Impacts of Intelligent Process Control on Product Design

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1. Overview of This Chapter

This chapter focuses on how intelligent process control can help maintain the integrity of product design. There are three specific areas covered: (1) using predictive neural networks during product design to test product quality issues, (2) using neural networks for modeling during production to estimate product adherence to specifications based on process parameters, and (3) using combined neural networks and expert systems in lieu of Shewhart control charts during production to detect undesirable shifts, trends and cycles. These three areas aim at similar objectives. First, a product should be designed to attain the desired performance level. Second, the process, including raw materials, equipment conditions and environmental factors, should be optimized in regards to product quality. Third, should shifts affecting quality occur, they should be detected in a timely and reliable fashion.

The current product design process is often iterative where mock up or prototype products must be built and tested for their performance on applicable quality measures prior to final design. Since product quality is increasingly becoming a competitive edge for companies, they need to circumvent this trial and error process without sacrificing quality. Process control has long been an area of study. This chapter is concerned with statistical process control, which attempts to predict quality based on process parameters and to diagnose quality problems. The objective is to find an optimum combination of values for the process variables so to maximize the probability of obtaining and maintaining acceptable quality. When products depart from quality standards, statistical process control should assist in the determination of which variable(s) were the cause, and what process adjustments are needed. Control charts, one facet of statistical process control, have been in place since the 1930's. They are constructed to provide robust detection of process changes which require investigation and correction.

This chapter covers the application of intelligent techniques, primarily neural computing, to the three areas discussed above in their respective order. Past work in each area, and the advantages of the intelligent approach are discussed. Disadvantages are also mentioned, as are the synergistic interfaces with traditional methods and humans.

2. Using Neural Networks During Design for Quality

The design process presents two interesting issues: first, products often have complex, irregular shapes with significant room for creative design contribution and functional improvement. Second, the design process is time consuming and fraught with uncertainty when it is based on iterative improvement. This trial and error feedback loop in design needs to be tightened by improving the analysis stage before manufacturing (Suri and Shimizu 1989). Predictive neural networks model can relate multiple quantitative and qualitative design parameters to product performance. These models can allow product designers to iteratively and interactively test parameter changes and evaluate corresponding changes in product performance before a prototype product is actually built and tested. This "what if" modeling ability would speed and economize the design process, and result in better quality products. A neural model can also supplement controlled experiments during product testing to help ascertain the optimum design specifications and tolerances. A third use of neural computing in product design for quality is to act as an expert system, where rules are learned directly through product instances rather than defined through knowledge engineering.

Neural networks are good solutions because of their capability to simultaneously relate multiple quantitative and qualitative variables. Also, their ability to form models based solely on the data, rather than assumptions of linearity or other static analytic relations, is especially useful. Because neural networks need training data, experimental results must be available. This, however, is usually a limited set. Unlike many neural network manufacturing applications (such as machine vision or quality control) copious amounts of data cannot easily be generated in product design. To obtain the best possible neural network models, and to validate results, strategies that maximize learning with sparse data must be adopted. One such method is the "leave-k-out" procedure for training (Lawrence 1991). A small number, k, vectors out of the training vectors are held back each time for testing, and networks are trained, changing the k hold back vectors each time. Since the size of each network is usually modest for product design applications, and the number of training vectors small, training proceeds rapidly and creating these multiple networks is not burdensome. Another method to make the most of sparse training data is to inject noise into the training set, creating multiple, noisy versions of each actual training vector.

Two previous works have used neural networks for product design by training a multi-layered perceptron to act as an expert system (Hung and Adeli 1991, Zarefar and Goulding 1992). The first trained a network to select a steel beam design while the latter trained a network to design a gear box. Both efforts used documented design policies, heuristics and calculations to construct a rule base (or decision table). The network was then trained on representative examples adhering to this rule base. This approach, like others which use neural networks in lieu of expert systems, is advantageous in that rules are learned directly through design examples rather than through tedious, and often problematic, knowledge acquisition. A disadvantage of this neural network acting as expert system is that explanation and tracing through the reasoning process are impossible; the neural network acts essentially as a black box.

Previous work using neural networks for predictive modeling in manufacturing design include (Chryssolouris et al. 1989, Liu and Liu 1990, Cariapa et al. 1991, Schmerr et al. 1991). The first paper dealt with design of manufacturing systems using simulation augmented with neural network interpolation. Liu and Liu used backpropagation neural networks to interpolate between test points of a circuit. The tests related three circuit design parameters and two voltage conditions to one performance parameter - the variability of output current of the circuit. They wished to find the design settings which yielded the smallest variation over all voltage conditions. The latter two works focused on interpolating between Taguchi design points using a neural network so that a full factorial design could be simulated to search for optimal design parameter settings. These works used small subsets of whole products to test their approach. The first looked at tool polishing operations with filamentary brushes, while the second tested fatigue cracking of a small structural member. The Taguchi approach is not appropriate for all products as many do not adhere to any known analytical description of performance.

Another approach used known quality tests on sanitary ware products to develop both predictive networks for quality and sensitivity studies of the effects of design parameter alteration on quality measures (Ben Brahim et al. 1992). After translating as many parameters as possible into continuously valued numeric measures so that products could be better compared, a leave-k-out training procedure was used to develop predictive networks for performance on each of the quality tests based on the design parameter specifications. A sensitivity model for each quality test neural network was built by changing each design parameter in small increments across its range, as shown in Figure 1. These models could be used interactively by design engineers to test the affects of product design changes on the resulting product performance. In this way, designs could be optimized for performance given cost and manufacturability constraints before prototype models are built and tested.

3. Neural Networks for Statistical Process Control

Typical process control procedures include statistical analysis of periodic batch samples, control charts of sample mean or range, and trial and error. One of the anticipated technologies for intelligent process control is artificial neural networks, as instanced by this excerpt from the trade literature in plastics: "In injection molding [neural networks] will take real-time action as the process is running. It will be the biggest thing in the next ten years" (*Plastics Technology* 1990).

Figure 1. Neural Sensitivity Model for Design for Quality (from Ben Brahim et al.).

One way neural networks can be useful for manufacturing statistical process control is the prediction of product quality based on process conditions. Product quality can be considered both in absolute terms (e.g. mean outer diameter) and in variable terms (e.g. standard deviation and range of outer diameters). Creating a model which relates input variables to output product has several uses. First, an automatic control system can base actions on the effects the process conditions have on the product, not just on the process conditions themselves. Second, process variables can be analyzed piece wise for their impact on the final product. Third, the relationship can be inverted so that desired product characteristics can dictate certain line conditions. An advantage of the neural network approach to data analysis is that significant variables need not be established prior to analysis, and networks handle correlation and autocorrelation among variables well.

Several factors have to be considered when selecting an appropriate neural network model. Since most operations have calibrated data available, training of a neural network model can be supervised. This adverts the problems of self organizing, or competitive, networks which can be instable and unpredictable. While binary representations can be formed of data, it is often desirable to retain all the information in the form of analog input and output. Qualitative variables, such as smooth or hot, should be translated to an appropriate numeric scales, retaining as much information about the variable as possible. If the process has temporal aspects, either time itself or relative time, this should be accounted for in the network selected. Time can be translated into an input variable, a moving window of input data can be used, or a network which allows temporal handling in its architecture (e.g. a recurrent network) can be selected. Since the vector lengths and training set sizes are usually relatively small, training can be infrequent and off line. This alleviates pressure to find quick, approximate methods for training.

In process control, work has been done to neurally relate input parameters to product variables in both an associative and a predictive model. Association tasks usually are diagnostics for use during manufacturing. Burke identified tool wear states during machining using a competitive learning network, a task normally done by human operators (Burke 1989). A similar subject was pursued by Guillot and Ouafi who used a supervised network to recognize tool breakage for use in untended machining (Guillot and Ouafi 1991). A third neural model for monitoring during machining used the frequency of the vibration signals to classify if machine deterioration was taking place (Knapp and Wang, forthcoming). The plastics industry was studied with a backpropagation correlation model of injection molding process parameters and product defects for diagnostics and corrective action (Wu et al. 1991). The input vectors were the quality defects while the output vectors contained recovery instructions.

Predictive models attempt to estimate product parameters based on process conditions before product manufacture. Andersen et al. used backpropagation networks to relate input parameters, arc current, arc voltage, travel speed and wire speed, predictively to quality measures of a weld, bead width, penetration, reinforcement height and cross section area (Andersen et al. 1990). Okafor pursued a similar approach for estimating surface roughness and bore tolerance in milling using input variables of cutting force components, acoustic emission and spindle vibration (Okafor et al. 1990). They used a moving window of inputs of size five to estimate the trend in the process. Smith and Dagli related many input variables of a plastic extrusion process to prediction of the lot quality with backpropagation (Smith and Dagli 1991). Smith used a similar approach for injection molding of brake linings to predict product quality, and its variability (Smith, forthcoming).

These works suggest that all processes can be diagnosed and modeled successfully by neural networks, although results may not necessarily be superior to statistical or other analytical techniques. There is sustained interest however, for reasons other than superiority of performance. One is the ability to learn relationships through the data itself rather assuming probability distributions or explicitly coding an empirical model. The second is that training can handle multiple, related or non-related, inputs and outputs simultaneously. The third is that a neural network can dynamically adjust to changing line conditions by continuous training, or sporadic retraining. The fourth is that hardwired neural networks are expected to be readily available in the near future, which implies cost effective, real time control.

4. Neural Network Control Charts

4.1 Overview of Control Charts and Their Implementation Problems

Control charts are commonly used in manufacturing environments to analyze process parameters to infer if the process is within or out of control, and to diagnose process evolution through temporal characteristics. Some processes which benefit from control chart tracking are filtration, extraction, fermentation, distillation, refining, reaction, pressing, metal cutting, heat treatment, welding, casting, forging, extrusion, injection molding, spraying, and soldering (Miller and Walker 1988).

W. A. Shewhart first proposed the use of control charts in 1931, which commonly bear his name as Shewhart control charts (Shewhart 1931). Figure 2 shows a typical Shewhart control chart. Through the ensuing years many different formulations became known, such as moving average and range charts, proportion (P) charts, number of defectives (C) charts, cumulative sum charts, and control charts with warning limits (Gibra 1975, Saniga and Shirland 1977, Montgomery 1980). However, most manufacturers use versions of the early control charts which track sample mean (X-bar charts) and sample range (R charts) as checks on the process state and the process variability. One reason these two charts are relied upon is the difficulty of choosing the best control chart from the many available for a given situation.

A difficulty with control charts is the determination of whether a process is actually within control or not. Since sample points are subject to noise due to measurement, human and other factors, they form a non-specified probabilistic distribution. An extreme point may come from a process which is, in fact, under control. Or a point within control boundaries may come from a process which has shifted to out of control. Misclassification of these overlapping sample points results in either Type I (α) or Type II (β) errors. Type I errors are false alarms, while Type II errors are the opposite, that is missing an out of control signal. Besides control limits, there are certain patterns of sample points which indicate the process in moving towards, or cycling through, out of control situations. Again, classifying these points correctly is stochastic, and requires a certain expertise in the process and the concept of control.

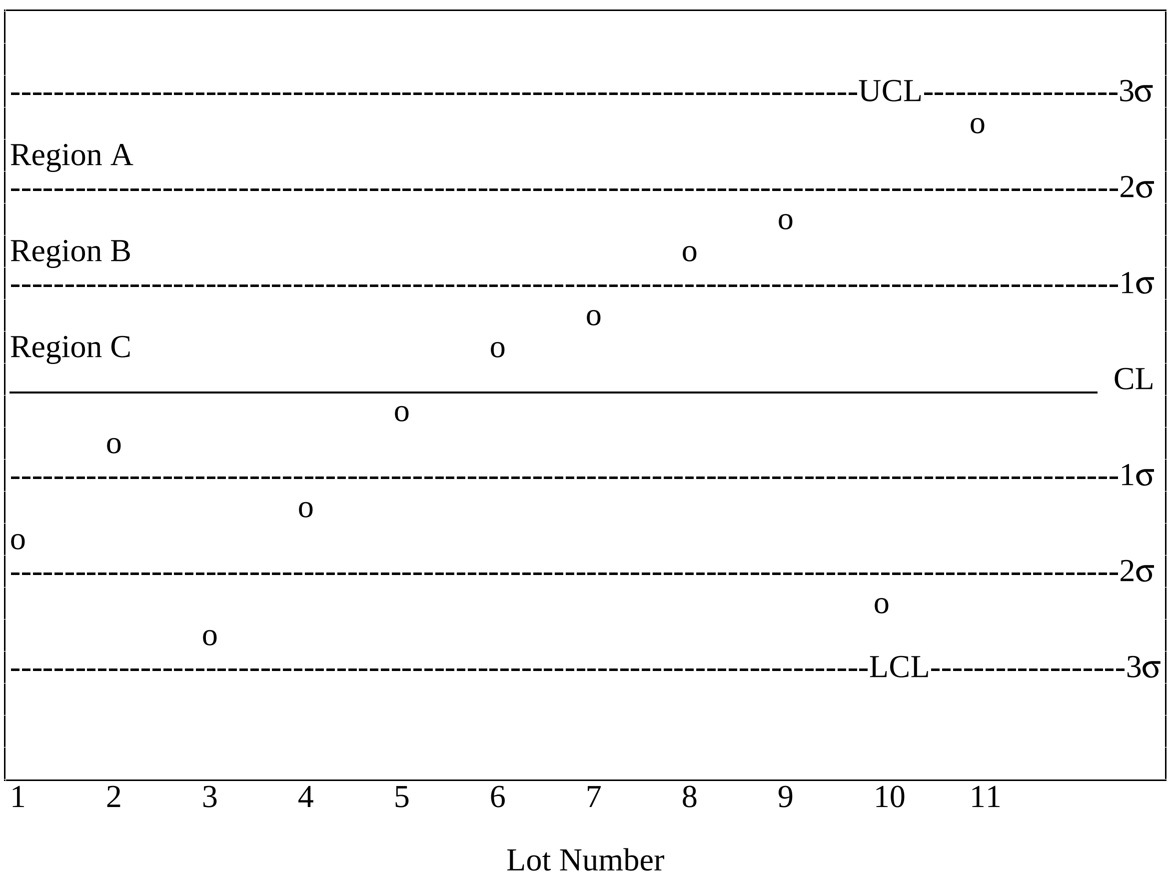

Figure 2. Typical Shewhart Control Chart.

4.2 Use of Expert Systems for Control Charts

Some earlier work has been done to relate intelligent computing to manufacturing control charts. Most of these have taken the form of using expert, or knowledge-based, systems to select proper control methodologies and advise on the analysis of the selected methodologies (Alexander and Jagannathan 1986, Dybeck 1987, Scott and ElGomayel 1987, Evans and Lindsay 1988, Hosni and Elshennawy 1988, Eid and Losier 1990, Willborn 1990, Dagli and Smith 1991). These systems do a good job where the problem involves analysis of relatively few alternatives and the analysis depends mostly or wholly on qualitative information. Thus, selection of the proper control chart or advice on corrective actions given a certain diagnosis are appropriate venues for the expert system approach. Where expert systems are clumsy and inadequate is in the analysis of voluminous, continuous, analytical data, which is what is usually available from line measurements.

4.3 Use of Neural Networks for Control Charts

A first use of neural networks for control charts is to simply act as barriers for signaling a point within control limits or beyond control limits. This was done by (Yazici and Smith 1992) for a plastic extrusion process. A neural network acted as X-bar control chart monitor for four process variables simultaneously with perfect results. While performance was not better than analytical or human monitoring, the ability to simultaneously monitor multiple variables is an advantage, which would become particularly distinct when using hardware neural network chips on the line for this purpose.

A few papers have used neural computing to detect location (usually mean) and variance (usually range) shifts. Pugh published two papers on using backpropagation networks to learn when mean shifts had occurred for a sample size of five (Pugh 1989, Pugh 1991). He found the neural networks produced average run length results about equal to a standard X-bar control chart with 2σ control limits, and improved significantly on Type II errors over X-bar charts. Guo and Dooley looked at positive shifts in both mean and variance using backpropagation neural networks compared to cumulative sum and moving sum charts (Guo and Dooley 1990). They found their best network reduced errors in classification about 40% from the control chart heuristics. Smith found that a backpropagation control chart could simultaneously act as both an X-bar and an R chart, and provide better detection than the traditional charts for processes which are slightly shifted in location or variance (Smith 1992).

Instead of detecting shift and variance changes, two papers examined neural pattern recognition to detect well known control chart patterns symptomatic of special cause infestation. Hwarng and Hubele used a backpropagation classifier on six control patterns - trend, cycle, stratification, systematic, mixture and sudden shift (Hwarng and Hubele 1991). They found a neural classifier with binary input and output performed well enough to serve as a supplement to traditional control charts. Smith used a similar approach with continuous input vectors representing four patterns - trend, cycle, stratification and over controlled (Smith 1992). Future control chart points, out to five time periods, were predicted based on previous points to try to assist with the pattern classification.

4.4 Composite Intelligent Systems for Control Charts

Analytic analysis is not the whole of control chart inference. There is often valuable information of a qualitative or intuitive nature to be considered. This information may come from line conditions, product attributes, or knowledge of the line operators or other personnel. Melding this information, if it is present, with the output of a neural network will result in a robust system that considers all pertinent factors. This also alleviates the drawback of the pure neural network approach being essentially a black box to the user.

Besides control analysis, the knowledge-based system can select the control chart strategies most effective for the manufacturing domain, as documented in Section 4.2. The system can also present likely specific causes or select corrective actions given the diagnosis of the pure neural network, or a combined neural/expert decision. This approach was tried in a prototype neural network/expert system quality monitoring and diagnostic system for plastic extrusion (Smith and Yazici forthcoming). Figure 3 shows the schematic of the prototype system which uses neural predictions to assist with the rule based diagnostics and corrective actions.

Figure 3. Composite System for Statistical Process Control (from Smith and Yazici forthcoming).

References

Alexander, S. M. and V. Jagannathan, Advisory system for control chart, *Computers & Industrial Engineering*, 10, 1986, 171-177.

Andersen, Kristinn, George E. Cook, Gabor Karsai and Kumar Ramaswamy, Artificial neural networks applied to arc welding process modeling and control, *IEEE Transactions on Industry Applications*, 26, 1990, 824-830.

Ben Brahim, Safouen, Alice E. Smith and Bopaya Bidanda, Estimating product performance and quality from design parameters via neural networks, *Proceedings of the IIE Research Conference*, 1992, 319-323.

Burke, Laura I., *Automated Identification of Tool Wear States in Machining Processes: An Application of Self-Organizing Neural Networks*, Ph.D. Thesis, University of California - Berkeley, 1989.

Cariapa, Vikram, Kunter S. Akbay and Rajesh Rudraraju, Application of neural networks for compliant tool polishing operation in *Computer-Aided Production Engineering* (V. Venkatesh and J. McGeough, Editors), Elsevier Science Publishers, Amsterdam, 1991, 271-280.

Chryssolouris, G., M. Lee, J. Pierce and M. Domroese, Use of neural networks for the design of manufacturing systems, *Proceedings of the Winter Annual Meeting of the American Society of Mechanical Engineers,* 1989, 57-63.

Dagli, Cihan H. and Alice E. Smith, A prototype quality control expert system integrated with an optimization module, *Proceedings of the World Congress on Expert Systems*, 1991, in press.

Dybeck, Martin, Taking process automation one step further: SPC, *Proceedings of the Sixth Annual Control Engineering Conference*, 1987, 643-651.

Eid, M. S. and G. Losier, QCMS: a quality control management system, *Computers & Industrial Engineering*, 19, 1990, 495-499.

Evans, James R. and William M. Lindsay, A framework for expert system development in statistical quality control, *Computers & Industrial Engineering*, 14, 1988, 335-343.

Gibra, Isaac N., Recent developments in control chart techniques, *Journal of Quality Technology*, 7, 1975, 183-192.

Guillot, Michel and Abderrazak El Ouafi, On-line identification of tool breakage in metal cutting processes by use of neural networks, in *Intelligent Engineering Systems Through Artificial Neural Networks* (C. Dagli, S. Kumara and Y. Shin, Editors) ASME Press, New York, 1991, 701-709.

Guo, Yuan and Kevin J. Dooley, The application of neural networks to a diagnostic problem in quality control, *Monitoring and Control for Manufacturing Processes*, ASME, New York, 1990, 111-122.

Hosni, Yasser A. and Ahmad K. Elshennawy, Knowledge-based quality control, *Computers & Industrial Engineering*, 15, 1988, 331-337.

Hung, S. L. and H. Adeli, A model of perceptron learning with a hidden layer for engineering design, *Neurocomputing*, 3, 1991, 3-14.

Hwarng, H. Brian and Norma F. Hubele, X-bar chart pattern recognition using neural nets, *ASQC Quality Congress Transactions*, 1991, 884-889.

Knapp, Gerald M. and Hsu-Pin Wang, Machine fault classification: a neural network approach, *International Journal of Production Research*, forthcoming.

Lawrence, Jeanette, Data preparation for a neural network, *AI Expert*, 6, 1991, 34-41.

Liu, Lihsin and G. H. Liu, Neural network computing applied in design for manufacturability, *Proceedings of the IEEE/SEMI International Semiconductor Manufacturing Science Symposium*, 1990, 107-110.

Miller, Richard K. and Terri C. Walker, *Artificial Intelligence Applications in Manufacturing*, SEAI Publications, Madison, GA, 1988.

Montgomery, Douglas C., The economic design of control charts: a review and literature survey, *Journal of Quality Technology*, 12, 1980, 75-87.

Okafor, A. C., M. Marcus and R. Tipirneni, Multiple sensor integration via neural networks for estimating surface roughness and bore tolerance in circular end milling, *1990 Transactions of NAMRI/SME*, 1990, 128-137.

Plastics Technology, Injection in the 90's: how high tech?, *Plastics Technology,* April 1990, 78-86, .

Pugh, G. Allen, Synthetic neural networks for process control, *Computers & Industrial Engineering*, 17, 1989, 24-26.

Pugh, G. Allen, A comparison of neural networks to SPC charts, *Computers & Industrial Engineering* 21, 1991, 253-255.

Saniga, Erwin M. and Larry E. Shirland, Quality control in practice...a survey, *Quality Progress*, 10, 1977, 30-33.

Schmerr, Lester W., Stephen M. Nugen and Babak Forourachi, Planning robust design experiments using neural networks and Taguchi methods, in *Intelligent Engineering Systems Through Artificial Neural Networks* (C. Dagli, S. Kumara and Y. Shin, Editors) ASME Press, New York, 1991, 829-834.

Scott, L. L. and J. I. ElGomayel, Development of a rule based system for statistical process control chart interpretation, *Quality: Design, Planning, and Control* (R. E. DeVor and S. G. Kapoor, Editors), ASME Press, New York, 1987, 73-91.

Shewhart, W. A., *Economic Control of Quality of Manufactured Product*, Van Nostrand Reinhold, Princeton, NJ, 1931.

Smith, Alice E., Control chart representation and analysis via backpropagation neural networks, *Proceedings of the 1992 International Fuzzy Systems and Intelligent Control Conference*, 1992, 275-282.

Smith, Alice E., Predicting product quality with backpropagation: a thermoplastic injection molding case study, *International Journal of Advanced Manufacturing Technology*, forthcoming.

Smith, Alice E. and Cihan H. Dagli, Controlling industrial processes through supervised, feedforward neural networks, *Computers & Industrial Engineering*, 21, 1991, 247-251.

Smith, Alice E. and Hulya Yazici, An intelligent composite system for statistical process control, *Engineering Applications of Artificial Intelligence,* forthcoming.

Suri, Rajan and Masami Shimizu, Design for analysis: a new strategy to improve the design process, *Research in Engineering Design*, 1, 1989, 105-120.

Willborn, Walter W. O., Expert systems in support of quality management, *ASQC Quality Congress Transactions*, 1990, 758-763.

Wu, Hsien-Jung, Cheng-Shin Liou and Hsu-Heng Pi, Fault diagnosis of processing damage in injection molding via neural network approach, in *Intelligent Engineering Systems Through Artificial Neural Networks* (C. Dagli, S. Kumara and Y. Shin, Editors) ASME Press, New York, 1991, 645-650.

Yazici, Hulya and Alice E. Smith, A composite system approach for intelligent quality control, *Proceedings of the IIE Research Conference*, 1992, 325-328.

Zarefar, Hormoz and John R. Goulding, Neural networks in design of products: A case study, in *Intelligent Design and Manufacturing* (A. Kusiak, Editor) John Wiley & Sons, New York, 1992, 179-201.