

Fuzzy Weighting of SPC Procedures

Kimmo Latva-Käyrä, Heimo Ihalainen and Jouko Halttunen
Tampere University of Technology / Measurement and Information Technology
P.O.Box 692, FIN-33101 Tampere Finland
Phone: +358-3-365 3575, Fax: +358-3-365 3575
email: kimmo@mit.tut.fi

ABSTRACT: Statistical process control (SPC) contains good methods for monitoring the quality variations in the process. When applying the SPC in to the process automation (Thermomechanical pulping (Sundholm 1999)) several things must be considered: sparse and correlated data, irregular sampling period and the uncertainty of the measurements. Process can be monitored with advanced SPC methods (EWMA, CUSUM). They can be combined by fuzzy weighting to achieve better quality control over process.

KEYWORDS: SPC, Fuzzy, Thermomechanical pulping, Quality

INTRODUCTION

The use of statistical process control procedures such as Shewhart charts is one of the corner stones of the quality revolution. The goal of statistical process control is the elimination of variability in the process. The Shewhart charts display data of the process under test and provide statistical decision making tools to assess the process quality (Shewhart 1931). These simple chart techniques have proven to be powerful tools for monitoring the 'health' of a process and for detecting special causes and events. In quality monitoring (Box 1997) applications of process industry we must often use uncertain measurements and SPC is a good tool for handling them.

STATISTICAL PROCESS CONTROL

The Shewhart control charts, although they are very useful in detecting significant mean deviations or high data scatter, are not very effective in detecting specific faulty events (Montgomery 1991). In fact, they fail if very slow drifts or cyclic disturbances hidden in by the natural dispersion of the process have to be detected early. Using advanced control charts, based on further processing of measurement results, such as the cumulative sum (CUSUM) and the exponentially weighted moving average (EWMA) can handle these problems.

Shewhart chart techniques and other basic SPC tools are mainly meant for the applications in parts manufacturing industries. To apply them to needs of the process industry requires further processing of these tools and knowledge of the process. This is because the measurements are often irregularly sampled and the measurement data is sparse, correlated and often uncertain.

In the case of highly autocorrelated data the usual Shewhart-type control charts will be ineffective. Useful approach in many cases is to apply an EWMA control chart directly to the process data. EWMA is a general control scheme that is useful in many processes where the observations are positively autocorrelated and the mean does not drift too fast. The EWMA method can also be applied to the irregularly sampled data and sparse data can be handled with weight coefficients of EWMA.

EWMA is a good alternative when small shifts and slow drifts are the main problems in the process. Normally EWMA is recursively calculated but in our case the data is irregularly sampled and sparse. So, we must use exponentially weighted moving window to calculate weight coefficients and then do the averaging. It is a bit slower than recursive calculation. Weight coefficient of EWMA can be calculated as shown in equation 1.

$$m_i = Pe^{(t_n - t_{(n-i+1)})b} \quad (1)$$

where:

$$b = \frac{\ln\left(\frac{k}{P}\right)}{\text{win}}$$

P is the maximum of weight coefficient,
 k is the minimum of weight coefficient,
 win is the window length.

Figure 1 shows an example of the weighting window when the maximum weight P is 1, the minimum weight k is 0.15 and the window length win is 4 hours.

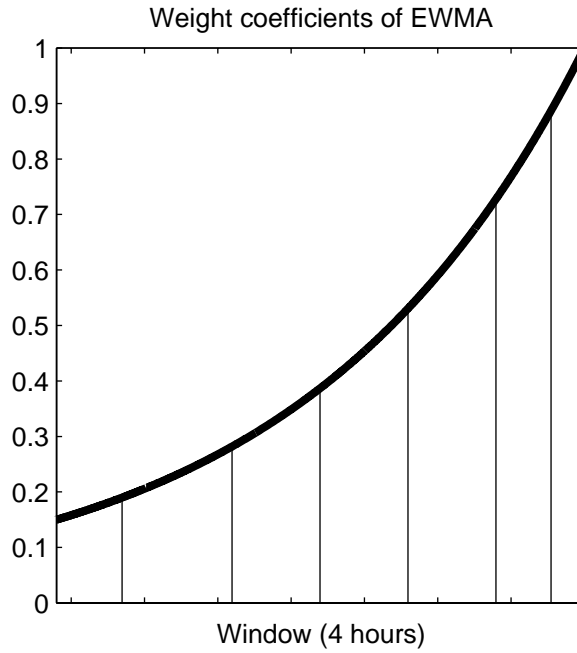


Figure 1: Weighting window of the EWMA. $P = 1$, $k = 0.15$ and $\text{win} = 4$ hours.

Weighted average \hat{x}_n can be calculated as shown in equation 2.

$$\hat{x}_n = \frac{\sum_{i=1}^{N_n} m_i x_{(n-i+1)}}{\sum_{i=1}^{N_n} m_i} \quad (2)$$

where:

x_n is a measurement at the time t_n ,

N_n is the number of measurements in win at the time t_n .

The sum of the weight coefficients can be used to form the relative weight. This is a method for handling the sparse data based on statistical reliability i.e. dependency on the number of measurements in the processing window. Figure 2 shows an example of how the relative weight can be formed from the weight coefficients of EWMA. In this case the relative weight gets values between $[-0.2, 0.2]$ but the values can depend on the process.

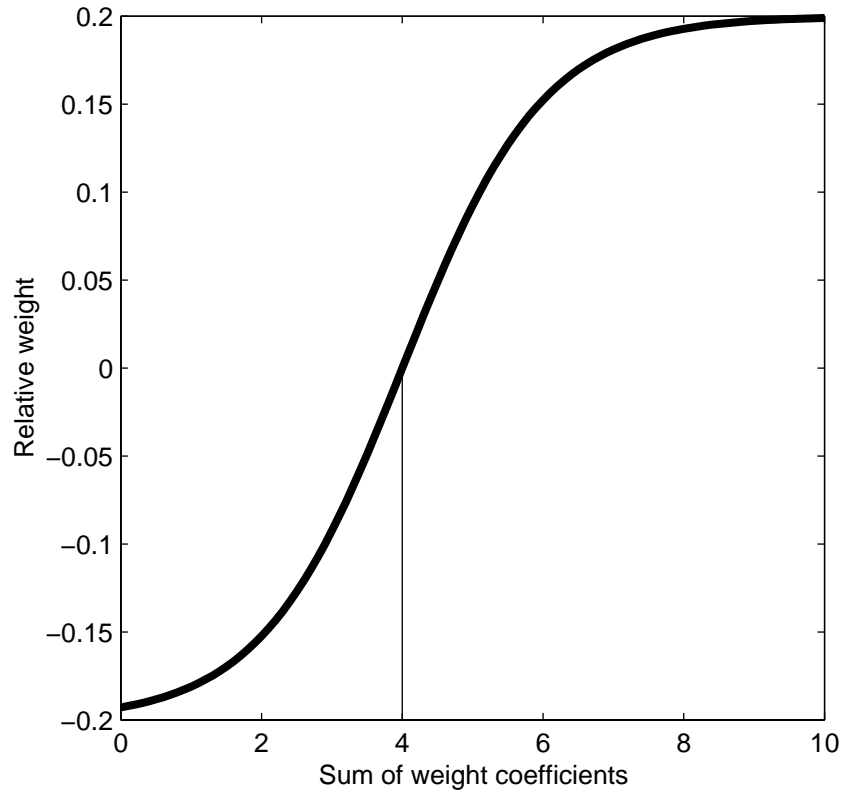


Figure 2: Relative weight.

The cumulative sum control chart is also a good alternative to the Shewhart control charts when we are interested in detecting small shifts (Macgregor 1988). Cusum can be calculated as shown in equation 3.

$$CUSUM_n = \sum_{i=1}^{N_n} (x_{(n-i+1)} - T) \quad (3)$$

where:

T is the target value

CONTROL LIMITS

Usually in the SPC the control limits are defined by standard deviation. Generally 3-sigma control limits are used. The EWMA control limits depend on the sample size (n) and the factor λ . Control limits for EWMA can be calculated as shown in equation 4.

$$CL = \bar{X} \pm A^* \sigma_x \quad (4)$$

where:

\bar{X} is the target value,

A^* is the control limit coefficient (DeVor 1992).

σ_x is the standard deviation of x .

Fuzzy control limits for the EWMA control chart can be set up so that control limits given in equation 4 have a membership value between $[0,1]$ depending on the chosen membership functions and how strict the limits should be. Figure 4 shows that the sigmoid membership function was chosen for EWMA and CUSUM control limits (Latva-Käyrä 1998).

V-mask is a tool that is used in cumulative sum to detect the process variations. The detection process consists of placing the V-mask on the cumulative-sum control chart with the point 0 on the last value of the sum. Detection is based on the slope of the cumulative sum. If all the previous cumulative sums lie within the two arms of the V-mask, the process is in statistical control. Fuzzification is also suitable for the V-mask as shown in figure 3.

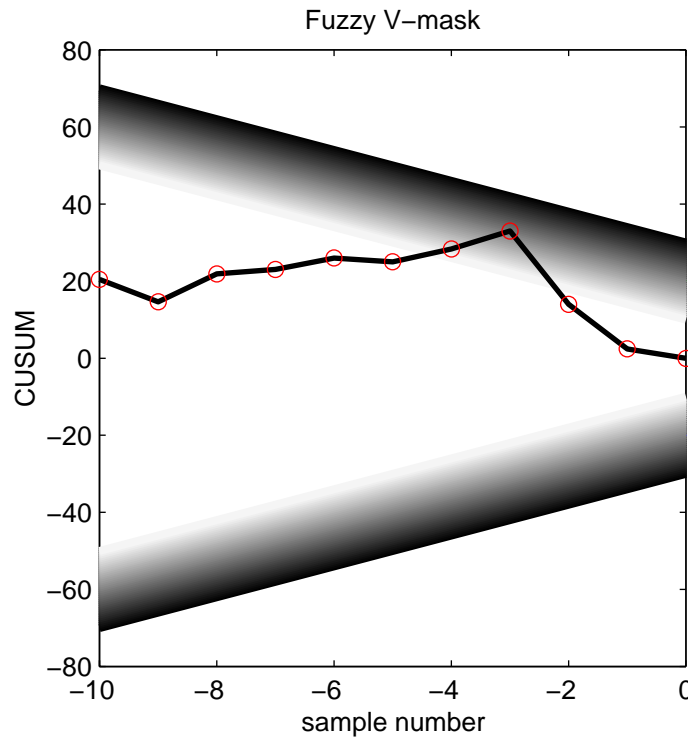


Figure 3: Fuzzyfied V-mask

QUALITY OBSERVER

Quality observer was developed for UPM-Kymmene Jämsänkoski TMP2-plant and its main purpose is to monitor mechanical pulp quality in TMP plant. This task is difficult for the operators because of the many parallel production lines in the plant. Also the data measured from these lines is more or less inaccurate. Two on-line quality measurements, freeness and fiber length, are monitored.

Every time a measurement is made, the quality observer is called and the degree of the warning is calculated. In figure 4 is shown how the degree of the warning is calculated. The quality observer uses SPC with fuzzyfied control limits and fuzzy combination of SPC procedures.

When either freeness or fiber length has exceeded the allowed quality limits the warning is published to all users that have subscribed the quality observer service. The warning contains information on the line and the quality variable that caused the variation and in addition there is possibility to look at a trend display.

The trend display contains data from all associated process variables (freeness, fiber length, specific energy consumption (SEC), power split and plate vibrations) for several hours before the warning occurred. In practice, this kind of display is very helpful to investigate the causes of the detected variation. Also the possible earlier warning events can be seen in the trend display.

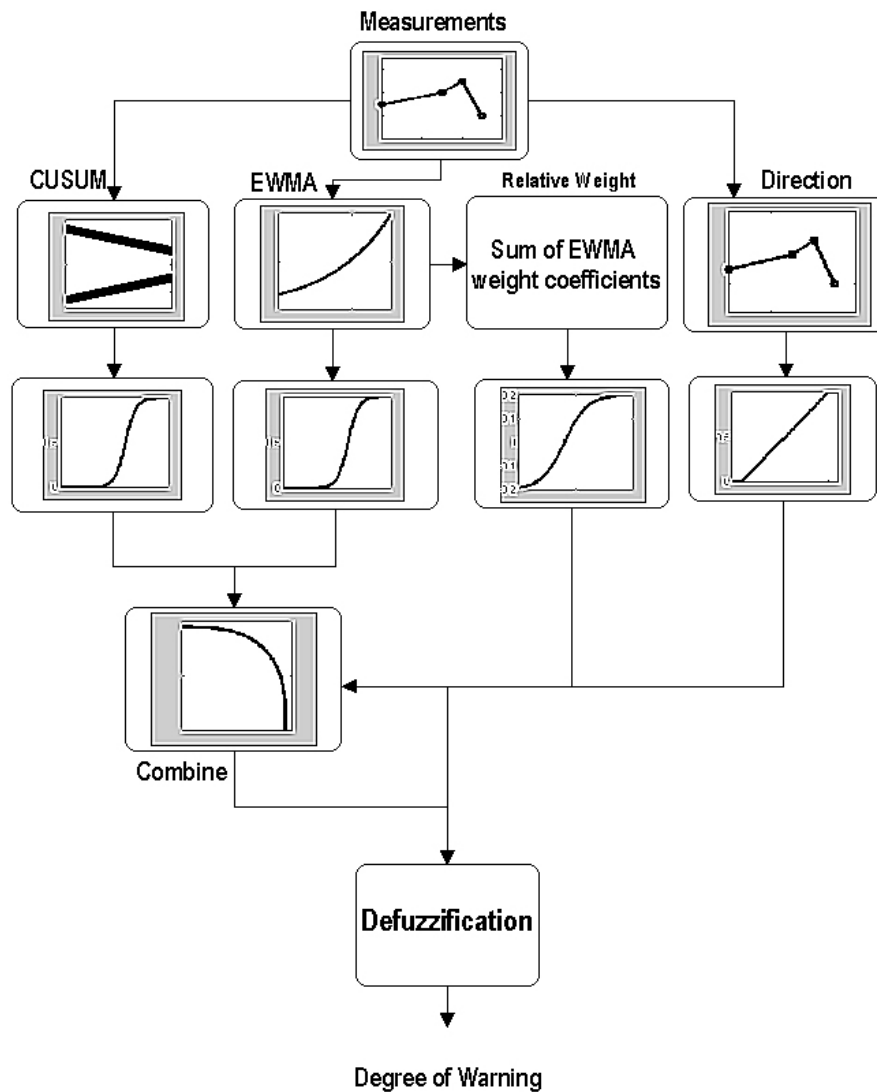


Figure 4: Flow diagram of the calculation of the degree of the warning.

WARNING LIMIT

Warning limit is combined from fuzzy indicative values of EWMA and CUSUM. Table 1 shows a comparison between the different warning limits. Testing of different warning limits was made by simulation using large database. The detected warning was right if there was enough alarming measurements after the detected variation. Scaling methods are:

1. Warning limits gets value 1 only if EWMA and CUSUM are both 1
2. Warning limit gets value 1 if either EWMA or CUSUM are 1.

Warning limit	Scaling method	Right (%)
Circle	1	87,68
Circle	2	87,17
Curve 1	1	88,33
Curve 1	2	87,10
Curve 2	1	88,39
Curve 2	2	87,49

Table I.: Comparison between the different warning limits and scaling.

Figure 5 shows weighting of SPC procedures in EWMA vs. CUSUM plane. The curve 1 was chosen because it detected more alarming situations than curve 2 although the chance for being right is slightly smaller. The relative weight is 0 in the figure 5. The relative weight and the direction of the last measurement also affect the final degree of warning as seen in figure 4.

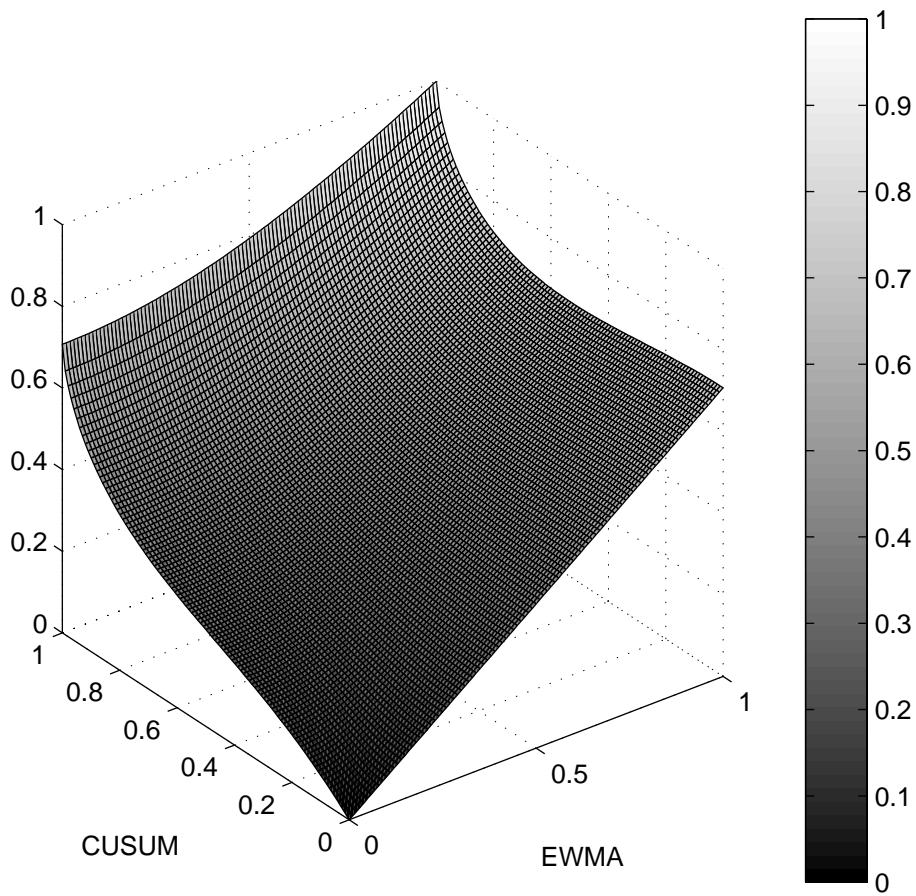


Figure 5: Warning limit with curve 1 and scaling method 1.

CONCLUSION

Statistical process control is an important tool for detecting quality variations in the process. Good results can be achieved by using advanced SPC methods like EWMA and CUSUM with fuzzy control limits and their fuzzy combination. The quality observer uses those methods to monitor the quality of the TMP pulp. It monitors two on-line quality measurements, freeness and fiber length and when either has exceeded the allowed limits the operator is informed.

REFERENCES

- Box, G., Luceño, A., 1997, "Statistical Control by Monitoring and Feedback Adjustment", John Wiley & Sons, New York, USA.
- DeVor, R. E., Chang, T. and Sutherland, J. W., 1992, "Statistical Quality Design and Control", Macmillan Publishing Company, New York, USA.
- Latva-Käyrä, K., 1998, "TMP pulp quality monitoring", TUT/MIT, Tampere, Finland (in Finnish)
- MacGregor, J. F., 1988, "On-line Statistical Process Control", Chemical Engineering Progress, October 1988, p.21-31.
- Montgomery, D. C., 1991, "Introduction to Statistical Quality Control", 2nd ed., John Wiley & Sons, New York, USA.
- Shewhart, W.A., 1931, "Economic Control of Quality of Manufactured Product", D. Van Nostrand, New York, USA.
- Sundholm, J., 1999, "Papermaking Science and Technology - Mechanical Pulping", Fapet Oy, Helsinki, Finland