LA-UR- 98-2012

Title:

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CONF-980810--

Author(s):

Ronald E. Smith, William J. Parkinson, Ralph F. Hinde,
Paul J. Wantuck, Kirk E. Newman

Submitted to:

2nd Int'l conf. Engineering Design & Automation
Maui, HI
August 9-12, 1998

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NEURAL NETWORK FOR QUALITY CONTROL OF SUBMUNITIONS PRODUCED BY INJECTION LOADING

Ronald E. Smith[1], William J. Parkinson[1], Ralph F. Hinde, Jr. [1], Kirk E. Newman[2], and Paul J. Wantuck[1]

Engineering Sciences and Applications Division[1]
Los Alamos National Laboratory
Los Alamos, NM 87545

Energetic Materials Research and Technology Department[2]
Naval Surface Warfare Center, Indian Head Division
Yorktown, VA 23691

ABSTRACT

Injection loading of submunitions for smart weapons is a novel automated processing technique that can benefit from adaptive process control. This paper describes how the quality of submunitions could be controlled by using a neural network code in real time. Future work is planned to demonstrate fewer rejects and pollution reduction during submunition manufacturing.

KEYWORDS

Neural Networks; Smart Weapons; Submunitions; Pattern Recognition; Process Control; Injection Loading

1. Introduction

The injection loading device discussed in this paper [1] was developed in order to produce submunitions filled with highly viscous material. Each run fills multiple submunitions serially, with high viscosity plastic bonded explosive (PBX) material. Even though most loads are acceptable and meet specifications, the rejection rate is often excessive. The loads that are not acceptable present a severe waste disposal problem. The current technology requires an X-ray inspection after the submunitions have been loaded with PBX. Loads that have voids, or that have density gradients will be rejected. Since operating conditions leading to rejectable products may occur at the beginning of an injection cycle, aliquots of ten pounds of PBX and the corresponding submunitions loaded may also be rejected. Therefore, it is imperative that the process control algorithm recognize disturbances in the injection loading parameters as soon as possible so that corrective action can be taken to resolve the upset before the PBX loading is completed. Each load requires about 30 seconds. In an effort to determine submunition quality on-line, the device was instrumented. Ram displacement, cavity pressure, and hydraulic pressure were measured at two second intervals for each load. Ram velocity, shear rate, shear stress, and viscosity were calculated at each time interval. The data were then compared with the post-mortem X-ray results to determine if the load was a pass or a fail. To the naked eye, no patterns emerged in the injection loading data that correlated specific processing parameters to the submunition pass/ fail criteria.

Several neural network models were applied before we found one that worked. A backpropagation model using two inputs, cavity pressure and viscosity, and three hidden nodes finally cracked the code. This model, even with a limited number of training sets, was able to predict bad or good loads 100%, after only four sensings, eight seconds into a run. A 96% correct prediction rate can be obtained from a similar neural network model that uses only the first four seconds worth of data. This information, when implemented on the injection loading device, will provide on-line information as to whether a reject load is being processed. We intend to incorporate the model into a control system and try to make on-line corrections to possibly produce 100% good loads (or "zero defects"). If our on-line corrections do not work, we can at least interrupt the device and prevent the production of hazardous waste.

2. System

The injection loader system is a unit operation that simultaneously degasses and injects viscous PBX into small submunitions or through narrow flow channels without the PBX ever turning a corner. This apparatus has two identical chambers for degassing and injecting PBX. See Figure 1. The PBX is first pumped through a splitter plate and degassed into the first chamber. Then the upper part of the machine rotates 180 degrees to align the degassed PBX with the inject ram. The second chamber is now available for degassing the next aliquot of PBX, while the first chamber is ready for injection loading. Meanwhile, the first submunition has been lifted into a sealed vacuum shroud and evacuated. A programmable logic controller (PLC) provides the signal to inject the correct PBX increment into each submunition serially. One submunition is loaded in each 30 second cycle. The PLC will allow about eight submunitions to be loaded from an aliquot of 10 pounds of PBX.

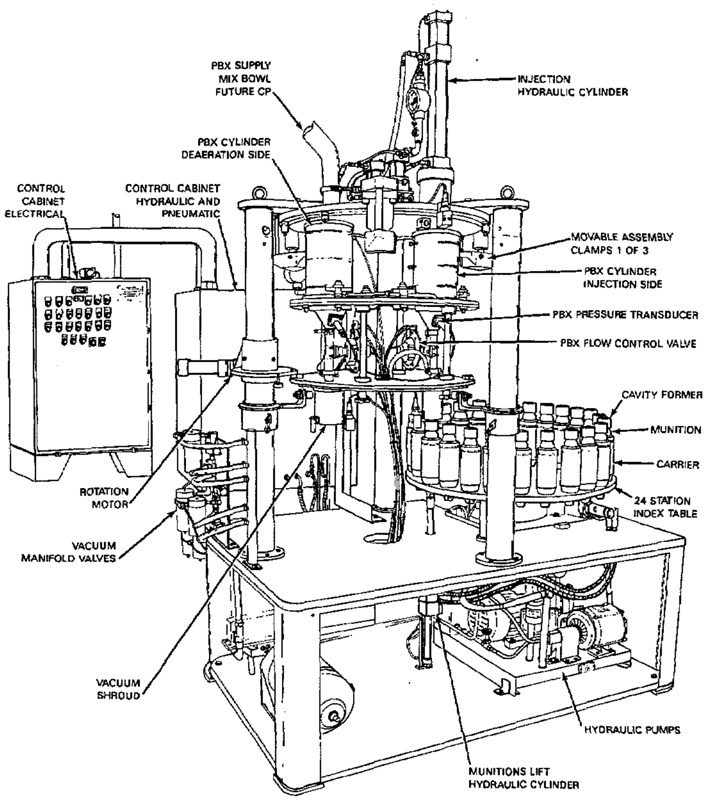

Figure 1. Injection loader apparatus at NSWCIHD Yorktown, VA

The supervisory process control software is run on a Pentium personal computer (PC), and monitors processing parameters necessary to track mass transfer and momentum transport phenomena. We track vacuum level in the degassing chamber, vacuum level in the shroud where the submunition is evacuated, temperature of the PBX in the injection chamber, ram displacement, hydraulic pressure driving the ram, cavity pressure of the PBX entering the submunition, and time. We calculate ram velocity, shear rate, shear stress, and PBX viscosity.

The data available for analysis consisted of 45 sets of injection loading time history data and a determination of whether the loading passed or failed inspection. Of the 45 runs of data, 29 passed inspection and 16 failed. Figure 2 shows the time history data for cavity pressure and ram velocity for ten (five pass, five fail) selected loadings. As is evident from this figure, it is difficult to discern passing loadings from failing loading by visual inspection of the time history data.

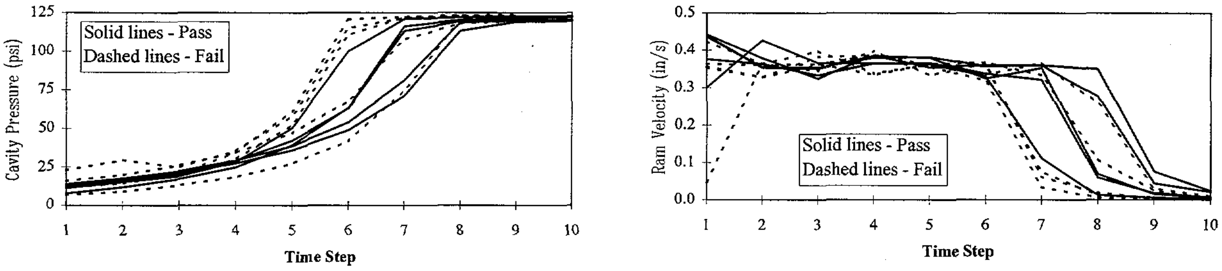

Figure 2. Cavity pressure and ram velocity time history for ten selected runs

3. Neural Network Model

Standard backpropagation neural networks [2] were used to solve this pattern recognition problem. The inputs to the network were the first N points of the time history data for one or more variables (explained in more detail later). The output of the network was a single value in the range 0 to 1, with 0 representing a failed loading and 1 representing a passed loading. A value of 0.5 was used as a cut-off for the pass/fail choice.

By analyzing the underlying equations relating the process variables and looking at correlations between the actual data, three significant variables emerge. These are cavity pressure (CP), ram velocity (RV), and viscosity (VIS). The 45 data runs were divided into a training set and a test set. The training set (34 runs) was randomly selected from the entire set so that it contained 75% of both the pass and fail subsets. The remaining 11 data runs were used as the test set.

A schematic of one of the networks used is shown in Figure 3.

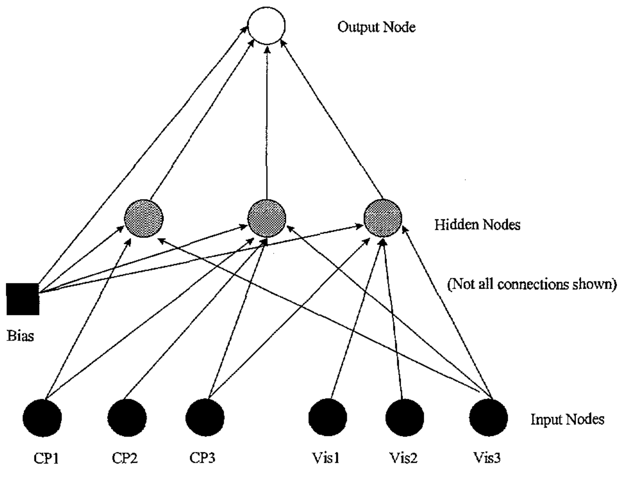

Figure 3. Neural network framework

4. Results

Initial attempts to design a neural network to recognize pass/fail patterns from the time history data focused on using the entire time history of CP and RV. However, there was simply not enough training data available to train neural networks of this size.

Later attempts focused on designing smaller networks that only looked at the first few time history data points to differentiate between pass/fail. Networks that used the first four time steps of data for a single variable were designed and trained. The number of hidden nodes was varied from two to five. The best networks had a 95% successful prediction rate using VIS, 90% using CP, and 75% using RV. Networks that used two of the significant variables were then tried. The networks using CP/RV and RV/VIS yielded 98% prediction rates while the CP/VIS network yielded a 100% prediction rate. Further efforts focused on using this set of inputs. The minimum number of hidden nodes that yield a 100% prediction rate was found to be three. The number of time steps used was then reduced to three and then to two. The results of the best networks are summarized in Table 1. The column labeled "Correlation" is a measure of how well the output of the network (a number between 0 and 1) correlated with the actual result (fail=0, pass=1).

Table 1. Results from CP/VIS neural networks of various sizes

# Time Steps	# Hidden Nodes	Set	Correct	Total	Correlation
4	3	Training	34	34	0.973
		Test	11	11	0.927
		All	45	45	0.962
3	3	Training	33	34	0.917
		Test	10	11	0.793
		All	43	45	0.879
2	3	Training	33	34	0.844
		Test	10	11	0.929
		All	43	45	0.865

These results indicate that an adaptive process control system using this neural network has the potential to identify process disturbances early in the injection cycle time. More work needs to be done, however, to identify appropriate manipulative variables that can be assigned corrective actions to preemptively resolve these upsets before the PBX loading cycle is completed.

Future work includes a plan to implement this neural network into process control system for injection loading submunitions. The hope is that we can demonstrate the utility of an adaptive process control system to inject several different kinds of submunitions at reduced cost and also producing significantly less pollution.

REFERENCES

1. Mahoney, T.I., Newman, K.E., Gusack, J.A. and Sallade, G.J. (1995). U.S. Patent 5387095, Apparatus for injection molding high-viscosity materials.
2. Hertz, J., Krogh, A. and Palmer, R.G. Introduction to the Theory of Neural Computation. Addison-Wesley, New York, 1991