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Solvent Manufacturing Process Monitoring using Artificial Neural Networks

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Abstract

Advances in sensors, actuators, and computers and developments in information systems offer unprecedented opportunities to implement highly ambitious automation, control and decision strategies. There are also new challenges and demands for control and automation in modern industrial practices. There is a growing need for an active participation from the information systems in industrial, manufacturing and process industry environments because currently there are many control problems. This paper provides pattern recognition to the monitoring system for solvent manufacturing process and shows performance in real-time response with multiple input signals. Data is learned by a multilayer feedforward network trained by error-backpropagation. The two kinds of test results show that the trained network has the ability to show the current system status with different input data sets.

Key Words : Process Monitoring, Pattern Recognition, Signal Processing, Neural Networks

1. Introduction

Automation is the heart of modern industrial development and progress. Tied with advances in information system design, the result is an unprecedented growth in performance, quality and profitability while improving response to changing market demands. A slow response to demands for automation and failure to incorporate information system practices generally results in inadequate performance in the market place which is evident from the failure of many organizations to compete in the cost competitive modern global economy, resulting in major crisis and corporate downsizing. The concept of global competition in industry practices demands better and faster response times, higher quality standards and greater flexibility in the introduction of manufacturing processes through automation.

A Distributed Control System (DCS) is part of the manufacturing systems being used in a wide range of engineering applications to monitor and control distributed equipments. Common components found in DCS are the field instruments, which are connected via wiring to computer buses or electrical buses to a multiplexer/demultiplexer. Since it is connected to physical equipment such as switches, pumps, and valves and monitored real time, the machine needs to store huge data for the maintenance process. One of the task of DCS is to diverge the risks within the system since several functions are distributed. Pneumatic control systems have been using DCS since 1990. Modern manufacturing processes are more complex and intelligent than before.

In monitoring systems, real time diagnosis is essential for safe and efficient operation and maintenance. It involves several on-line and off-line diagnostic tasks. The alarm handling, trouble shooting, and dispatching must be handled within real time. Real time monitoring, diagnosis, and control tasks in industrial environments are solving the complex decision making problems associated with a system [1].

In an artificial intelligence (AI), a variety of techniques can be dedicated to core applications in rigid environments or can be highly flexible. A flexible automation generally implies the use of industrial processes and AI has been receiving more attention for its characteristic advantages such as learning capability and reasoning. Monitoring systems should provide information regarding the current situation of operational status. It can be done by recognizing patterns within a time series of captured data while monitoring and classifying these patterns as known conditions. Monitoring using pattern recognition and classification methods can be found in [2].

Monitoring processes without AI require expert experience and knowledge of that specific system. It is not easy to express the knowledge for anygiven system. An artificial neural network is used for the monitoring system in which human operators are not usually involved at the direct level of automation. Monitoring systems using neural networks are highly dependant on pattern recognition techniques.

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A neural network is a computing system composed of a number of highly interconnected layers of simple processing elements. The networks are trained to recognize data representing the different situations of the dynamic system. Current researches have been focused on the application of such advanced AI techniques as artificial neural networks, fuzzy logic, and genetic algorithms to solve various problems [3]. In this paper, solvent manufacturing process monitoring using artificial neural networks developed will be discussed.

2. Description of a Monitoring System

2.1 Research motivation

The Ilil industry takes the raw material from chemical plants and examines the Hydrogenation process under high temperature and high pressure. Olefin components in the raw material are converted to paraffin in this process, through which products are produced distillation apparatus. The DCS has been being used for monitoring these processes.

The machine is equipped with data collection systems and is monitored by human operators. So, the operators should stay in front of the machine for monitoring and diagnosis purpose while the machine is operating. They just observe simple graphs on the monitor screen and write down the data value on a log sheet. This is a waste of manpower. It only finds that the data value is within the range of operating. It cannot find the current processing state. Fig.1 is the manufacturing process for monitoring that is being used in the chemical plant. As you can see, a human operator can monitor all operation situations in the control room.

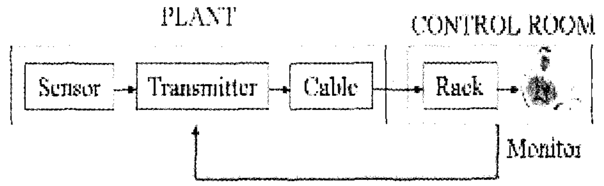


Fig. 1. Manufacturing process used for monitoring in DCS.

Currently, human operator are involved the process situation for monitoring and diagnosis of the system. An operator attempts to estimate the current state of a process from real-time plant data. Fuzzy control has been used in dealing with theses problems and showing useful approaches [4]. The human operator, however, is needed to make the final decision. This is not easy for the human operator when the operational condition is abnormal. Psychological investigations of engineering say that human operators cannot handle above seven variable forms of logical decisions making.

The pattern recognition approach for monitoring using neural networks and signal processing are found in [5, 6]. In this paper, we use the pattern recognition technique adapting neural networks to achieve the solvent manufacturing process monitoring system. The trained system gives the resulting alarm if the measured data has the particular types of faults.

2.2 Artificial neural networks

Artificial neural models are composed of highly parallel building blocks that are interconnected to construct highly complex systems. These models have highly interconnected layered architectures with uniform simple nonlinear processing elements (neurons). Every neuron model consists of processing elements carrying synaptic input connections and a single output. Several learned algorithms allow it to self adapt by changing parameters.

The weight matrix is usually initialized with random values. An input vector is a class vector that represents a specific mode of operation (normal or fault). The network memorizes the inputs by altering its weight matrix. Thus the training consists of using the training examples to tune the appropriate weight values between layers. Training examples are presented at the input layer. The vector is then propagated throughout the network. Selected learned algorithms are applied to determine weight adaptations.

The network can be trained at each point value or after each epoch. An epoch represents one complete pass through the training data set. This learning procedure should be repeated until an acceptable error rate is achieved or until a certain number of iterations are completed using training examples. The size of the network can be changed to increase the performance of the system.

Backpropagation uses a gradient search algorithm to minimize an objective function which is equal to the mean square errors between the desired and the actual output. The networks take the input samples from the input layer, propagate them to the output layer, and generate the network output. Present error signal terms are propagated backward for tuning each layer's weights. The threshold value for a decision in the verification phase should be determined during the training stage. Detailed algorithms of backpropagtion will be found on [7].

3. Neural Network Implementation for Process Monitoring

With neural networks, we can monitor the process by training. What is more, untrained data will also be compensated efficiently. Although the network doesn't have previous knowledge of the internal behaviors, it can learn given data, build a system, and assign the output for a new process.

3.1 Data acquisition

The data acquisition system is necessary to get data from the system using an adequate A/D (Analog-to-Digital) interface. ADC (Analog-to-Digital Converter) is used to convert the raw data from the plant into an input for the rack as shown in Fig. 1. Training and test data are made of C classes of vectors for dynamic systems $\{X_i^c\}$, $c = 1, 2, \ldots, C$, where c denotes the sequential number of the class and i denotes the specific realization of the class.

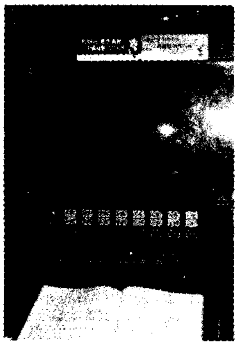


Fig. 2. DCS used for our experimental tests

The DCS used for this study is presented in Fig. 2. In this study, we used the signals coming from sensors in tower DA204 during processing such as pressure, temperature, level, and gage. Normal operation conditions were examined in this study listed on Table 1. We also generated a condition to reflect a range of faulty operating values for training and test purpose.

Table 1. Data analysis for the experiments

	Tag	Operation Range	Unit
DA204	PI-220	-600 ~ -750	mmHg
	TG-2101	125 ~ 300	℃
	TG-203	250 ~ 300	℃
	LG-2101	0 ~ 100	%
	LG-2102	0 ~ 100	%
	GA-209	0 ~ 5	KG/cm^{2}G
	GA-210	0 ~ 5	KG/cm^{2}G

The data is prepared to construct a network for achieving a desired monitoring system. The system is regulated by a data set, which consists of input-output pairs. The training data set should cover the widest range of points possible. The normalization scheme for the data is one of the critical issues for network performance. We also normalized the data to have values between 0.0 and 1.0 for the study.

The proposed scheme is illustrated in Fig. 3. The procedure consists of two stages. The first is the parameters via DA204. The values are passed to the neural networks for classification. The neural network estimates the process condition in terms of pressure, temperature, level, and gage. The structure of the neural network is described in the next section.

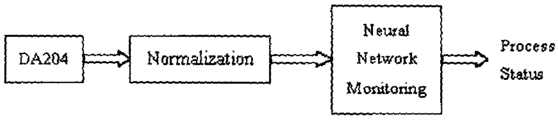


Fig. 3. Process monitoring scheme

3.2 The structure of artificial neural networks

The proposed network scheme for process monitoring is designed with simple backpropagation. First, we explain the structure of and behavior of the network. The network in this study is restricted to having a single hidden layer with a variable number of neurons. The Sigmoid activation functions are used for the neurons in the hidden layer.

Fig. 4 shows the schematic of the proposed network structure for the monitoring system in DCS. The network is a computing system with multilayer feedforward type, which consists of an assemblage of interconnected computational elements [8]. The elements are known as neurons, which process information by their dynamic response to external inputs. The proposed network has seven units, one hidden layer with undetermined units, and one output unit. The seven inputs correspond to the value of sensor variable being normalized at each time.

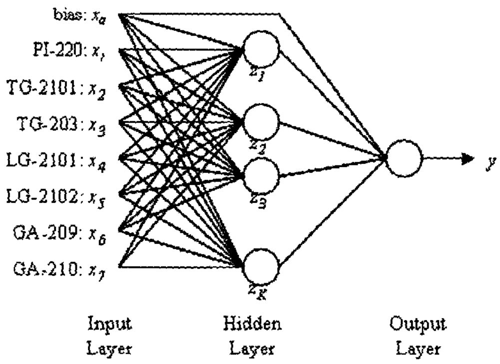


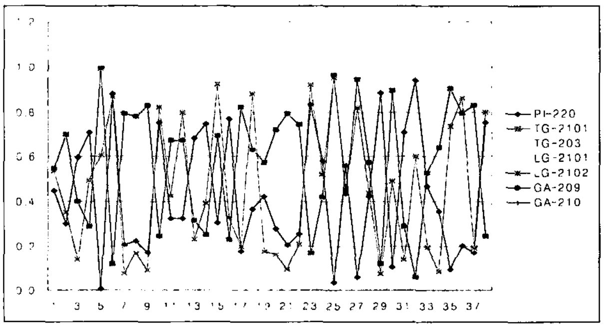
Fig. 4. Network configuration for the artificial neural network for the process monitoring

The learning algorithm of backpropagation can be seen as a generalization of the LMS algorithm. It uses a gradient search approach to minimize an objective function equal to the square of the difference between the desired and the actual network output. The networks are trained by initially picking small random weight values between -1 and 1, selecting internal thresholds and then presenting all training data repeatedly. Weights are either revised instantaneously after each training vector is presented or only after all training data vectors have been presented. This process is repeated until weights converge and the objective function is reduced to an acceptable value.

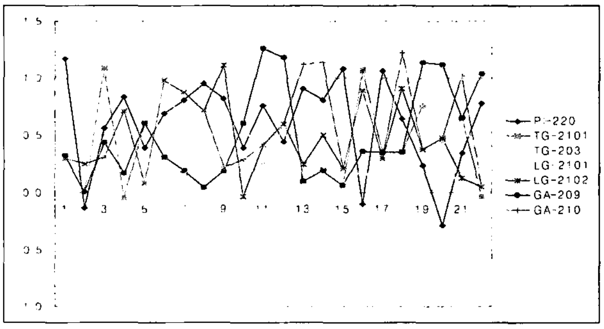
3.3 Experimental results

We carried out simulations in order to validate our model based on The Ilil industry DA204 configuration. The main goal of the study is to find out the system status. The input to the system is the set of vectors representing the different types of process status. In this study, we used only two kinds of classes to be trained, normal or faulty. So, the output layer yields a coded value associated with the current process status. The target values used for the output nodes are set to 0.0 for faulty and 1.0 for normal.

The first group of experiments uses a data set with 7 attributes shown in Fig. 5. The solvent manufacturing process parameters include pressure, temperature, level, and gage. The normal types are shown in (a) and the faulty types are shown in (b).



(a)

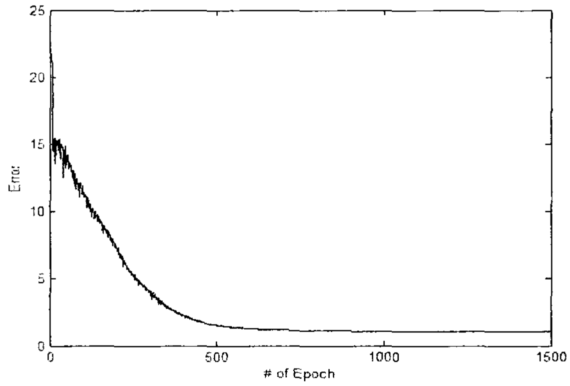


(b)

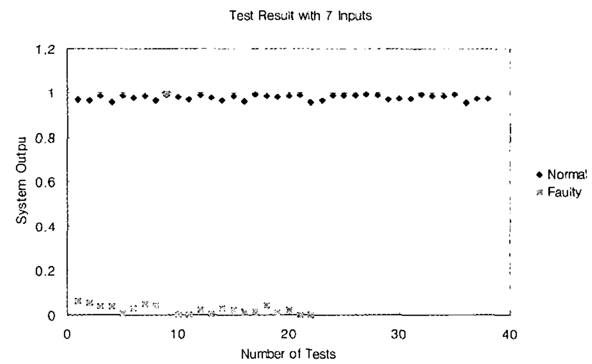
Fig. 5. Normalized normal and abnormal data from measurement for the network

In order to characterize the applied neural network for process monitoring, we describe the experiments performed on two different data sets. The first experiment is done by 7 inputs for training and testing the monitoring systems. The neural networks have 14 neurons in the hidden layer, and one output node associating to a process condition. A linear function is used for the output layer and the learning constant is 0.25. The neural networks have a target error of 0.025.

Fig. 6 (a) shows learning curves for the learned approaches. It is the learning curve of the least mean square error with respect to the number of iterations when we used the proposed approach. We had an error rate of 0.7 after 700 epochs necessary to reach the same error rate. The error rate remained 0.25 after 800 epochs. The obtained result in Fig. 6 (b) shows that one of the abnormal data results is considered as normal. It then would make a wrong decision in a real process environment. In the case where 7 neurons were in the input layer and 14 neurons in the hidden layer, gave us a 98.4% accurate monitoring. This indicates that the network has successfully learned to monitor the process with the given input.



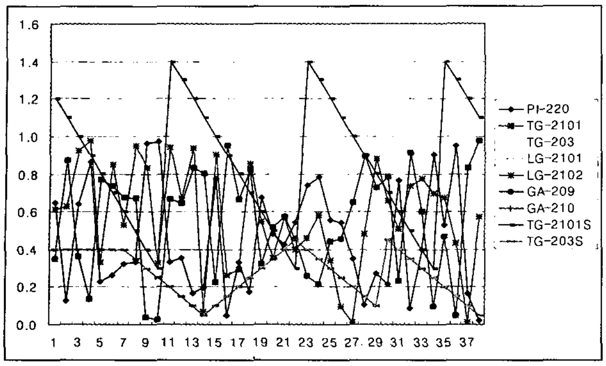
(a)



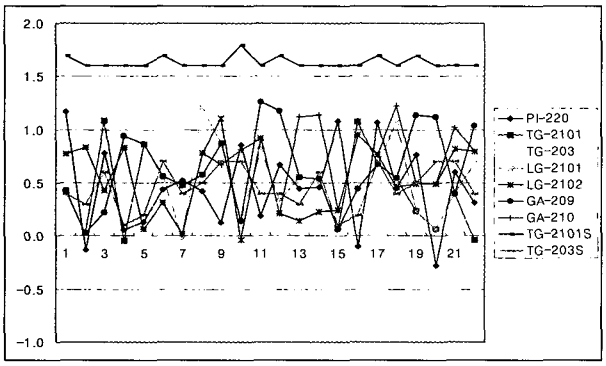
(b)

Fig. 6. The error curve and output of the proposed monitoring system with 7 inputs

The second group of experiments uses a time delay signal for TG2010 and TG203. In this case, we consider temperature as an important factor. If the temperature increases or decreases steadily for some time, it is assumed a normal operation. If the temperature is the out of range during a given time, the network sends out a warning. Those two things are added to the training data. So, the experiment is done by a collective of 9 inputs for the networks to investigate the monitoring system



(a)



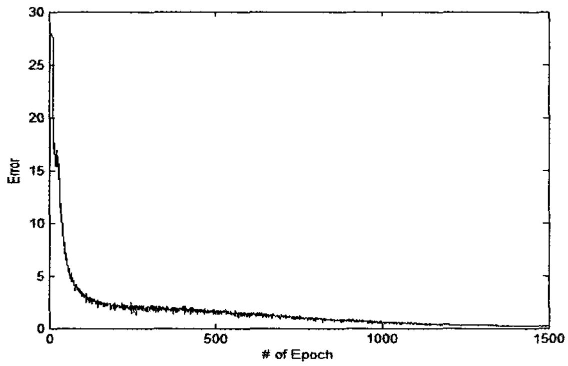
(b)

Fig. 7. Normalized normal and abnormal data from measurement for the network with slop (9 inputs) TG2010S and TG203S

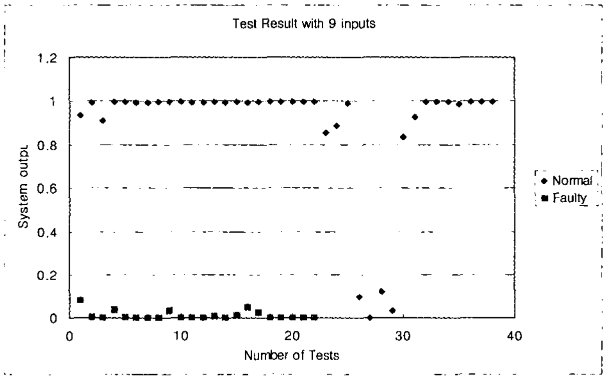
Fig. 8 (a) shows learning curves for the learned approaches with 9 neurons in the input layer and 14 neurons in the hidden layer. In this case, we can see a little quicker convergence around 700 iterations but the second approach converges to 0.18438 with the same iteration. With the reference to Fig.8 (b), the output of the network is shown as a worse performance than the previous test. Furthermore, it is seen that the network is able to diagnose a normal operation as a faulty status. The network performance results show a quite acceptable training procedure even though it has some fluctuations. Four of the tests resulted in misleading normal data as abnormal. This would result in 2 wrong decisions within the real process environment.

In the next simulations, we have prepared a different number contained in the neurons of hidden layer and input layer within the network shown in Fig. 4. Twenty different test scenarios are simulated and tested using the proposed model. Initial parameters for input are the same as previous experiments. In the case of the proposed approach, the total epochs are 1,500. For each test, the ideal number of neurons in the hidden layer is increased from 10 to 20 increasing by one each time. According to the Fig. 9, increasing the neurons in the input layer does not result in better performance.

We also have examined monitoring tests with different network structures for comparing the number of errors. Fig. 9 shows the result for using different numbers of neurons in the hidden layers. As we can see, we used more neurons in the hidden layer. The result demonstrates that performance increased when we used the parameter from DA204 directly as input vectors. We also used more input values as feature vectors, which increased processing time. Fig. 9 shows the monitoring results obtained using different numbers of neurons in the hidden layers. These results represent the total number of errors, 7 inputs and 9 inputs as we mentioned. Intuitively, it can be seen that 7 inputs (97.8%) has a slightly better performance than 9 inputs (94.2%). This comparison is provided in Fig. 9.



(a)



(b)

Fig. 8. The error curve and output of the proposed monitoring system with 9 inputs

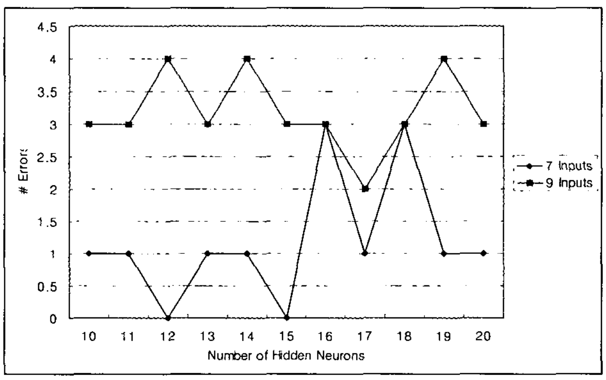


Fig. 9. A comparison of the number of neurons in the hidden layers with 7 input nodes and 9 input nodes

4. Conclusion

In this work, we have characterized the needs and requirements of monitoring systems in manufacturing environments and provided an important demands of diagnosis for the given and various practices in place. An overview of the dynamics of automation with recent technological advances in terms of neural networks is presented. A neural network is used for monitoring process from DA204 data. Results show that the method proposed here is quite promising to neural networks as process monitoring.

The future research will include simulating more complex data as an input and employing a hybrid model of the monitoring system such as fuzzy and genetic algorithms. Modern industrial controls, in one way or the other, are increasingly depending on computer integration. The role of modern information systems in fuzzy controller design is very obvious as well as advancement in the area of computer vision for automatic navigation and task or process identification for autonomous industrial robots and controls. It consists of decision making and optimization techniques to increase the system performance. By using cooperative soft computing techniques for monitoring and diagnostic activities, this will lead in the near future to an important diagnostic embedded system.

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