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Fuzzy Set Theory Applied to Measurement Data for Exposure Control in Beryllium Part Manufacturing

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ABSTRACT

Fuzzy set theory has been applied to some exposure control problems encountered in the machining and the manufacturing of beryllium parts at Los Alamos National Laboratory. A portion of that work is presented here. The major driving force for using fuzzy techniques in this case rather than classical statistical process control is that beryllium exposure is very task dependent and this manufacturing plant is quite atypical. It is feared that standard techniques produce too many false alarms. Our beryllium plant produces parts on a daily basis, but every day is different. Some days many parts are produced and some days only a few. Some times the parts are large and sometimes the parts are small. Some machining cuts are rough and some are fine. These factors and others make it hard to define a typical day. The problem of concern, for this study, is the worker beryllium exposure. Even though the plant is new and very modern and the exposure levels are expected to be well below the required levels, the Department of Energy (DOE), who is our major customer, has demanded that the levels for this plant be well below required levels. The control charts used to monitor this process are expected to answer two questions:

1. Is the process out of Control? Do we need to instigate special controls such as requiring workers to use respirators?
2. Are new, previously untested, controls making a difference?

The standard Schewart type control charts, based on consistent plant operating conditions do not adequately answer this question. The approach described here is based upon a fuzzy modification to the Schewart Xbar-R chart. This approach is expected to yield better results than work based upon the classical probabilistic control chart.

KEYWORDS

Fuzzy Logic; Statistical Process Control; Exposure Control; Measurement Data; Beryllium Parts Manufacture

1. Introduction

Los Alamos National Laboratory has recently completed a new beryllium part manufacturing facility. The new facility is intended to supply beryllium parts to the DOE complex and in addition act as a research facility to study better and safer techniques for producing beryllium parts. Exposure to beryllium particulate matter, especially very small particles has long been a concern to the beryllium industry. The industrial exposure limit has been 2 $\mu g/m^3$ per worker per eight-hour shift. The DOE has set limits of 0.2 $\mu g/m^3$ or ten times lower than the previous industrial standard for this facility. In addition, they have requested continual quality improvement. In other words, in a short period of time they intend to set even lower limits. Several controls have been implemented to assure that the current low level can be met. But there is a real management concern that the process remains under control and that any further process improvements are truly improvements. Since the facility is a research facility with manufacturing capabilities, the workload and type of work done each day can vary dramatically. This makes the average beryllium exposure vary widely from day to day. This in turn makes it very difficult to determine the degree of control or the degree of improvement with the standard statistical control charts. For this reason we have implemented a fuzzy control chart to improve our perception of the process.

The plant has four workers and seven machines. Each worker wears a device that measures the amount of beryllium inhaled during his or her shift. The devices are analyzed in the laboratory and the results are reported the next day after the exposure has occurred. A Shewhart [1, 2] X bar-R chart can be constructed with these data and presumably answer the questions of control and quality improvement. Although such a chart can be useful, because of the widely fluctuating daily circumstances, these tests for controllability are not very meaningful.

There are four variables that have a large influence upon the daily beryllium exposure. They are the number of parts machined, the size of the part, the number of machine set ups performed, and the type of machine cut (rough, medium, or fine). In the fuzzy model, a semantic description of these four variables and the beryllium exposure are combined to produce a semantic description of the type of day that each worker has had. The day type is then averaged and a distribution is found. These values are then used to produce fuzzy Shewhart-type X bar and R charts. These charts take into account the daily variability. They provide more realistic control limits than the typical X bar-R charts and make it easy to correctly determine whether or not a process change or correction has made a realistic improvement to the overall process.

The basic idea behind a control chart is that there are two types of variability. The first one is called Common-cause. All processes have this. It is a random variability in the process and/or in the sensing or measurement of the variable of interest. It is something that is always present that cannot really be removed or controlled. The other type of variability is called a Special-cause event. These events are disturbances that can be understood physically and corrected. The control chart is a tool that is used to determine the difference between these two causes and thereby determine if and when corrective action should be taken.

2. Background

Improving productivity and the quality of products are two of the major objectives of statistical process control or SPC. The term "statistical" is used in the name because the procedure involves the use of numerical data and probability theory in an attempt to derive useful information about the process under observation. We assume that the process is at steady state or not undergoing any systematic change. There are, however, variations that are beyond our control. This is the Common-cause variability. The reason to use SPC and a control chart isto determine if the variability in the process that is observed over a period of time is Common-cause variability or a Special-cause event. If the variability is Common-cause then we continue the process as before. If we determine that the variability is due to a Special-cause event then we exercise the control portion of the SPC and stop the process and determine, if you can, the cause and then remedy the situation before continuing the process. The upper and lower control limits for X-bar are usually set to approximate three standard deviations about the grand average, or the average of all the sample aet average taken over a specified number of samples, or run time. The upper and lower control limits for the range or R charts are defined in a similar manner. The X-bar chart shows variability about the grand average over a period of time. The R chart shows variability within a sample over a period of time. Both charts are useful, but the X-bar chart proved more useful than the R chart in this study. Any standard text on SPC will contain a thourough discussion on control limits for these charts, for example see Wheeler and Chambers [3] or Mamzic [4].

3. The Fuzzy System

The fuzzy system consists of five input variables or universes of discourse and one output variable. Each input universe has two membership functions and the output universe has five membership functions. The input and the output are connected by thirty-two rules. The five input variables are:

1) Number of Parts – with a range of 0 to 10 and membership functions:
   a) Few.
   b) Many.
2) Size of Parts – with a range of 0 to 135 and membership functions:
   a) Small.
   b) Large.

3) Number of Set Ups – with a range of 0 to 130 and membership functions:
    a) Few.
    b) Many.
4) Type of Cut – with a range of 1 to 5 and membership functions:
    a) Fine.
    b) Rough.
5) Beryllium Exposure – with a range of 0 to 0.4 and membership functions:
    a) Low.
    b) High.

The output variable is:

1) The Type of Day – with range from 0 to 1 and membership functions:
    a) Good.
    b) Fair.
    c) OK.
    d) Bad.
    e) Terrible.

For each of the five input variables there are two membership functions represented in each case by two equal triangles. Figure 1. shows the five output membership functions. The rules are based on some simple ideas. For example, if all of the four mitigating input variables indicate that the beryllium exposure should be low, and it is low, then the "type of day" is OK. Likewise, if all four indicate that the exposure should be high, and it is high, then the "type of day" is also OK. If all four indicate that the exposure should be low, and it is high, then the "type of day" is Terrible. If all four indicate that the exposure should be high, and it is low, then the "type of day" is Good. Fair and Bad days fall in between the OK days and the Good and Terrible extremes. The form of the rules is:

If (**Number of Parts**) is …and If **(Size of Parts**) is … and If (**Number of Set Ups**) is … and If (**Type of Cut**) is… and If (**Beryllium Exposure**) is… Then (**The Type of Day**) is….

The Size of Parts is determined as the number of parts multiplied by the average diameter of each part, measured in centimeters. The Type of Cut is determined by a somewhat complicated formula based on a roughness factor for each part, the number of parts and the size of those parts and the number of set ups required for each worker each day. A fine cut has a roughness factor (rf) of 1, a medium cut has an rf equal to 3 and a rough-cut has an rf equal to 5. The calculation for Type of Cut is a bit complicated but it provides a daily number between 1 and 5 (fine to rough) for each worker, which is meaningful. An example of the use of the fuzzy technique will follow a discussion of the plant simulation.

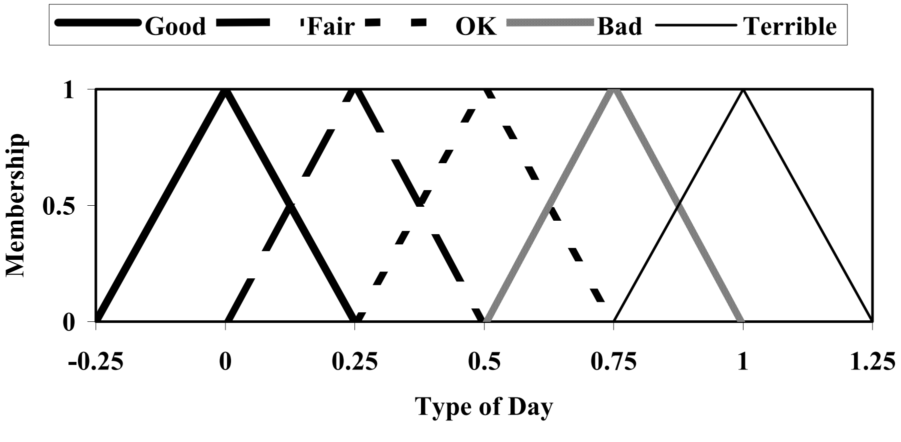

Figure 1. Output membership functions.

4. Plant Simulation

The Los Alamos beryllium facility has been completed, but has only recently been put into production. Since an exposure control technique had to be developed before the plant was put into production a computer program was written in order to provide a simulation of the facility operation and provide a demonstration of the fuzzy control chart technique. The results of this study are being supplied to plant workers in order for them to provide input to further improve the technique. The result of the computer study is the subject of this report. Some actual beryllium exposure data were available for this study. These data provided insight that made it possible to develop some reasonably realistic simulations for each of the intermediate process steps for manufacturing the beryllium parts.

The model has the following limitations or boundary conditions:

1. There are four machinists.
2. There are seven machines.
3. Machines 1 and 2 do rough-cuts only.
4. Machines 3 and 4 do both rough-cuts and medium-cuts.
5. Machines 5, 6, and 7 do only fine-cuts.
6. Machine 7 accepts only work from machines 3 and 4.
7. Machines 5 and 6 accept only work from machines 1 and 2.
8. Each machinist does all of the work on one order.
9. All machinists have an equally likely chance of being chosen to do an order.
10. There are ten possible paths through the plant. (At this point all are equally likely.)

The simulation follows the algorithm below:

1. A random number generator determines how many orders will be processed on a given day. (One to 40.)
2. Another random number generator picks a machinist.
3. A third random number generator picks a part size.
4. A fourth random number generator picks a path through the plant. For example, Machine 1 to Machine 3 to Machine 7.
5. The machine and path decide the type of cut, (rough, medium, or fine). Machines 1 and 2 are for rough-cuts only, machines 5, 6, and 7 are for fine cuts only, and machines 3 and 4 do rough-cuts if they are the first machines in the path and medium- cuts if they are the second machines in the path.
6. A random number generator picks the number of set ups for each machine on the path.
7. Another random generator picks the beryllium exposure for the operator at each step.

The above procedure is carried out for each part, each day. The entire procedure is repeated the following day, until the required number of days has passed. For this study the procedure was run for thirty days to generate some sample control charts. A description of the fuzzy control chart construction follows in section 5, with an example.

5. Establishing Fuzzy Membership Values

In this example we follows each step of the process for a specific machinist for a given day. The description will then be extended to the work for the entire day for all machinists. From the simulation, on day one, thirteen part orders were placed. Machinist two processed four of these orders, machinists one processed three, machinist three processed four, and machinist four processed two orders. Machinist two will be used to demonstrate the fuzzy system.

The cumulative size of the four parts that machinist two processed on day one was calculated to be 64.59. The number of set ups that he/she performed was 45. The numeric value for the type of cuts he/she performed on that day was 1.63. Finally, the machinist's beryllium exposure was 0.181 $\mu g/m^3$ for that eight-hour period.

Upon inserting the input values into the simple input membership functions described above, we obtain the following values: For Number of Parts = 4 the membership in Many is 0.4 and the membership in Few is 0.6. For Size of Parts = 64.59 the membership in Small is 0.52 and the membership in Large is 0.48. For Number of Set-Ups = 45 the membership in Many is 0.35 and the membership in Few is 0.65. For Type of Cuts = 1.63 the membership in Rough is 0.16 and the membership in Fine is 0.84. The Beryllium Exposure is 0.181. The membership in High is 0.45 and the membership in Low is 0.55.

In this study the Min-Max technique was used to resolve the "and-or" nature of the rules and the centroid method was used for defuzzification. For example, Rule 1 is fired with the following weights:

- Number of Parts --Few = 0.6,
- Size of Parts -- Small = 0.52,
- Number of Set Ups -- Few = 0.65,
- Type of Cut – Fine = 0.84, and
- Beryllium Exposure – Low = 0.55.

The consequent of rule 1 is "Fair"and takes the minimum value, 0.52. Of the 32 rules which are all fired, "Fair" is the consequent of ten of them with values ranging from 0.16 to 0.52, for this example. The Min-Max rule assigns the maximum value of 0.52 to the consequent Fair. Similarly, the consequent, "Terrible", appears five times with a maximum value of 0.45. "OK" appears twice with a maximum value of 0.35. "Bad" appears ten times with a maximum value of 0.45, and "Good" appears five times with a maximum value of 0.4. The centroid defuzzification method when combined with the Min-Max rule "clips" the output membership functions at their maximum value. In this example the membership functions are clipped as follows: Good = 0.4, Fair = 0.52, OK = 0.35, Bad = 0.45, and Terrible = 0.45. The shaded area in figure 2. shows the results of the clipping operation in this example. The defuzzified value is the centroid of the shaded area in figure 2. In this case the centroid is equal to 0.5036. So on day one, machinist two had an OK "type of day" ($0.5036 \approx 0.5$)

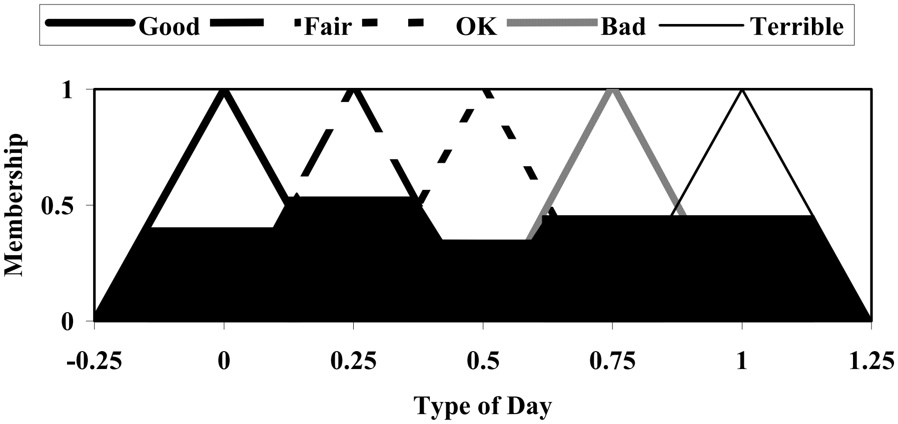

Figure 2. "Clipped" output membership functions for the example.

The next step is to provide an average and a distribution for the entire day based on the results from each machinist. The procedure outlined above can be followed for each machinist, for day one. The results for the other machinists were: machinist one = 0.4041, machinist three = 0.4264, and machinist four =0.4088. The set average, or X bar, for day one is 0.4357. This is the point for the first data set shown in figure 3, the fuzzy type of day X bar chart. For the same 30-day run, the daily average beryllium exposure and beryllium exposure ranges were plotted in the form of X bar-R charts. The X-bar chart is presented in figure 4. In figure 3., the fuzzy example, all of the important variables are taken into account and the control chart indicates that nothing is out of control. This is the result that we would expect from this simulation since it is based on random numbers, representing only Common-cause variation. In figure 4, the normal SPC technique, two points are above the upper control limit, representing an out of control situation. This represents two false alarms generated because all of the important variables are not factored into the solution of the problem.

Other simulations were run, in which the system was purposely perturbed. In all cases where the significant variables influenced the outcome the fuzzy SPC technique significantly outperformed the standard SPC technique. Finally a least squares approach, which did take into account the effect of the important variables, was used with the standard SPC technique. This method worked better than the standard SPC approach where only beryllium exposure was considered, but didn't work quite as well as the fuzzy technique.

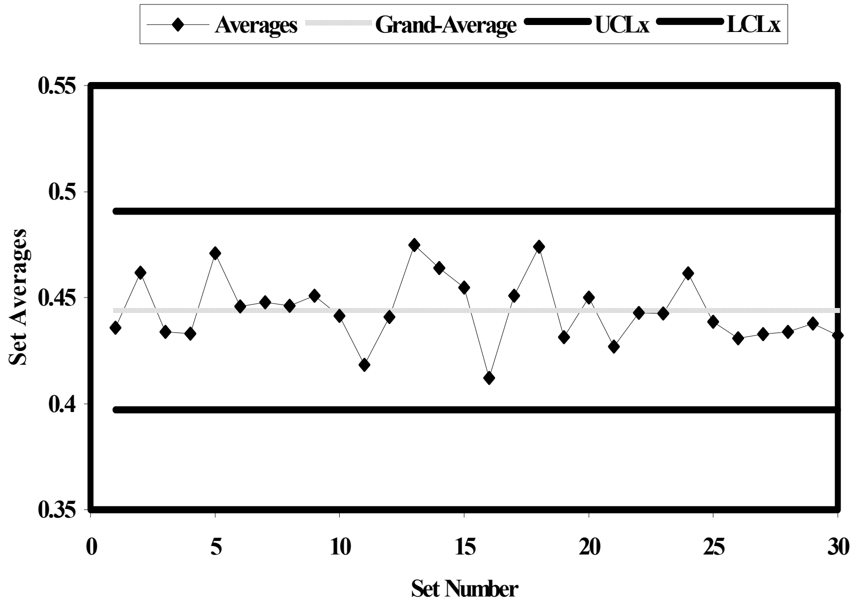

Figure 3. Fuzzy X bar chart for a "normal" 30-day beryllium plant run.

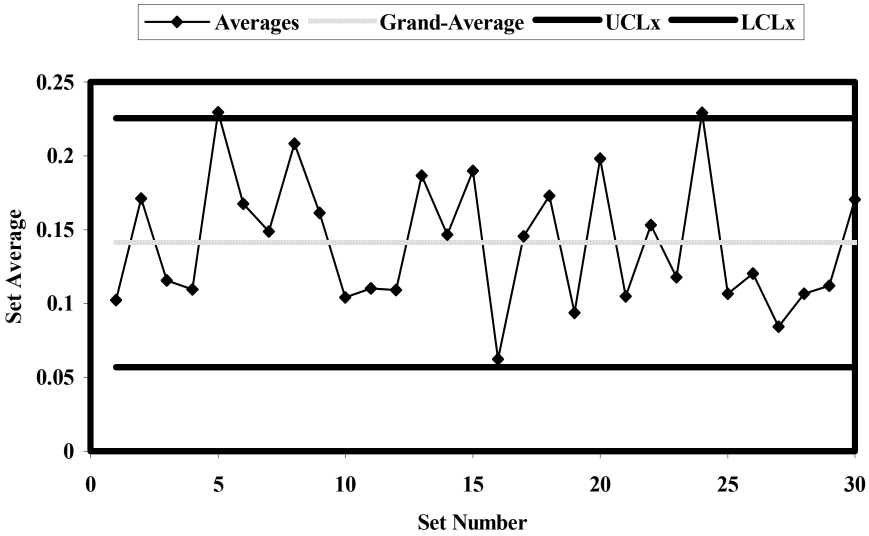

Figure 4. Beryllium Exposure X bar chart for a "normal" 30-day beryllium plant run.

8. Discussion and Conclusions

The fuzzy "type of day" Shewhart-type X Bar-R control chart has the potential to take into account the task dependency beryllium exposure for beryllium plant operations. Based upon the studies completed to this point, we believe these control charts will provide more realistic information than the standard single-variable X Bar-R chart using only beryllium exposure information. Because of the ability to take into account task dependency, "the type of day" chart can be used to determine the significance of plant improvements as well as trigger "out of control" alarms. This fuzzy technique should work well with many other task dependent problems, as long as they are well defined semantically. The least-squares approach will also work for this type of problem, but in many cases will not be as descriptive as the fuzzy approach. The least-squares approach can produce problems if the data used to develop a control chart has many out of control points in it. This is because the technique squares the difference between the expected value and the measured value.

Finally, the computer models of the beryllium plant operation described here were built from a semantic description of the process as was the fuzzy rule base and membership functions. Consequently the correlation between the fuzzy model and the plant simulation was quite good. Both models come from the same description. It is important when developing a fuzzy model of a process that a lot of care is taken to listen to the experts and get the best model possible. If the domain expert is knowledgeable this task is usually not that difficult, but it may require several iterations to get it right. The fuzzy control chart will only be as good as the fuzzy rules and membership functions that provide the input to it.

REFERENCES

1. Shewhart, Walter A., (1980) *Economic Control of Quality Manufactured Product,* American Society for Quality Control, Milwaukee, WI.
2. Shewhart, Walter A., (1986) *Statistical Method from the Viewpoint Economic of Quality Control,* Dover Publications, New York.
3. Wheeler, D. J. and D. S. Chambers, (1992) *Understanding Statistical Process Control, 2ed.,* SPC Press, Knoxville, TN.
4. Mamzic, C. L. ed., (1995) *Statistical Process Control.* ISA Press, Research Triangle Park, NC.