 1.9984 2.0083 1.9906 1.9935 2.0008

1

2.0148 2.0002 2.0020 2.0044 2.0072 2.0066 1.9944 2.0028 2.0236

2.0049 2.0108 1.9971 1.9960 1.9913 1.9872

1

2.0030 2.0014 1.9882 1.9876 1.9794 1.9918 2.0006 2.0059 1.9958

2.0101 2.0010 1.9843 1.9922 1.9965 2.0093

1

2.0217 2.0035 2.0059 1.9967 2.0001 1.9719 2.0043 2.0051 1.9984

1.9923 1.9986 2.0055 1.9968 1.9967 1.9995

1

2.0205 1.9798 2.0277 1.9760 2.0028 1.9982 2.0160 1.9904 2.0372

1.9766 2.0244 1.9848 2.0376 1.9829 2.0128

0

2.0267 1.9725 2.0229 1.9697 2.0331 1.9689 2.0333 1.9741 2.0154

1.9853 2.0116 1.9905 2.0216 1.9737 2.0420

0

2.0341 1.9794 2.0213 1.9756 2.0145 1.9858 2.0257 1.9700 2.0268

1.9802 2.0140 1.9964 2.0072 1.9866 2.0184

0

2.0067 1.9925 2.0029 1.9897 2.0131 1.9889 2.0133 1.9941 1.9954

2.0053 1.9916 2.0105 2.0018 1.9937 2.0220

1

2.0417 1.9835 2.0259 1.9767 2.0201 1.9519 2.0243 1.9851 2.0184

1.9723 2.0186 1.9855 2.0168 1.9767 2.0195

0

1.9919 1.9843 2.0251 1.9784 2.0123 1.9765 2.0255 1.9768 2.0167

1.9810 2.0298 1.9752 2.0250 1.9754 2.0222

0

2.0023 2.0006 2.0075 1.9988 2.0067 1.9952 1.9958 1.9897 2.0070

1.9974 2.0002 2.0036 1.9914 1.9998 2.0008

1

2.0151 2.0070 2.0333 1.9932 2.0135 1.9823 2.0197 1.9455 2.0319

1.9907 2.0141 1.9659 2.0183 1.9831 2.0164

0

2.0119 1.9987 1.9981 2.0059 1.9943 1.9831 2.0124 1.9863 2.0036

1.9995 2.0068 1.9907 1.9950 1.9918 2.0092

1

1.9951 2.0133 2.0132 1.9935 2.0023 1.9997 1.9655 2.0119 2.0346

2.0107 1.9941 1.9859 1.9983 2.0031 1.9964

1

1.9967 1.9970 2.0058 2.0032 1.9890 2.0034 1.9942 2.0056 1.9934

2.0018 2.0026 1.9799 1.9858 1.9881 1.9950

1

2.0219 1.9758 2.0126 1.9730 2.0083 1.9602 2.0045 1.9753 2.0307

1.9805 2.0149 1.9977 2.0051 1.9729 2.0093

0

2.0167 1.9770 2.0258 1.9832 2.0090 1.9834 2.0142 1.9856 2.0134

1.9818 2.0226 1.9599 2.0058 1.9681 2.0150

0

2.0230 1.9814 2.0082 1.9767 1.9994 1.9716 2.0206 1.9859 2.0158

1.9901 2.0210 1.9643 2.0122 1.9876 2.0657

1

2.0015 1.9919 2.0147 2.0221 2.0019 2.0063 2.0031 1.9924 1.9863

1.9846 2.0115 2.0028 1.9947 1.9910 2.0038

1

1.9816 2.0094 1.9898 2.0066 2.0039 1.9938 2.0041 1.9950 1.9903

2.0102 2.0025 1.9953 1.9887 1.9825 1.9849

1

2.0308 1.9956 2.0249 1.9788 2.0291 1.9880 2.0233 1.9792 2.0155

1.9903 2.0102 2.0025 1.9953 1.9888 2.0201

0

2.0223 1.9806 2.0275 1.9788 2.0926 1.9752 2.0158 1.9692 2.0270

1.9774 2.0202 1.9836 2.0114 1.9798 2.0206

0

2.0016 1.9894 2.0098 1.9866 2.0239 1.9786 2.0241 1.9750 2.0215

1.9902 2.0225 1.9753 2.0087 1.9834 2.0087 1.9625

0

2.0215 1.9719 2.0347 2.0021 2.0219 1.9863 2.0231 1.9724 2.0063

1.9646 2.0315 1.9646 2.0315 1.9828 2.0147 2.0049

Appendix D

input number 1 15

hidden 30

output 1 1

display input number 4 20 21 10

display output number 4 50 16 10

display pattern number 4 60 16 10

display screen 4 33

capable

minimum

.0092887	.0119	.0052157	.003909	.0087909	0075648	.00521527	.0063366	.0078056
.0113	.005786	.0111	.0047068	.002851	.009714			

0

maximum

.0304	.0282	.0364	.0439	.07	.0794	.0895	.0919	.0912
.1291	.1212	.1048	.124	.1293	.1854			

facts

0.0245	0.0191	0.0162	0.0251	0.0127	0.0129	0.0185	0.0310	0.0304
0.0113	0.0172	0.0192	0.0128	0.0226	9.9475E-03			

1

0.0235	0.0265	0.0249	0.0203	0.0054	0.0174	0.0550	0.0401	0.0580

0.0592 0.0537 0.0468 0.0765 0.0679 0.01402

0

0.0218 0.0214 0.0208 0.0434 0.0700 0.0346 0.0130 0.0865 0.0961

0.1597 0.0646 0.0765 0.0652 0.0410 0.0418

0

0.0245 0.0137 8.7909E-03 0.0156 0.0211 7.1228E-03 0.0146 0.0183 0.0226

0.0397 0.0150 0.0144 4.7068E-03 0.0183 0.0150

1

0.0270 0.0162 0.0220 0.0210 0.0221 0.0227 0.0148 0.0282 0.0120

0.0220 0.0195 0.0206 0.0140 0.0183 0.0107

1

.0.186 0.0253 0.0253 0.0272 0.0502 0.0395 0.0248 0.0463 0.0679

0.0500 0.0438 0.0658 0.0770 0.01078 0.1509

0

0.0245 0.0171 0.0132 0.0132 0.0274 0.0422 0.0160 0.0371 0.0504

0.0679 0.1291 0.0524 0.054 0.0188 0.0776 0.0677

0

0.0254 0.0179 0.0112 0.0216 0.0185 0.0206 0.0204 0.0155 0.0243

0.0469 0.0248 0.0225 0.0242 0.0113 0.0202

1

0.0218 0.0143 0.0169 0.0145 0.0169 0.0126 0.0174 0.0193 0.0256

0.0173 0.0107 0.0261 0.0274 0.0181 0.0164

1

9.2887E-03 0.0268 0.0186 0.0343 0.0273 0.0316 0.0331 0.0543 0.0590

0.0769 0.0465 0.0543 0.0434 0.0121 0.0104

0

0.0290 0.0250 9.8479E-03 0.0139 0.0542 0.0794 0.0565 0.0232 0.0656

0.0955 0.0823 0.0673 0.0797 0.0438 0.1098

0

0.0235 0.0212 0.0166 0.0116 0.0277 7.7171E-03 0.0220 0.0146 0.0193

0.0182 0.0153 0.0125 0.0191 0.0160 0.0312

1

0.0186 0.0202 0.0169 0.0155 0.0251 0.0176 9.9136E-03 0.0168 0.0226

0.0154 0.0125 0.0176 0.0192 0.0254 0.0335

1

0.0170 0.0189 0.0243 9.9350E-03 0.0243 0.0243 0.0153 6.7917E-03 0.0209

0.0219 7.7154E-03 0.0111 0.0198 0.0159 0.0412

1

0.0248 0.0225 0.0242 0.0113 0.0202 0.0245 0.0191 0.0162 0.0251

0.0127 0.0129 0.0185 0.0310 0.0309 9.7140E-03

1

0.0776 0.0380 0.0714 0.0682 0.0774 0.0561 0.0777 0.0483 0.0561

0.1801 0.0987 0.0238 0.0436 0.0634 0.0483

0

0.0190 0.0190 7.8235E-03 0.0210 0.0275 0.0640 0.0360 0.0255 0.0234

0.0876 0.1212 0.0850 0.0231 0.0691 0.0133

0

0.0218 0.0179 0.0254 0.0254 0.0338 0.0283 0.0435 0.0532 0.0769

0.0563 0.0375 0.0978 0.1097 0.0770 0.0737

0

0.0910 0.0521 5.2157E-03 0.0210 0.0137 0.0285 0.0144 9.2752E-037.8056E-03

0.0296 0.0346 0.0227 5.7859E-03 0.0163 0.0296

1

0.0248 0.0281 0.0363 0.0199 0.0404 0.0551 0.0248 0.0281 0.0363

0.0477 0.0446 0.0752 0.0412 0.0452 0.0296

0

0.0245 0.0238 0.0243 0.0439 0.0254 0.0291 0.0463 0.0853 0.0912

0.0368 0.0603 0.0722 0.0514 0.0959 0.0448

0

0.0168 0.0232 0.0182 0.0316 0.0357 0.0553 0.0290 0.0594 0.0692

0.0646 0.0203 0.1048 0.0744 0.0843 0.1221

0

0.0136 0.0126 0.0238 0.0198 0.0162 7.8097E-03 0.0139 0.0213 0.0216

0.0241 0.0171 0.0198 0.0186 0.0203 0.0223

1

0.0153 0.0163 0.0300 0.0255 0.0405 0.0347 0.0647 0.00174 0.0517

0.0543 0.0550 0.0700 0.0639 0.8360 0.1271

0

0.0168 0.0185 0.0121 0.0180 0.0178 0.0246 0.0116 0.0216 0.0231

0.0199 5.780E-03 0.0280 0.0186 0.0876 0.0257

1

0.0143 0.0225 0.0103 3.9090E-03 0.0238 6.8559E-03 0.0168 0.03348.5018E-03

0.0134 0.0171 0.0217 0.0158 0.0257 0.03

1

0.0304 0.0149 0.0334 0.0295 0.0331 0.0372 0.0897 0.0377 0.0350

0.0431 0.0528 0.0542 0.0710 0.0507 0.0980

0

0.0143 0.0236 0.0364 0.0174 0.0487 0.0551 0.0383 0.0187 0.0627

0.0712 0.0270 0.0417 0.0792 0.0676 0.0712

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