Contributed Paper

An Intelligent Composite System for Statistical Process Control

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Combining statistical process control, artificial neural networks and an expert system for the intelligent analysis and control of a plastic extruder facility is described. Statistical methodology is compared and contrasted to the exploratory neural network technique, which learns to relate and classify dependent production variables based on measurements taken on-line during the process. Integrating the neural network analysis into a composite control system using an expert system is presented.

Keywords: Statistical process control, neural networks, expert systems, intelligent process control, plastic extrusion, quality control, knowledge-based systems.

1. INTRODUCTION

1.1. Statistical process control in the plastics industry

With the increasing use of plastics over the last few decades, producers have looked for solutions to stay competitive in the market. After 1985, monitoring the process variability using statistical process control (SPC) was recognized to improve quality and productivity and to reduce scrap and overall manufacturing costs. Currently, the automation of SPC and the application of artificial intelligence (AI) techniques are being investigated, with AI expected to prove important for control systems to learn a process and provide real-time action.

The PVC pipe industry represents a segment of the extrusion industry in which real-time and automated on-line process-control techniques have been poorly recognized and infrequently implemented. One of the reasons is that the PVC industry operates on high-volume, mass production with little incentive for process improvement because customers' quality expectations are not stringent and product rejects are remarkably rare. Another factor which makes it difficult to implement SPC is related to the education of the work force. Many workers have a great deal of experience, but are not familiar with scientific methods, and control their process through trial and error.

In addition to the industry profile, the process itself is complex, involving a large number of variables. The sensitivity of plastic extrusion to heat and residence time, and to the chemical properties of the incoming material create difficulty in maintaining a stable process. The combined effect of these variables increases the opportunity for process fluctuations which often cause significant dispersion and inconsistency in product characteristics. The problem exists throughout the industry, and in most cases, with a lack of diagnoses and knowledge of corrective action.

1.2. Overview of the process

The plant studied is one of four belonging to a large PVC pipe producer whose annual production of conduit, sewer and pressure pipes totals 50.5 million pounds. The products range in diameter from 0.5 inches to 10 inches with various lengths and thicknesses. The plant has seven single and dual strand extruders working on separate lines, with each line producing one type of product. (For complete process information see Ref. 4.)

The process can be described in three stages: incoming material, blending and extrusion. In each stage of the process, a group of variables interact with each other in a complex fashion creating difficulty in controlling the process, as shown in the Ishikawa cause-effect diagram in Fig. 1. Variation in pipe quality can first be caused by changes in the raw material proper-
ties, which in turn influence residence time, fusion time and melt temperature of the compound. After the compound is prepared, it is vacuumed to the extrusion lines. During the extrusion process extruder speed, barrel and screw heat profiles, torque amps, screw feeder rate, backpressure settings, vacuum pressure, vent conditions, puller speed and pipe wall thickness influence pipe quality. Ambient conditions, i.e. temperature and humidity, also affect the process.

Also contributing to unwanted product variation is the heavy production schedule, requiring frequent product changes on the lines. The plant produces over 200 different specifications of pipe and each requires lengthy adjustments on the line. Frequent changeovers and heavy production schedules also cause barrel and screw wear, an additional cause of variation in the process. Human carelessness and differences of opinion constitute yet another group of influential variables. Line supervisors and operators frequently adjust process parameters and try different raw material compounds.

Quality of the pipe is primarily measured by impact strength. The impact strength test, as defined by the American Society for Testing and Materials (ASTM), drops a 20 lb weight on a 6" length of pipe from a specific height. The drop height ranges from 2.5 to 4 ft for small-diameter pipe. Impact strength is determined by counting the number of pipes per sample which crack. The plant management wanted to define the relationship of impact strength to process parameters so that the line could be adjusted to produce acceptable-quality pipe. Forming this relationship using statistics and neural networks are compared in Section 2.

1.3. Neural networks for statistical process control

Backpropagation neural networks are computing architectures formed of many simple feedforward processing units (neurons) arranged both in parallel and sequence, as shown in Fig. 2. Intelligence is stored in the connecting weights which alter during the training phase, iterating to a stable state near the error surface minimum. A complete discussion of the mathematical foundations of the backpropagation neural networks can be found in Rumelhart et al.⁵

Backpropagation neural networks are good alternatives to traditional cause-and-effect analysis because they form relationships purely from sampling the data itself, and can handle noisy and incomplete data. Since probability distributions do not have to be declared explicitly, there is no need of statistical analysis, and there can be no prediction error attributed to incorrect assumption of data properties. This is particularly valuable when working with data which does not adhere to known distributions as is often the case in SPC. Another property of neural networks is their ability to adapt to changing conditions through periodic retraining, useful for temporal statistical process control when classification boundaries need altering.

Some uses of neural networks in SPC are sorting product into quality categories, diagnosing process

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Fig. 1. Ishikawa diagram of the process.
state, predicting out-of-control situations and relating product characteristics to process inputs. Past research using neural networks for quality and statistical process control have achieved results at least comparable to traditional techniques.\[1,6-11\]

2. PROCESS ANALYSIS USING STATISTICS AND NEURAL NETWORKS

2.1. Statistical analysis of the process/quality relationship

A series of 87 samples of impact failures over time was available. Impact failures for this series ranged from 0 to 36, with a mean of 10.46, a median of 10, a standard deviation of 7.263 and a coefficient of variation of 69.41%. Long cycles of up and down trends indicated that the process was out of control, with the possibility of multiple assignable causes of variation.

Using the 87 samples, multivariate linear regression analyzed various combinations of the independent variables and their relationship to the dependent variable of interest, impact failures. The best four independent variable model used bulk density of resin, screw feeder speed, puller speed and vent pressure. Besides the best four variable regression, a regression using all 14 independent variables was created so that it could be compared to a neural network also using all available independent variables. Table 1 lists the important statistical parameters of the two regressions. While most of the variance in the sample points is not explained by either regression, the independent variables do have a significant linear relationship with impact failures.

2.2. Neural networks for data analysis

Neural networks were formulated as an input layer with each independent variable as one normalized analog vector component, one or two hidden layers, and an output layer with each classification/prediction decision as one vector component. Two formats of output representation were tested; the first was a normalized analog vector representing the number of impact failures per sample and the second was a binary vector which classified each process parameter as within or beyond control limits. The former formed the process parameters-to-quality relationship while the latter modeled a control chart.

Networks were trained on the identical set of 87 observations used in the regressions above with a training rate of 1.0 and a smoothing factor of 0.9. The training rate determines the step size down the error surface and the smoothing rate allows past weight changes to be incorporated into present ones. The transfer function selected was a sigmoid ranging from 0 to 1 because of its superiority for most problems.\[12,13\]

2.3. Results of the process/quality relationship analysis

Figure 3 shows the actuals and predictions for a test set of 10 randomly held back samples relating the most significant four process variables to pipe quality. Both one- and two-hidden-layer neural networks and the multivariate linear regression did a good job of representing the actual quality function; however all missed the last sample point, an outlier, where sample impact failures rose to their maximum of 36. Although most neural-network implementations use one hidden layer,

<table>
<thead>
<tr>
<th>Regression</th>
<th>Adjusted $R^2$</th>
<th>$F$ Value</th>
<th>$P$ Value</th>
<th>Significant $F$ value at $\alpha=0.05$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All variables</td>
<td>0.2409</td>
<td>3.18</td>
<td>0.00051</td>
<td>1.8143</td>
</tr>
<tr>
<td>Four variables</td>
<td>0.2429</td>
<td>8.70</td>
<td>0.00001</td>
<td>2.4707</td>
</tr>
</tbody>
</table>

Table 1. Statistical properties of regressions for impact failures
the superiority of two hidden layers for analog data has been previously suggested.\textsuperscript{14-16}

The results of a second approach using all 14 available independent variables is shown in Fig. 4. If data collection and handling costs are low, it is prudent to include all variables impacting the process. While this might invalidate some statistical techniques by the inclusion of non-significant variables, a neural network builds its representation automatically, discounting unimportant inputs. Again, both techniques modeled the actual function well, with the exception of the last observation.

Table 2 summarizes the mean absolute error for the test set over the techniques and process parameters discussed in this section. The neural networks were similar to the regression for the four-variable model while average error was reduced by considering all 14 variables. For this data set neural networks were not particularly advantageous for quality predictions over linear regression. Data that more poorly fits a known distribution would probably show a greater incremental improvement using neural networks over statistics. However, there are other advantages to the neural approach, including eliminating the need to predetermine relationships among independent variables, continuous training to adapt to changing relationships, and real-time, on-line analysis when using hardwired neural networks.

2.4. Results of control chart networks

Statistical process control is often done through control charts where independent variable measures are plotted in temporal order, such as the X-Bar control chart which tracks sample mean. The process is classified as in control or out of control depending on the values and trends of each variable relative to its specification, with a control boundary usually set at two or three standard deviations from the process mean (2\(\sigma\) or 3\(\sigma\) limits).

A neural-network approach to an X-Bar control
chart used the four most significant independent variables analyzed above. Two neural networks were built and trained to classify each variable as within or beyond a 2\sigma control limit. The first network had two hidden layers with 5 neurons in each hidden layer, while the second had 10 neurons in each hidden layer. A binary representation, with an output of 1 signaling beyond control limits, was used. These networks classified control situations on the randomly held back test set near-perfectly with a percentage mean absolute error for the larger network of 0.247 and for the smaller, 0.417 on the random test set.

Although normal algorithms handle control classifications equally well, a neural network can have several advantages. First, many related or unrelated parameters can be monitored simultaneously by the same chip or (in this case) software simulation. Second, control chart limits can be altered at will by allowing a network to train incrementally rather than using static weights. This would not require batch data gathering and analysis as would SPC.

### 3. THE INTELLIGENT COMPOSITE SYSTEM

#### 3.1. Role of the expert-system approach

The diagnosis and solution of control problems is problematic in the complex and high-volume extrusion industry, and one that is not addressed completely by either statistical analysis or neural network classification. An expert system can use the quality level predictions and control statuses to diagnose how and why the process is changing, and to recommend areas of investigation or courses of corrective action. Expert systems have recently been used successfully for process control in other industries.\(^{2,37}\) They are good as integrators, can analyze both quantitative and qualitative factors, and have friendly user interfaces.

#### 3.2. Knowledge base and rule generation

The knowledge base (KB) for diagnosing the on-line process problems was developed using an expert-system shell, Nexpert Object, and its knowledge acquisition tool, Nextra.\(^{18,19}\) Nexpert Object was selected because of its object-oriented programming approach which provides dynamic structuring and flexible programming. Nextra efficiently creates the knowledge base by providing a menu-driven and graphical interface which makes available a minimal set of relevant attributes and a complete set of critical cases with correct decisions. Objects, classes, meta-slots, hypotheses and rules are generated using a decision table, or prism approach, developed by Cendrowska.\(^{20}\) Reasons for using the decision matrix approach rather than a standard tree structure are to prevent unnecessarily large and complex rule sets, and to avoid testing unnecessary conditions.

Nextra's structured approach to knowledge acquisition facilitates further development by eliminating syntax errors and reducing time spent in representing a problem. The expert begins to build the knowledge base by entering the possible diagnostics to be generated and all the input variables which must be considered. The input variables here were screw feeder speed, extruder speed, torque, throughput, barrel heat zones, backpressure, puller speed, vent pressure, fusion time, pipe wall thickness and resin bulk density. Information was also entered on the consistency of line parameters and material characteristics. A decision table was created for these attributes with each assigned a probability rating on a graphical scale of 1 (the lowest) to 9 (the highest). Three levels for each variable, High, Low and Normal, represented a range of numeric values and are used to facilitate the structuring of the knowledge base. A cluster representation of the knowledge base is shown in Fig. 5. Here, the structure of nine diagnostics based on 23 process attributes are represented and evaluated on the probability scale of 1 to 9.

The KB system developed serves as an expert investigator by making diagnoses and recommending corrective action to bring the process under control. Table 3 shows two example sessions in which the input attributes are requested from the user, and the output includes diagnostics and recommendations. Recommendations are in italics, while the other outputs are conclusions reached by the system.

#### 3.3. Implementation of the composite system

The expert system described above acts as user interface and analyzer of complex decisions where qualitative and quantitative factors are considered. Analytic input to the expert system comes from both the statistical package, which performs data sorting, calculating and exploratory analysis, and the neural networks, which forecast pipe quality and classify process parameters as within or beyond control limits.

The software used is purposefully standard and relatively unsophisticated so that plant personnel can be trained to use and ultimately understand it. The statistical and neural computing techniques and the knowledge base construction are straightforward and are within the mainstream of their respective disciplines. This will contribute to the successful transfer of intelligent statistical process control to an environment accus-
Cluster: SpC  Entitles: 9, Attributes: 23, Range: 1 to 7, Context: strength problem diagnosis

![Cluster representation of the knowledge base.](image)

Fig. 5. Cluster representation of the knowledge base.

**Table 3. Example sessions**

<table>
<thead>
<tr>
<th>First case</th>
<th>Second case</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>User input:</strong></td>
<td><strong>User input:</strong></td>
</tr>
<tr>
<td>Feeder_RPM is the same</td>
<td>Feeder_RPM is the same</td>
</tr>
<tr>
<td>Main_RPM is the same</td>
<td>Main_RPM is the same</td>
</tr>
<tr>
<td>Torque is the same</td>
<td>Torque is high</td>
</tr>
<tr>
<td>Throughput is the same</td>
<td>Throughput is high</td>
</tr>
<tr>
<td>Barrel_zone is overheated</td>
<td>Barrel_zone is overheated</td>
</tr>
<tr>
<td>Back_pressure_PSI is high</td>
<td>Back_pressure_PSI is the same</td>
</tr>
<tr>
<td>Puller_speed is the same</td>
<td>Puller_speed is low</td>
</tr>
<tr>
<td>Vent_pressure is normal</td>
<td>Vent_pressure is normal</td>
</tr>
<tr>
<td>Fusion_time is low</td>
<td>Fusion_time is high</td>
</tr>
<tr>
<td>Wall_thickness is the same</td>
<td>Wall_thickness is high</td>
</tr>
<tr>
<td>Bulk_density is the same</td>
<td>Bulk_density is the same</td>
</tr>
<tr>
<td>Line_parameters are not consistent</td>
<td>Line_parameters are not consistent</td>
</tr>
<tr>
<td>Material_parameters are consistent</td>
<td>Material_parameters are not consistent</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>System output:</strong></th>
<th><strong>System output:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Feeder_RPM is not the problem</td>
<td>Vent_pressure is not the problem</td>
</tr>
<tr>
<td>Vent_pressure is not the problem</td>
<td>No compound change detected</td>
</tr>
<tr>
<td>No compound change detected</td>
<td>Barrels and screws are OK</td>
</tr>
<tr>
<td>Extruder_RPM is not the problem</td>
<td>Extruder_RPM is not the problem</td>
</tr>
<tr>
<td>Ambient conditions are not the problem</td>
<td>Check material</td>
</tr>
<tr>
<td><strong>Impact_strength is low</strong></td>
<td><strong>Impact_strength is low</strong></td>
</tr>
<tr>
<td>Change line parameters</td>
<td>Change line parameters</td>
</tr>
<tr>
<td>Barrels_and_screws are worn_out</td>
<td>Increase feeder_RPM</td>
</tr>
</tbody>
</table>
tomated to trial-and-error manual methods. The system could be operated successfully in such an environment; however, enlargement or modification of the knowledge base would require outside expertise. Similarly, new or additionally trained neural networks would be best constructed under guidance. Figure 6 shows the proposed architecture for this extrusion implementation. The PC platform ensures affordability, portability and familiarity. The quality control technician could access modules individually or collectively, depending on the task to be done. Modules can be expanded or modified together or separately. Matching the ability of each computing technique—expert system, neural network, statistical analysis—to each task ensures efficient quantitative and qualitative analysis.

Process parameters and quality performance are measured periodically, and stored in spreadsheet format. This data is used to develop training and test sets for the neural networks and for statistical analysis. The neural network outputs of control status and forecasted quality level are used by the knowledge base during interactive process diagnoses. The knowledge base itself contains the rules governing the diagnosis of process drifts, and the suggested causes and solutions for these. Knowledge is gained initially and incrementally through user interaction with the knowledge acquisition tool. The user has access to each component directly, but will interact primarily with the user interface of the expert system during system operation.

4. CONCLUSIONS

The advantages of this intelligent approach are twofold. First, process analysis and control decisions are comprehensive and standardized. The line situation is analyzed completely using analytical and qualitative information. The second advantage is linked to the first, and this is more-responsive decision making. Analysis is virtually instantaneous and takes into account all variables simultaneously, ensuring that the process can be modified quickly. In a plant where production output is the main concern, speed is a valuable asset. Improved quality, standardized data collection and analysis, and quickened response time would all translate into dollars saved for this manufacturer.

REFERENCES