Application of the multi-vari method in identification of the problem assignable cause set of variation

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Abstract: Any working process is designed with the intent to create an output that will satisfy either predetermined requirement or a potential customer. One of the parameters that will influence customer satisfaction is the variation of the working process output that is within or outside the originally predetermined or expected range of variation. The meaning of 'expected range of variation' in this context is related to a relatively recently recognized dimension of quality 'perceived quality', whereas a 'predetermined range of variation' is a synonym for Crosby's quality definition of conformance to requirements and specifications (Crosby, *Quality is free: The art of making quality certain*, 1979, McGraw-Hill). The working process output is controlled by variables that are functions of time and/or working environment specifics. A change of variables may create an 'uncontrolled' output that shows a level of variation outside the predetermined or expected requirements. From a management prospective this is called either a problem or an opportunity.

The 'uncontrolled' outputs have a negative impact on the performance of the working environment, which is, in most cases, closely related to the production cost. The unknown assignable cause of variation (or root cause of variation) that is contained within the unknown critical set of variation (or family of variation) is the main reason for the uncontrolled outputs. In view of the cost as a function of time, in any working environment, it is important to identify quickly the critical set of variation which would lead to a quicker problem solution and better control of the financial figures.

Multi-vari is a statistical engineering method used to analyse a set of data acquired in an organized manner and analysed graphically or analytically. There are two basic applications of this method: (i) *to determine statistically the homogeneity of the data distribution* and (ii) *to identify the critical set of variation that contains the assignable cause of the variation*. This paper focuses on the second application of this method, which gives the greatest return on investment with respect to day-to-day operations in different working environments. The multi-vari method presented and application examples should help readers to understand the essential features, to evaluate the method, and to identify its potential for application in their areas of expertise.

Keywords: multi-vari, cost, working environment, set of variation, main cause of variation

1 INTRODUCTION

Many statistical engineering techniques developed during the last century were first applied in the unique working environments of military or space science. They helped researchers to understand the behaviour of a system in relation to ever-changing inputs. At that point, the financial impact of the system behaviour was not the most important driver for utilization of the statistical engineering techniques. Over time, statistical engineering methods have been used more and more in ordinary industrial working environments. Statisticians were working on a theory to give a more formal and rigid approach to many statistical engineering methods, where

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inferences were sometimes more intuitive than analytical in nature. Despite the level of knowledge achieved, the developing world of industry and related science has posed a fresh set of expectations for statistical engineering. The financial aspect of business today is the key factor in globalized industry. The application of statistical methods in industry is valued based on financial benefits that these methods will provide to an industrial or any similar working environment. This paper demonstrates the benefits of multi-vari, a statistical engineering method that has been underutilized for many years; its revival, in the most essential form, came with the introduction of concepts of lean manufacturing and six sigma. These two work-environment-related philosophies drive for a culture of waste elimination, and therefore support the implementation of statistical engineering methods that will help in waste elimination. The applications presented of the multi-vari method show the return it can provide in the manufacturing environment.

1.1 Financial aspect

The behaviour of critical outputs $Y_i(t, x)$ (where *t is time* and *x* represents '*other variable*'* independent and nested or crossed variables in statistical terms) must be controlled in any working environment. As mentioned earlier, the existence of a working environment or business mostly depends on its financial performance, which is why it is very important to identify the controllable parameters that may influence the financial performance. Business decisions are based on the forecasted financial figures, which could significantly change if some of the business-related parameters become out of control.

To have better control of the financial outcome ($F_i(t)$), of any specific operation within the working environment, the sets of variation ($S_i\ (t, x)$) that influence the distribution $\mathcal{N}$ $(0, \sigma^2{}_i)$ of the critical outputs must be understood. The set of variation that influences the critical output to become out of control is one of particular interest. This set contains the assignable cause of variation (i.e. the main cause of variation). The problem is that most of the time it is not known which set of variation influenced the critical output to become out of control. The answer must be obtained quickly to be able to reduce the impact of uncontrolled output behaviour on the business financial performance. This is where multi-vari comes into play.

1.2 Statistical aspect

The multi-vari method originated from the $(\overline{X}, R)$ control charts used to monitor the variation within a statistical sample taken at an instant of time, as well as between statistical samples taken at different, instants of time. Besides the previous two sets of variation, the multi-vari method provides the opportunity to analyse additional sets of variation that are process specific (batch production, different machines, different production shifts, additional product streams, and so on). Regardless of the number of additional sets of variation, the statistics used for analysis are still range (R) and mean ($\overline{Y}$) of the different sets of variation [1]. Derived from the graphical $(\overline{X}, R)$, the multi-vari method is considered to be graphical in nature, although many statistically sound inferences could be made based on simple analytical calculations with data collected for multi-vari analysis. The graphical approach is mostly used because, as Tukey [2] pointed out, the graphical tools can help us to notice 'what we never expected to see'. The value and expedience of the analytical approach for simple problems analysis has been previously presented by the present authors [3].

As stated in the Abstract, the *second application* of this method will be described at the operations level, with all references made to requirements at that level in an ordinary industrial environment. The intent is also to simplify the relevant theory and help lean philosophy practitioners to use the method at the lowest possible level of expertise, while at the same time maximizing the benefits.

2 PROCESS DEFINITION

Unlike $(\overline{X}, R)$ control charts, this method is used not to monitor process behaviour regularly, but rather to perform an analysis of process behaviour when an out-of-control output condition owing to an assignable cause is present or when repeated out-of-control conditions occur. The multi-vari method will help in isolating the critical set of variation $S_{RX}\ (t, x)$ that has the main impact on the critical output ($Y_i(t, x)$) that went out of control. The level of confidence in the obtained answer depends greatly on the approach that is taken in the multi-vari method application. The set of variation that contributed to the out-of-control condition can be identified only if the impact of the predetermined set of sets of variation on the critical output is monitored without any attempt to change the parameters within the considered sets during the observation.

As in any other statistical studies, the information must be collected in an organized, predetermined way. The critical output $Y_i(t, x)$ could be either attribute or variable data. It is usually easier to analyse the variable data. If the critical output is attribute data, often some method is used to describe the attribute data as variable data: this may be achieved by relating

* ('Other variable' refers to, for instance, machine 1, 2, ..., *p*; shift 1, 2, 3; process 1, 2, ..., *q*; etc.)

the attribute data to something that is countable or scalable. Before commencing the study, it is necessary to establish a reliable and repeatable measurement system for monitoring the critical output $Y_i(t, x)$. The selected measurement system must have an internal error significantly smaller than the distribution of the critical output influenced by the identified sets of variation. Gauge R@R or Isoplot are some of the methods used in operations to verify the suitability of the selected measurement system [**4**].

Good understanding of all aspects of the studied working environment is crucial for proper identification of the relevant sets of variation S_i (t, x). Failing to identify a set within sets of variation that contain S_{RX} (t, x), world mean that the process of problem identification could last much longer, which in turn would increase the cost related to the out-of-control condition. This situation is characterized by endless attempts to solve the problem, simply described as 'cure of the symptoms while root cause stays hidden'.

The behaviour of the critical output $(Y_i(t, x))$, influenced by different sets of variation, is monitored in predetermined time or 'other variable' increments. Thus $(Y_i(t, x))$ is a discrete function of *t and/or x* that mostly has an equal predetermined number (n) of values at predetermined *t and/or x* increments. The *t and/or x* increments depend on the type of process monitored and the working environment.

The sets of variation are attribute functions, the description of which is derived from the working environment specifics. They could be divided into three basic groups: positional, cyclical, and temporal [**5**]. Some of the most common sets of variation are 'within observed object', 'from object to object', 'from set to set', 'from tool to tool', 'from equipment to equipment', 'from working environment to working environment', 'from man to man', 'from shift to shift', and 'from time to time'. The 'within observed object' set of variation is present in all cases, when the critical output has multiple values at a specific time increment or instant (e.g. different diameters at the same end of the machined shaft). Quick elimination of non-relevant sets of variation would reduce the study time significantly, which is why it is very important that during the process resources are deployed that have information and knowledge relevant to the working environment (e.g. if two pieces of equipment are producing the same product at the same scrap rate, the 'from equipment to equipment' set of variation *is not* S_{RX} (t, x) and it does not contain the main cause of variation related to scrap rate). Each set of variation should have a rationale that will better define the part of the study relevant to that set of variation (e.g. rationale – study performance of three plotters per hour, or where the problem is related to the manufacturing plant number 1 only).

The sampling plan for the study should not include less than three measured values [**1**] of the critical output $Y_i(t, x)$ concerning each set of variation. The studies need to be conducted 'on the spot' where the problem exists. Proper observation is very important for identification of the critical set of variation. Once the S_{RX} (t, x) is identified the multi-vari study does not need to continue.

3 ANALYTICAL DEFINITION

Researchers deMast *et al.* [**6**] have described the statistical background and hypothesis that justify the validity of the multi-vari method and its application in identification of the critical set of variation. This paper will show a simplified analytical approach that is easy to follow and apply in both graphical and analytical form.

Data collected during the study should be tabulated in ascending order of *t and/or x*. The measurement starts with critical outputs related to the set of variation that covers the x at t or lowest time increment Δt (e.g. diameter of the produced part that was machined in the time interval Δt_0, which is significantly smaller than the total observed amount of time T) and then passing through the sets of variation that cover multiple x or t increments (e.g. batch of parts produced in interval $m\Delta t$ where m is the integer in the sense of time increment) usually up to the set of variation of time S_T simply measured in units of time increments (e.g. two hours of production, or two days of sales, or three months of shipments). Among the selected sets of variation the critical one must be identified, S_{RX}, which influences the appearance of the full distribution or at least 80 per cent [**1**] of distribution of the critical output $Y_i(t, x)$. The analysis is based on a comparison between the point estimates of the central tendency and dispersion of the measured critical output $Y_i(t, x)$. The multi-vari method uses range as the measure of dispersion and mean as the measure of central tendency. The distribution of critical output Y_{mj} in relation to the first set of variation, which is almost always 'within observed object' (assuming there is potential for the object to have multiple output values at moment Δt), at Δt, can be presented for the k increments of *t and/or x* in the form of ranges

$$\begin{aligned} \Delta R_{11} &= \max|Y_{11} - Y_{1n}|_1 \\ \Delta R_{1j} &= \max|Y_{11} - Y_{1n}|_j \\ \Delta R_{k1} &= \max|Y_{k1} - Y_{kn}|_1 \\ \Delta R_{kj} &= \max|Y_{k1} - Y_{kn}|_j \end{aligned} \tag{1}$$

or in generalized form as

$$\Delta R_{mj}(\Delta t, \Delta x) = \max|Y_{i1} - Y_{mn}|_j \tag{2}$$

where $m=1,2,\ldots,k$ is the number of measurements taken on the critical output $Y_i(t,x)$ in relation to the first set of variation observed at Δt *and/or* x increments; j is the integer determined by the rational on the second set of variation (which could be nested or crossed with first set of variation [**7**]); Y_{kn} is the nth measure of kth sample.

For simplicity the critical range related to the first studied set of variation is

$$R_A = \max \Delta R_{mj}(\Delta t, \Delta x) \tag{3}$$

Figure 1 shows the graphical interpretation of equation (3) in the form $\boxed{\mathbf{R_A}}$.

If the second critical outcome is designated as R_B, the full distribution of the R_B in relation to the second set of variation observed in $j(\Delta t, \Delta x)$ increments l times can be presented in the form of ranges of the means, of distributions associated with the first set of variation, as

$$\begin{aligned} \Delta R_{B1} &= \max\left|\left(\overline{Y_1}\right)_1 - \left(\overline{Y_j}\right)_1\right|_1 \\ \Delta R_{B2} &= \max\left|\left(\overline{Y_1}\right)_2 - \left(\overline{Y_j}\right)_2\right|_2 \\ \Delta R_{Bl} &= \max\left|\left(\overline{Y_1}\right)_l - \left(\overline{Y_j}\right)_l\right|_l \end{aligned} \tag{4}$$

or in the generalized form as

$$\begin{aligned} R_B &= \max \Delta R_{Bl}(l * j(\Delta t, \Delta x)) \\ &= \max(\Delta R_{B1}, \ldots, \Delta R_{Bl}) \end{aligned} \tag{5}$$

where

$$\left(\overline{Y_j}\right)_l = \frac{\sum_n (Y_{mn})_l}{j} \tag{6}$$

and

$$\begin{aligned} &l = 1, 2, \ldots (l<m) \\ &l = m/a \\ &a \in I \end{aligned}$$

The graphical interpretation of equation (5) is presented in Fig. 1 as $\boxed{\mathbf{R_B}}$.

In the same manner the subsequent outcome designated as R_C can be presented in the following form

$$\begin{aligned} \Delta R_{C1} &= \max\left|\left(\overline{Y_{B1}}\right)_1 - \left(\overline{Y_{Bl}}\right)_1\right|_1 \\ \Delta R_{C2} &= \max\left|\left(\overline{Y_{B1}}\right)_2 - \left(\overline{Y_{Bl}}\right)_2\right|_2 \\ \Delta R_{Cp} &= \max\left|\left(\overline{Y_{B1}}\right)_p - \left(\overline{Y_{Bl}}\right)_p\right|_p \end{aligned} \tag{7}$$

or in the generalized form

$$\begin{aligned} R_C &= \max \Delta R_{Cp}(p * j(\Delta t, \Delta x)) \\ &= \max(\Delta R_{C1}, \ldots, \Delta R_{Cp}) \end{aligned} \tag{8}$$

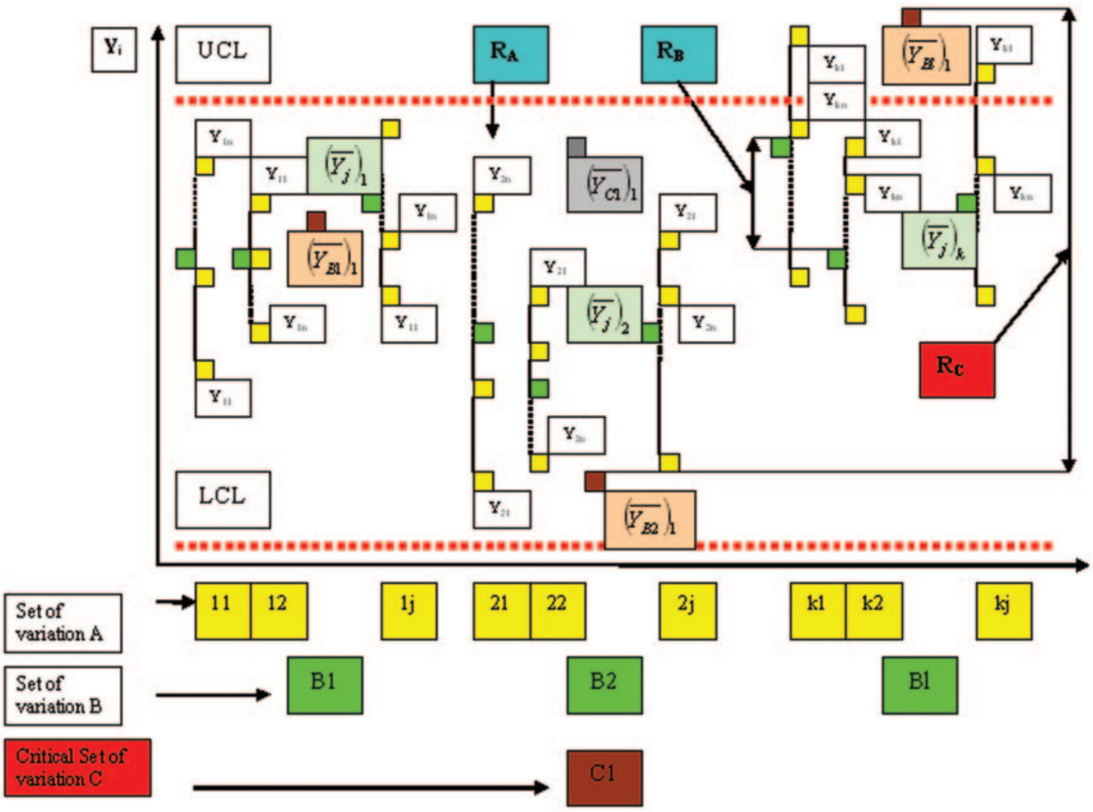

Fig. 1 Multi-vari chart, basic form

where

$$\left(\overline{Y_{Bl}}\right)_p = \frac{\sum_j \left(\overline{Y}_{jl}\right)_p}{j} \tag{9}$$

and

$$p = 1, 2, \ldots (p < l)$$
$$p = l/b$$
$$b \in I$$

In Fig. 1 the critical range related to this set of variation is presented in the form $\boxed{\mathbf{R_C}}$. The next subsequent outcome will follow the same pattern.

When the study has been completed and the significantly full distribution of outcomes related to individual sets of variation has been determined, it is possible to determine which set of variation contains the main cause of the out-of-control outcome, from the following equation

$$\forall\{A, B, C, \ldots\} \Rightarrow S_{RX} \ni \max(R_A, R_B, R_C, \ldots) \tag{10}$$

where $\{A, B, C, \ldots\}$ is the set of studied sets of variation. From Fig. 1 it can be seen that the last critical range points to the set of variation, $S_{RX}(t, x)$, which contains the main cause of the out-of-control condition.

The next step towards the problem solution is to use the other statistical engineering methods to identify the main cause of the problem within the identified set of variation S_{RX}. Sometimes the answer can be found simply in the approach that identifies the cause for the difference between the outcomes that are considered to be on the 'good' side of the distribution versus the outcomes that are considered to be on the 'poor' side of the distribution. This and many other methods used to identify the main cause of variation are outside the scope of this paper.

3.1 Multiple processes

From time to time problems can be much more complex. Products with critical outcomes Y_i from the set of processes P_i are transferred into the set of subsequent processes P_{ij} with critical outcomes Y_{ij} and then into another set of subsequent processes P_{ijk} with critical outcomes Y_{ijk} and so on. One set of variation from the r sets of processes hypothetically may sway the critical outcome Y_{ijk} out of control and inevitably pose a threat to the financial performance of the working environment.

How can multi-vari be applied in such a situation? As previously mentioned, it is very important to understand the process flow as a whole. The study should be performed with sets of variation that are identified within designated sets of processes. The number of sets of variation within the sets of processes, and number of outcomes associated with each, would determine the statistical sample to be studied. If, for example, set of processes P_i is affected by the set of variation A, B, and C, and each set of variation has the number of outcomes R_A, R_B, and R_C respectively (see Fig. 1 where set A has j number of outcomes and set B has l number of outcomes), the statistical sample for that process, a_i , will be the product of the number of outcomes designated as R_A, R_B, and R_C. In the same manner the size of statistical samples (Ss) would be determined**,** for P_{ij} processes as b_i and for P_{ijk} processes as c_i. The size of the statistical sample for the whole population would be the highest number from the set $\{a_i, b_i, c_i\}$ adjusted, for practical reasons, in such a way that statistical samples for the other two processes are the whole multiples of sample size for the whole population – the common denominator principle (e.g. 18, 27, $48+6=54=Ss$, where 6 is the 'correction number').

Once the sample size for the whole population is determined, the sample from the first set of processes should be collected, where the number of outcomes for each set of variation within a particular set of processes is the whole multiple, determined relative to the population statistical sample (e.g. if $a_i = 18 = 1\times3\times3\times2$ and $Ss = 54$ then the study with a_i sample has to be repeated three times; number 1 is related to the 'within observed object' set of variation; depending on the nature of the selected set of variations, it is possible sometimes to avoid the repeated studies simply by increasing the number of outcomes related to the specific set of variation as $a_i = 54 = 1\times3\times9\times2$).

$$a_i = 1 \times a_{i1} \times a_{i2} \times \ldots \times a_{in} \tag{11}$$

where 1 is the number related to the 'within observed object set of variation', which is always one, and a_{in} is the number that designates size of the nth set of variation.

Before processing is commenced, individual objects of the population sample have to be identified with a set of computer-generated random numbers for purposes of traceability. The whole set is then divided in the number of even subsets that is equivalent to the number of P_{ij} processes. When the population sample passes the second set of processes, it is again randomized and divided into the number of even subsets that is equivalent to the number of P_{ijk} processes, before it enters the P_{ijk} set of processes.

Upon completion of the study the influence of the sets of variation related to each process must be analysed individually and the set of variation that contains a main effect on the out-of-control output must be identified.

4 GRAPHICAL DEFINITION

The process that takes place for the graphical form of the multi-vari method is equivalent to that explained in the analytical definition section 3. The only difference is that data are entered on the previously prepared blank forms with identified sets of variation and designated limits. Data are then transferred into some statistical software that performs the multi-vari analysis and draws the chart (or the chart is manually plotted on graph paper) in scaled format with identified sets of variation and control limits. The critical output values are plotted on the y axes and sets of variation on the x axes (see Fig. 1). Statisticians [**6**] have developed methods for the calculation of control limits. Those methods were developed to test the hypothesis of data homogeneity and they will not be used for the present application. Instead, the design specification limits are used, as they are directly related to customer satisfaction (UCL: upper control limit; LCL: lower control limit).

Figure 1 is the basic form of the multi-vari chart. For interpretation purposes, it may be assumed that within the three sets of variation presented in Fig. 1, there is a set of variation that contains the main cause of variation. To identify which set of variation contains the main cause, the data would be plotted from the data collection table. The table would contain the sections that correspond to the set of variation associated with the largest variable (*t or x*) increments (set of variation C), subtabled by the section for the set of variation that corresponds to the next smallest variable increments (set of variation B), down to the section that corresponds to the time instant (set of variation A). Plotted values will define the ranges for each set of variation, either directly as for the 'within observed object' set of variation (distance between two furthest apart yellow squares per sample) or indirectly through calculated means (from individual part to individual part – green squares). Once all the ranges, associated with different sets of variation, have been marked on the graph, a simple comparison of their size will determine the largest range that is associated to the set of variation containing the main cause of the out-of-control output. This justifies the main purpose of this type of multi-vari chart application.

5 CONCLUSION

The multi-vari, statistical engineering method, has great importance in today's fast-paced production environment where rapid identification of the main cause of a problem and swift solution implementation are required. Despite the fact that some statistical methods, such as F-test or ANOVA, can provide similar conclusions to those developed from the multi-vari method, they are much more difficult for non-statisticians to understand and apply. Rather than calculating data homogeneity, multi-vari, in essence, quickly provides the clue to which set of variation contains a main problem cause. Its graphical nature sometimes allows engineers and statistical engineering practitioners to perform studies and come to a useful conclusion 'on the spot', which is considered to be one of the main advantages of this method. In many situations properly prepared tables for data collection can be easily used for simple calculations of range and mean that lead to the same conclusion as those developed from a properly designed graph.

The simplicity and value of the multi-vari method are two factors that will promote and extend its application beyond the production environment where this method has lately regained recognition.

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APPENDIX

Illustrative examples of applications from industry

AIAG – C_{pk} requirement (Figs 2 and 3)

Automotive suppliers for General Motors (GM), Chrysler, and Ford are obliged to follow the number of specific requirements prescribed in AIAG manuals and customer-specific procedures. The ultimate goal of such an approach is to have satisfied customers at all levels. One of the requirements is related to process capability, described by capability indices C_{pk}. Capability indices are indicators of the process ability to produce the products that meet customer requirements with a predefined probability of making non-conforming products. The historic standard for the manufacturing processes has been $C_{pk} > 1.33$ [**8**] what was equivalent to four sigma capability or failure rate of 66 807 PPM (defective parts per 1 million produced parts: all presented PPM numbers include 1.5σ process drift). Today's requirements are very different. C_{pk} of 1.67 (five sigma: 233 PPM) and even $C_{pk} = 2$ (six sigma: 3.4 = PPM) are standards in today's North American automotive industry. To meet these standards, suppliers have to develop a robust design and much more robust and capable processes.

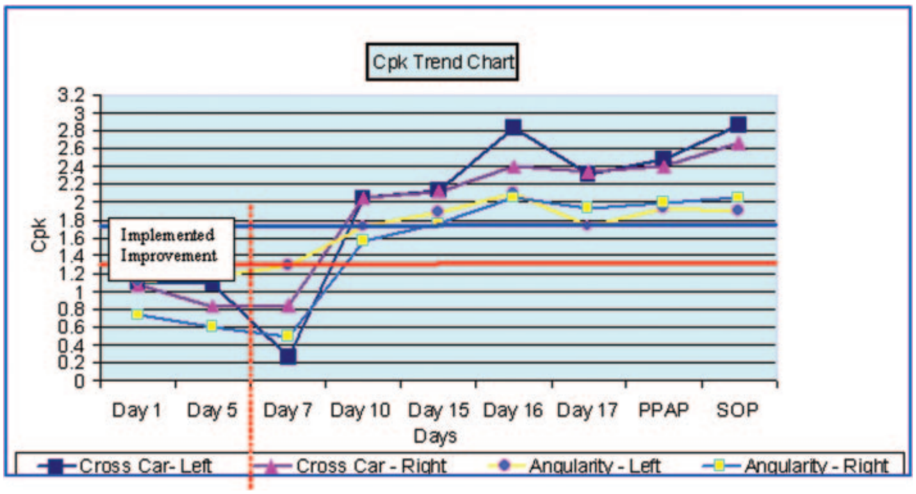

Fig. 2 Performance gap – required versus achieved C_{pk}

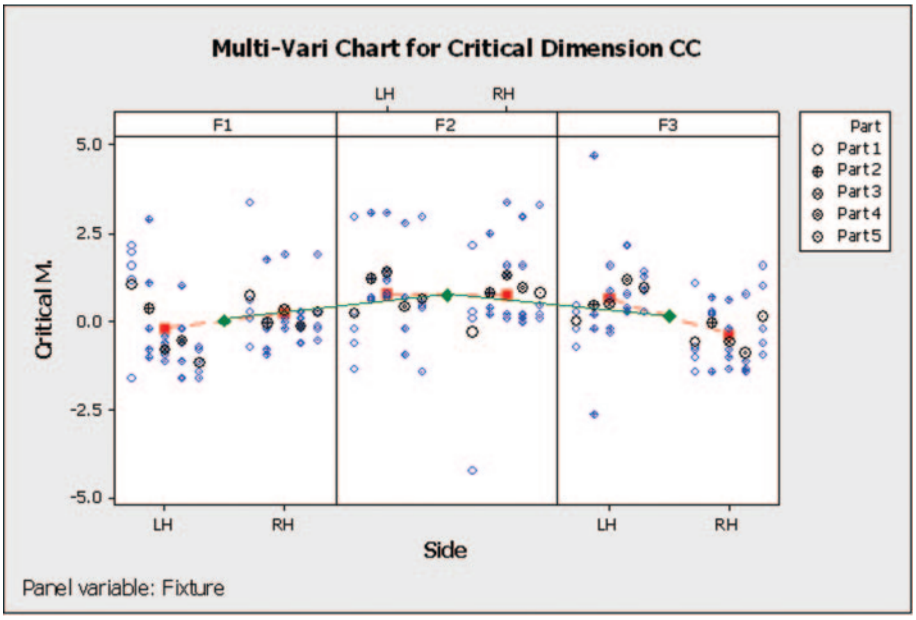

Fig. 3 Multi-vari chart for critical dimension CC

The example presented shows a case from the pre-production stage, where installed tooling and process set-up demonstrated an inability to meet the customer requirements of $C_{pk} > 1.67$ (Fig. 2). The set of variation, main cause of problem, and solution have been identified and implemented prior to production part approval process (PPAP). The multi-vari chart was used to identify the critical set of variation. Three relevant sets of variation were studied: 'part to part', 'fixture to fixture' and 'time to time' (Fig. 3). The 'part to part' set of variation had the widest distribution of values.

Scrap and uptime

Cost of quality and uptime are two critical elements for the overall business performance in manufacturing. Production of non-conforming products and scrap related to it are major contributors to the increase in cost of quality. These factors also have a negative impact on the uptime figures, which, expressed in financial terms, may exceed the scrap cost.

Example 1 This example (Figs 4 and 5) shows the scrap issue related to the tooling and equipment that was not set up properly to handle the range of

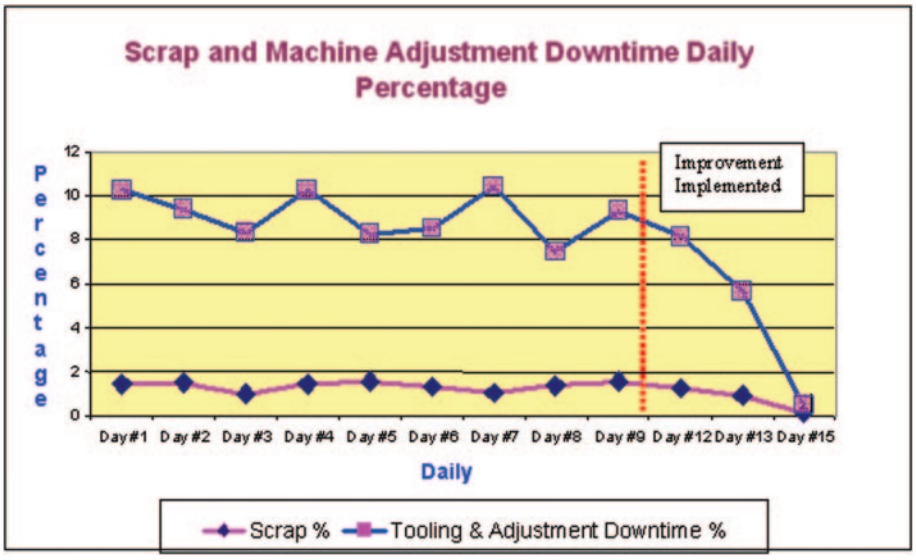

Fig. 4 Performance gap – scrap and uptime

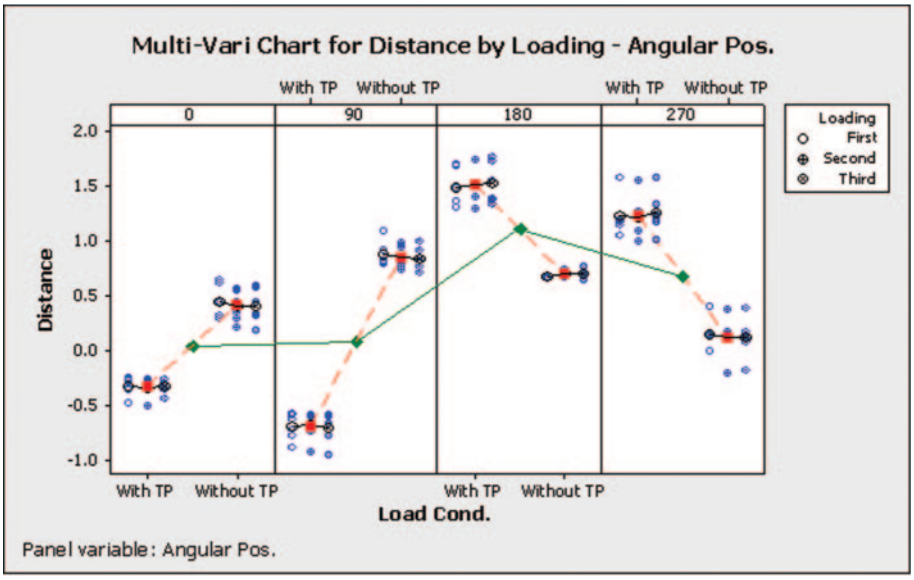

Fig. 5 Multi-vari chart for distance by loading – angular position

variation of the components introduced in the welding process. The position of the welding point on the circumferential weld in relation to the stationary welding torch was changing in the direction of the welding torch. This was creating welding defects in the form of burn-through and leaks. Four sets of variation were identified as potential holders of the problem main cause: 'loading to loading – same location', 'location to location – on the same part', 'part to part – of the same batch' and 'load condition to load condition – on the same number'. The widest distribution of measured data was observed in the 'load condition to load condition' set of variation.

Example 2 This example (Figs 6 and 7) is related to the scrap caused by production of non-conforming welded assemblies. In this type of case, if it is not easy to recognize the main cause for the production of non-conforming parts, operation is prone to continuous adjustments of the process and tooling set-up. The intent is to solve the problem, when as a matter of fact, more often than not, this approach cures only the symptoms and the problem stays hidden within the critical set of variation that influences the quality of components. The components issue is sometimes linked to the assumption that non-key component characteristics will not influence

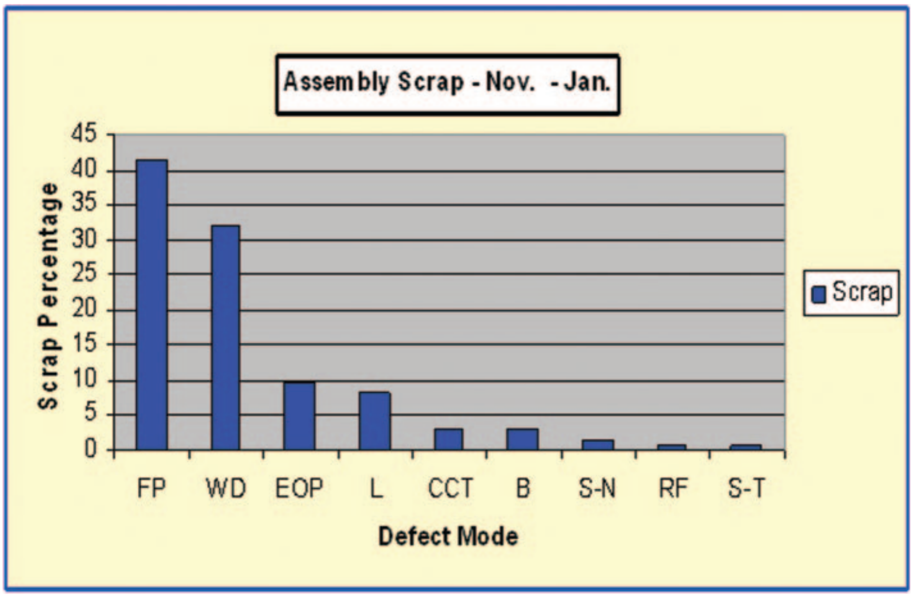

Fig. 6 Performance gap – scrap by mode of failure

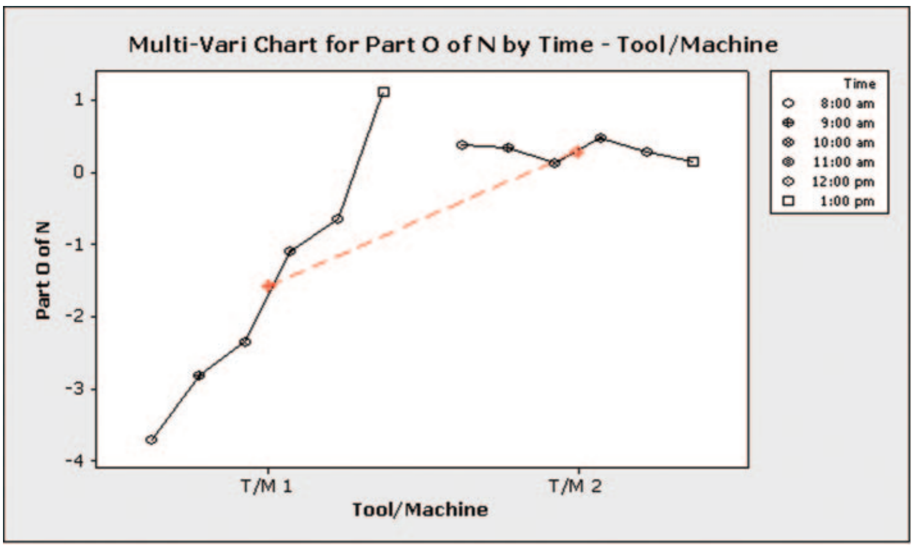

Fig. 7 Multi-vari chart for part out of nominal by time – tool/machine

the quality of the part and the assumption that regular wear and tear of the equipment could always be compensated by the adjustments, as was related to this case. It was proved that the 'within part' set of variation (prior to forming operations) was not relevant to this case, as the key measure for the components was the overall length produced on the machines with high capability of maintaining the end part geometry. The 'time to time' set of variation was showing the largest contrast and was related only to tooling and machine number 1. This leads to the conclusion that something is happening with tooling and machine number 1 as time progresses and the product manufactured at that machine shows constant growth of the measured dimension.