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Article *in* International Journal of Production Research · April 2003

DOI: 10.1080/0020754021000042409

International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tprs20

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Published online: 14 Nov 2010.

INT. J. PROD. RES., 2003, VOL. 41, NO. 6, 1239–1254

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Application of artificial neural network to identify non-random variation patterns on the run chart in automotive assembly process

KHI-YOUNG JANG†*, KAI YANG† and CHANGWOOK KANG‡

A developed methodology of using an artificial neural network to identify non-random variation patterns to improve dimensional quality in automotive assembly process is presented. The proposed pattern recognition algorithm that integrates with the process knowledge basis is designed not only to detect variation patterns, but also to address the identification of unacceptable variation manifested by non-random patterns on the control chart. Once any non-random patterns occur on the control chart, the root causes of dimensional variations can be located systematically by investigating each possible cause based on the knowledge of the assembly process. This information will help to make process modifications that reduce dimensional variability for automotive body assembly process in real time. Therefore, it can be expected that the control chart with the proposed pattern recognition algorithm will play a more important role as a systematic diagnosis tool rather than only as a statistical monitoring tool.

1. Introduction

In order to maintain good dimensional quality of an automotive body assembly, it is critical to detect non-random variation patterns and identify variation sources correctly. From a process control point of view, identification of non-random/unnatural patterns, such as trends, cycle and systematic pattern not only can extract the set of possible causes that must be investigated and greatly help to find the diagnostic corrections, but also can be used to make process modifications that reduce variability (Montgomery 1996).

Control charts have been widely used for monitoring process stability and capability over the whole automotive body assembly process. However, the current process control charts, including multivariate control charts, have failed to produce meaningful results because they have been used only for process monitoring tools rather than for analysis and diagnostic tools. Moreover, with the advent of a number of technological advances in the field of measurement system, automated in-line measuring machines are capable of measuring the dimensions of every automotive Body-in-White produced. Owing to a huge amount of data with high dimensionality, it is not easy to detect whether the process has any systematic non-random variation patterns by visual inspection of the data in real time. For example, if an auto-body has 500 different measurements (500 variables), at least 500 different control charts are required to check the existence of any non-random patterns. Clearly, simple use of a control chart is not appropriate for identifying any non-random patterns in an

Revision received November 2001.

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International Journal of Production Research ISSN 0020–7543 print/ISSN 1366–588X online © 2003 Taylor & Francis Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/0020754021000042409

automated manufacturing environment where data come from on-line measurement systems. Therefore, a new efficient data analysis technique has been required to implement the current data analysis in the auto-body assembly process.

The objective of this paper is to develop a monitoring and diagnostic system using an artificial neural network (ANN) that can automatically detect non-random variation pattern and rapidly classify the corrective action to the manufacturing process in real time to improve a dimensional quality of automotive assembly process.

The paper is organized as follows: the automotive assembly process and dimensional data will be briefly described in Sections 2 and 3, respectively; Section 4 describes the methodology of the process diagnosis for each non-random pattern; Section 5 presents a brief literature review of ANNs; Section 6 describes the structure of a proposed neural network with the necessary assumptions; Section 7 presents a case study to show how the proposed network can be applied in an automotive assembly process; a summary and conclusion are presented in Section 8.

2. Automotive body assembly

A typical automotive body assembly process consists of between 350 and 400 stamped parts passing from subassemblies to the main assembly line, with spot-welding performed at approximately 3500–4000 points to assemble the vehicle body skeleton. The assembly work begins with the inputting of parts from the preceding process by the automatic setting device. An automotive body assembly without the hang-on-panels such as doors, hood, and lift gate is called the Body-in-White (BIW). The BIW is composed of several major components: the underbody, the left and right bodyside frames, shelf, rear end, and the roof panel. Figure 1 provides the typical substructure break-up of the passenger automotive BIW. Each component is assembled in a different subassembly line and transported by a conveyer which takes the place of the conventional jig in the positioning and welding operations. Parts are held in place by positioning robots and spot-welded by welding robots to join the parts permanently. Clearly, dimensional variation can occur during any of the steps in the subassembly and main assembly processes. All major components and the final BIW are checked by using various types of dimensional checking equipment such as gage-talkers, Coordinate Measuring Machine (CMM) and Optical Coordinate Measuring Machine (OCMM).

3. Dimensional data description

The XYZ coordinates that represent the auto-body coordinate system are used to explain dimensional variations. The spatial positions of any point on the body are referenced to three planes: fore and aft (F/A), high and low (H/L), and in and out (I/O). The F/A measurement directions correspond to the deviation of the work piece in the X-axis direction; the I/O corresponds to the deviation of the work piece in the Y-axis direction; while the H/L corresponds to the deviation of the work piece in the Z-axis direction. All tooling and parts are referenced to these three planes.

4. Diagnosis of non-random patterns in automotive assembly process

4.1. *Non-random variation patterns on control chart*

The control charts may indicate an out-of-control condition when either one or more points fall beyond the control limits or plotted points show some non-random patterns of behaviour. The Western Electric *Handbook* (1956) suggests a set of

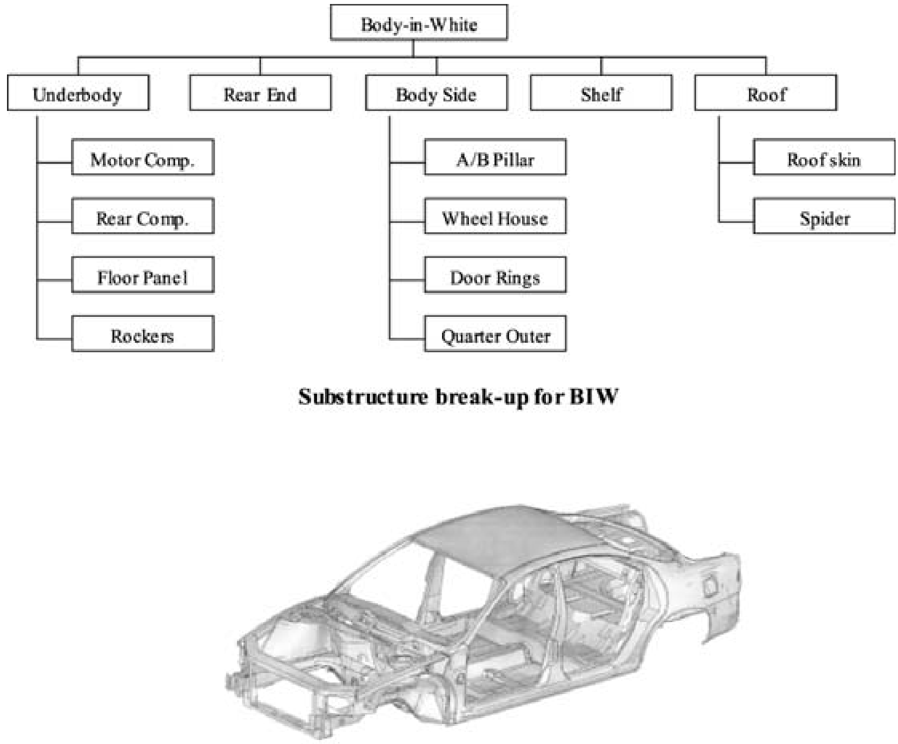

Figure 1. Structure of Body-in-White.

decision rules for detecting non-random patterns on control charts. Specifically, it suggests concluding that the process is out of control if:

- one or more points outside of the control limits;
- two of three consecutive points outside the 2-sigma warning limits but still inside the control limit;
- four of five consecutive points beyond the 1-sigma limits; or
- a run of eight consecutive points on one side of the centre line.

Over the years, many rules have been developed to detect non-random patterns within the control limits. Grant and Leavenworth (1980) recommended that non-random variations are likely to be presented if any one of the following sequences of points occurs in the control charts.

- Seven or more consecutive points on the same side of the centre line.
- At least 10 of 11 consecutive points on the same side of the centre line.
- At least 12 of 14 consecutive points on the same side of the centre line.
- At least 14 of 17 consecutive points on the same side of the centre line.

Under the pattern-recognition approach, numerous research (Western Electric 1958, Nelson 1985, Besterfield 1986) have defined several types of out-of-control patterns (e.g. trends, cyclic pattern, mixture, etc.) with a specific set of possible causes. When a process exhibits any of these non-random patterns, it implies that those patterns may provide valuable information for process improvement.

Therefore, once any of the non-random patterns are identified, the scope of process diagnosis can be greatly narrowed down to a small set of possible root causes that must be investigated.

To analyse 100% of the data obtained by OCMM in an automotive assembly process, a run chart for individual observation will be considered rather than subsample means. There are four most common and practical non-random patterns that are studied here. Figure 2 shows these non-random patterns and they are described as follows.

- Upward/downward trends: a trend pattern is a series of points indicating a continuous movement in upward or downward direction.
- Cyclic pattern: a cycle pattern is represented by a sinusoidal shape, with short upward and downward trends in the data occur repeatedly.
- Systematic variables: in this case, the pattern has become predictable. A systematic pattern is a series of points that hugs the centre line with a systematically up and down manner. An example of this is a low point always being followed by a high one and vice versa.

4.2. *Diagnosis of non-random patterns based on process knowledge*

After any non-random variations are detected on the automotive body assembly process, corrective action will be required in order to improve the dimensional quality. Roan (1993) and Ceglarek (1994) developed several case studies and

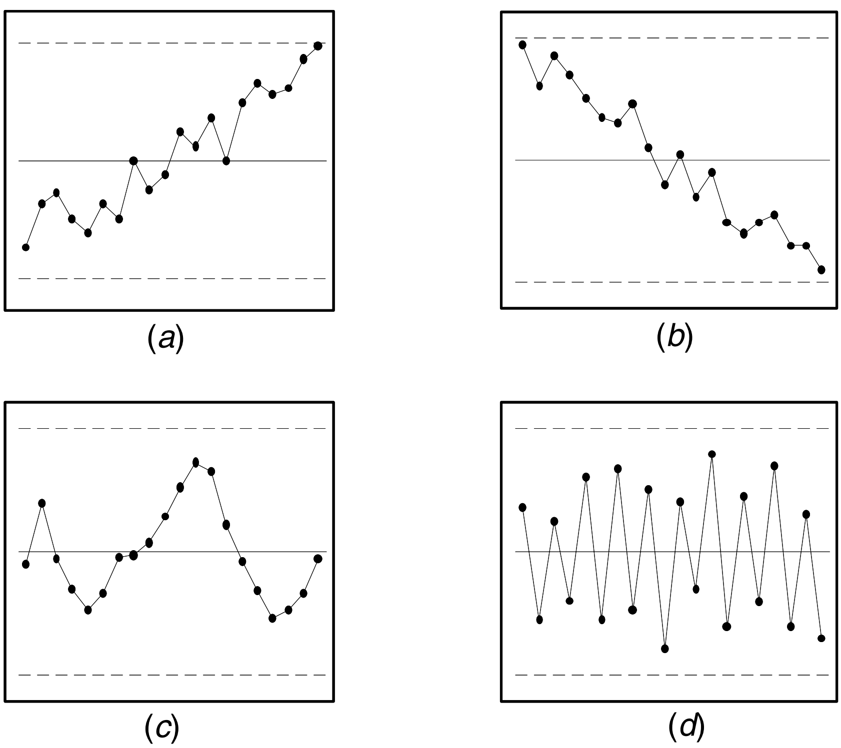

Figure 2. Example of non-random patterns: (*a*) upward trend; (*b*) downward trend; (*c*) cycle; (*d*) systematic pattern.

strategies to locate the root causes for the diagnosis of the process fault using knowledge of assembly process. However, they focused only on the sudden process change and large variations. Unfortunately, there are no attempts to identify and diagnose non-random variation patterns in the assembly process. Based on their approach, diagnosis for a non-random variation pattern defined in this research can be categorized by using manufacturing experiences, existing case studies and the knowledge of the assembly process. They are as follows.

- Upward/downward trends:
  - Not enough spot-welding.
  - Tooling problems (clamp, welding).
  - Inconsistent dimensional quality of stamping process.
- Cyclic pattern:
  - Difference between measuring machine.
  - Rotation of fixtures or gages.
  - Regular movements of measurement sensing devices.
  - Incorrect positioning for measuring machine station.
- Systematic pattern:
  - Difference in spread between different conveyors or shifts.
  - Assembly fixtures.
  - Locating holes.
  - Worn positions or treads on locking devices.

There are tremendous possible root causes from any assembly stations, tools, fixture, etc. The root causes listed above might not be enough to help rapid corrective actions; however, the comprehensive root-cause database/expert system can be built up gradually. The use of non-random pattern recognition based on a process knowledge basis will greatly narrow the search to find possible causes and will make it possible to take rapid corrective reactions to improve dimensional quality.

5. Brief review of ANN

Several ANN algorithms have been recently applied as a new data analysis tool due to their adaptive nature and fast computational capability. One of the most significant attributes of ANN is its ability to learn by interacting with its environment or with an information source. Since ANN can identify some patterns, neural networks have been considered recently as the new alternative to overcome statistical analysis problems (White 1989). As shown in figure 3, ANNs are computing systems containing a number of interconnected processing element called neurons. Initially, each sample can be 'loaded' onto the input layer of the network and the input nodes simply send these values to output nodes. Each output node calculates the weighted sum of the inputs. The output value of a network is determined by an activation function and the weight values are adjusted by a specified learning rule. One of the most significant attributes of a neural network is its ability to learn by interacting with its environment. This learning in the neural network is normally performed by using specified learning rules. For various reviews of learning rules, see Hogan *et al.* (1996) and Hassoun (1995). The ANN system is inherently parallel in the sense that many units can carry out their computations at the same time.

Not much has been published on detecting a shift in the mean and/or identifying some of unnatural variation patterns using neural network on control charts. Pugh (1989, 1991) published two papers about performance comparisons between tradi-

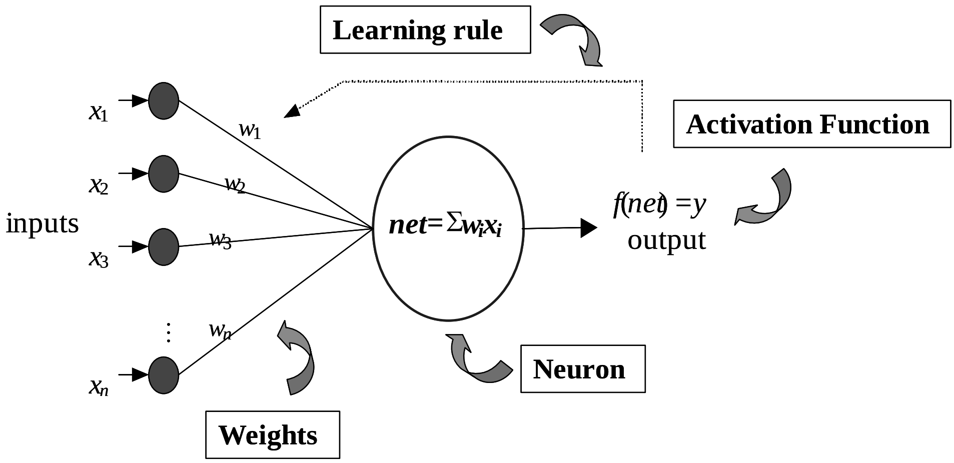

Figure 3. Artificial neural network architecture with four basic components.

tional statistical process control methods and neural networks. He used back-propagation networks to detect mean shifts and found that in terms of average run length (ARL) his application results were equivalent to a standard X-bar control chart with 2σ control limits and it improved significantly on type II errors over X-bar charts. Guo and Dooley (1992) compared the performances of a back-propagation neural network with cumulative sum and moving sum charts. They found that their best network reduced errors in classification by about 40% from control chart heuristics.

Those researches, however, focused merely on detection of the change. They did not highlight whether a particular pattern of change had occurred. Hwarang and Hubble (1991, 1993) used a back-propagation classifier to detect non-random variation patterns. They found that a neural classifier with binary input and output performed well enough to detect the non-random patterns. Cheng (1997) developed two types of pattern recognizers based on different neural network architectures: multilayer perceptron trained back-propagation and a modular neural network for identification unnatural patterns. He found the outstanding capability to detect unnatural patterns starting anywhere in the sequence of data by using a neural network.

These prior researches have been performed and evaluated by using simulated datasets rather than by using any real datasets from manufacturing process.

6. Network structure and algorithm

The proposed network described here was developed based on existing LVQ networks. We will show how the modified LVQ network can be used to detect predetermined non-random variation patterns correctly.

6.1. *Basic assumptions*

There are several basic assumptions to build an effective pattern recognition system.

- A trained network will only be able to identify a data set as being in one of defined non-random patterns during a period of time.
- To avoid ambiguity between patterns that can result in poor convergence of the network, each non-random pattern must be generated as clearly as possible. For example, a small random noise-contaminated cyclic or systematic pattern can be classified as a natural pattern.
- Most of the training and testing data set will be generated within the control limit.
- Knowledge on and previous information about the manufacturing process, herein the automotive body assembly process, to which this automatic pattern recognition system is already known. It is impossible to construct an effective pattern recognition system for identifying all sorts of cycle periods and amplitudes.

6.2. *LVQ model*

The LVQ is a self-organizing network that can classify input vectors based on a set of reference vectors. The original LVQ model was developed by Kohonen (1990) for adaptive pattern classification. It is based on vector quantization, which is mapping of an n-dimensional vector into one belonging to a finite set of representative vectors. That means vector quantization involves clustering input samples around a predetermined number of reference vectors.

The LVQ network is trained by competitions between the hidden layers. The competition will be based on the Euclidean distances between weight vectors of reference vector and the input vector. The Euclidean distances will decide on the region to which the input $\mathbf{x}$ belongs. The distance d_i between the weight vector ($\mathbf{w}$) of neuron and input vector x can be calculated by:

$$d_i = ||\mathbf{w} - \mathbf{x}|| = \sqrt{\sum_j (w_{ij} - x_j)^2}. \tag{1}$$

The neuron with the minimum distance wins the competition between hidden neurons and is allowed to change its connection weights. The weights of the other neurons remain unchanged. If the winning neuron is classified correctly, then we move the weights $\mathbf{w}$ of the winning hidden neuron toward input $\mathbf{x}$. The following updated rule may use for learning network:

$$\mathbf{w}^{\text{new}} = \mathbf{w}^{\text{old}} + \eta(\mathbf{x} - \mathbf{w}^{\text{old}}). \tag{2}$$

However, if the winning neuron is in the wrong category, then we know that the wrong hidden layer won the competition. Therefore, we move the its weights $\mathbf{w}$ away from input $\mathbf{x}$. The following updated rule may use for learning network:

$$\mathbf{w}^{\text{new}} = \mathbf{w}^{\text{old}} - \eta(\mathbf{x} - \mathbf{w}^{\text{old}}). \tag{3}$$

At each learning iteration, the LVQ network is only told whether or not its input is correct. Then, the neuron that wins the competition by being closest to the input vector is activated and allowed to modify its connection weight. This result will be that each hidden neuron moves toward vectors that fall into the same category and away from vectors that fall into other categories. See Hassoun(1995) and Hogan *et al*. (1996) for more details regarding LVQ network.

6.3. *Generating training and testing dataset*

Selection of the training data set is a key issue to the training of a neural network because it will strongly affect the performance of the networks. However, it is not easy in practice to collect a training dataset, such as trend, cycle and systematic pattern, from the assembly process. Thus, the pattern generator will be used to generate a training dataset and a testing dataset in this research. The pattern generator designed to make a specified pattern has been described in Hwarang and Hubble (1993).

6.3.1. *Natural/random pattern*

First, a natural pattern will be generated by a general form which includes the process mean and random variations as follows:

$$y(t) = \mu + x(t), \tag{4}$$

where $y(t)$ is measurement at time t and μ will be a process mean when the process is in-control. The random noise, $x(t)$, will be expressed by a random normal variate at time t, where $x(t)$ is $N(0, p\sigma_x)$ and σ_x is the process standard deviation when the process is in-control, and p will be the magnitude of random noise in terms of σ_x. p will vary between 0 and 1.

6.3.2. *Upward/downward trends*

The training and testing dataset for trends will be generated by following equation:

$$y(t) = \mu + x(t) + (t - t_o)m\sigma_x, \tag{5}$$

where m is the slop of the trend in terms of σ_x, and where m will be positive for upward trends and negative for downward trends. The m between 0.2 and 0.4 by increasing 0.05 will be generated to train the upward trend to the network. If the slope m is more than 0.4 or less than -0.4, the dataset will be out of the control limit. Thus, those cases are not considered in this research. to is a time reference point which indicates the starting point of this pattern.

6.3.3. *Cycle*

An equation for cyclic patterns with a disturbance component may be described as below:

$$y(t) = \mu + x(t) + \sin[2\pi(t - t_o)/T]k\sigma_x, \tag{6}$$

where k is the amplitude of the cycle in terms of σ_x and $k > 1$. T is the period of the cycle. The selection of training and testing patterns for cycle can be very complicated because it involves many parameters. To avoid ambiguity between patterns and unnecessary weight changes which can result in poor convergence, the period of cycle, T, will be limited from 14 to 18 based on the process knowledge and past experience. In this study, the period of 16 was selected to generate a training and testing dataset. The amplitude of the cycle, k, will be generated from 1.5 to 2.5 by increasing 0.05 to train the network.

6.3.4. *Systematic pattern*

The systematic patterns will be generated by the following equation:

$$y(t) = \mu + x(t) + (-1)^t Q\sigma_x, \tag{7}$$

where Q is the magnitude of the systematic pattern in terms of σ_x. The parameter values of Q are generated from 1.5 to 2.5 by increasing 0.05 to train the network.

Equations (4–7) in the pattern generator will generate several datasets by using several parameters that determine the specific shape of the pattern of interest. Each pattern as defined above must be generated as clearly as possible so that the pattern classes can be distinguished as much as possible. For example, the upward trend patterns with small slopes less than 0.1 may be classified as a natural pattern. The parameters for each pattern class are limited to the range of the defined domain as long as all points are within the control limit. A subset of all possible values for these parameters will be investigated here. Figure 4 shows the examples of generated training sets for each pattern with various combinations of parameters. To train the network, the 100 different training datasets for each combination of parameters were generated.

6.4. *Input and output layers*

The input of a network will be any specific value of the deviation from a nominal position on each measurement point. Therefore, the number of input neurons must be equal to the number of observations in a given period in the automotive assembly process. The general rule in ANN is that the input size should be as small as possible for efficient computation because the size of the input usually determines the size and structure of the network. After several trials with different sizes of input, it was found that more than 16 input nodes do not improve significantly the performance of the proposed network. Thus, 16 input nodes were selected in the first layer in the network. To apply the proposed algorithm, the input value of each input node will be the same as the deviation of the each measurement point.

There are five output nodes corresponding to four unnatural patterns and a natural pattern of interest. The desired output vector of each pattern class is defined in table 1. To determine the on/off (1/0) state of the output node, any maximum value in the output vector set to 1 and other values are set to 0. For example, if a real output vector is $[0.32, 0.01, -0.43, 0.03, 0.97]^T$, the classified output will be $[0, 0, 0, 0, 1]^T$, which indicates the systematic pattern.

6.5. *Hidden layer and transfer function*

There are no general rules to decide the number of hidden layers and the number of nodes in the hidden layer. In all cases found during this literature review, the number of hidden layers had been decided on through trial and error. Guo and Dooley (1992) highlighted that there was no standard way of deciding the number of hidden layers and stated that as a rule of thumb either one or two hidden layers should be sufficient for almost any classification problem. To decide the number of nodes in the hidden layer, we can apply Kolmogorov's theorem that the maximum number of nodes in a hidden layer should be restricted to $2n + 1$, where n is the number of input nodes. In this algorithm, the number of node will be less than $33\,(= 2{*}16 + 1)$. Since too many nodes of a hidden layer merely create more chance for problems to arise from a local minimum, several cases of a hidden layer will be performed and compared with those performances to decide the best fitted model in this research. Figure 5 shows the evolution of the network with 16 inputs, eight hidden nodes and five output nodes. The network was smoothly trained

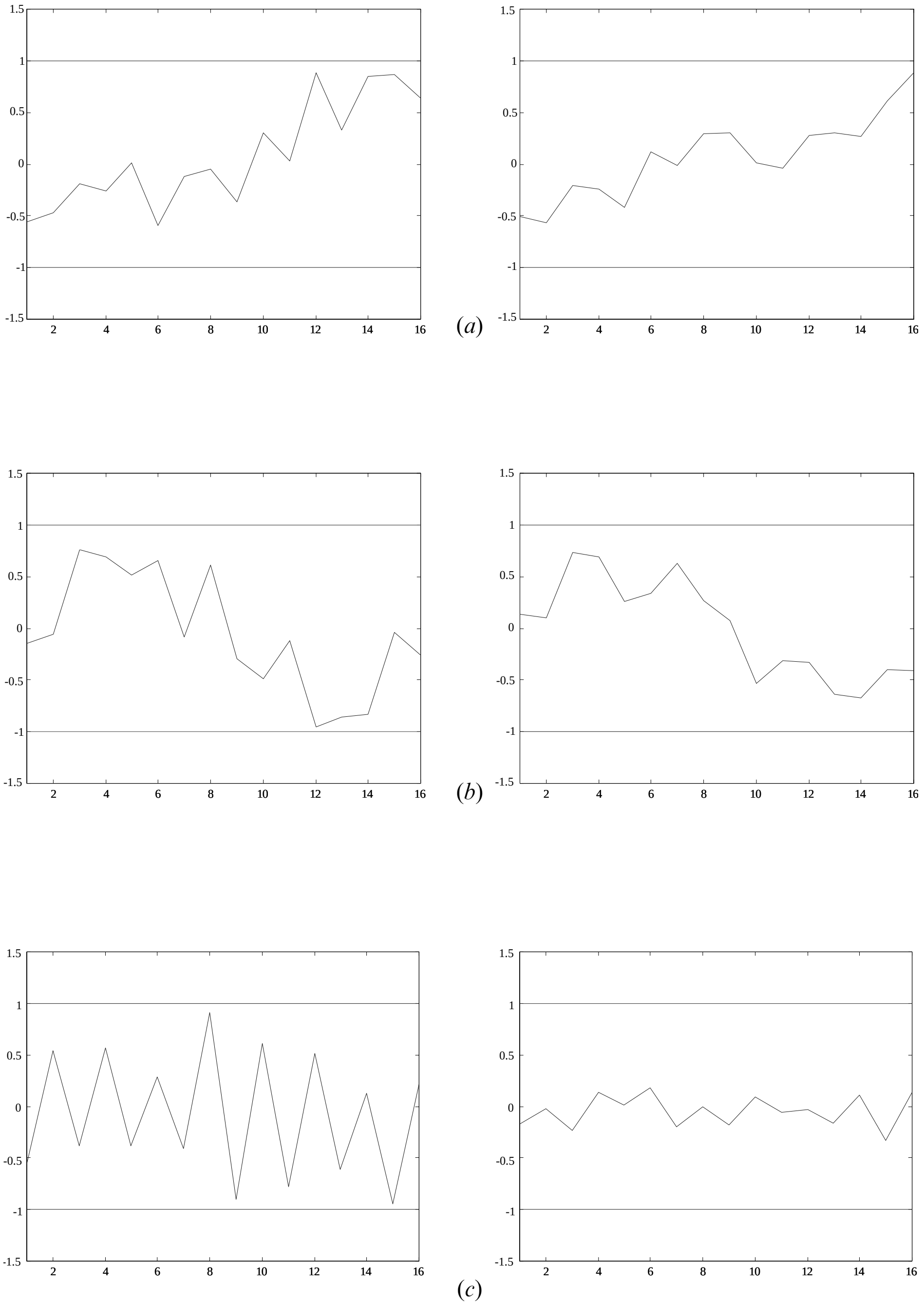

Figure 4. Examples of non-random patterns for training the network: (*a*) upward trends; (*b*) cyclic patterns; (*c*) systematic patterns.

after 6000 iterations (researched SSE = 0.01). Thus, a 16-8-5 network gives the best-fit model for a non-random pattern recognition system in this research.

Any differentiable transfer function can be used here. The most widely used is the sigmoid (it is also called logistic sigmoid) function with output values ranging from 0

Patterns	Desired outputs				
	1	2	3	4	5
Natural	1	0	0	0	0
Upward trend	0	1	0	0	0
Downward trend	0	0	1	0	0
Cycle	0	0	0	1	0
Systematic	0	0	0	0	1

Table 1. Representation of the output categories.

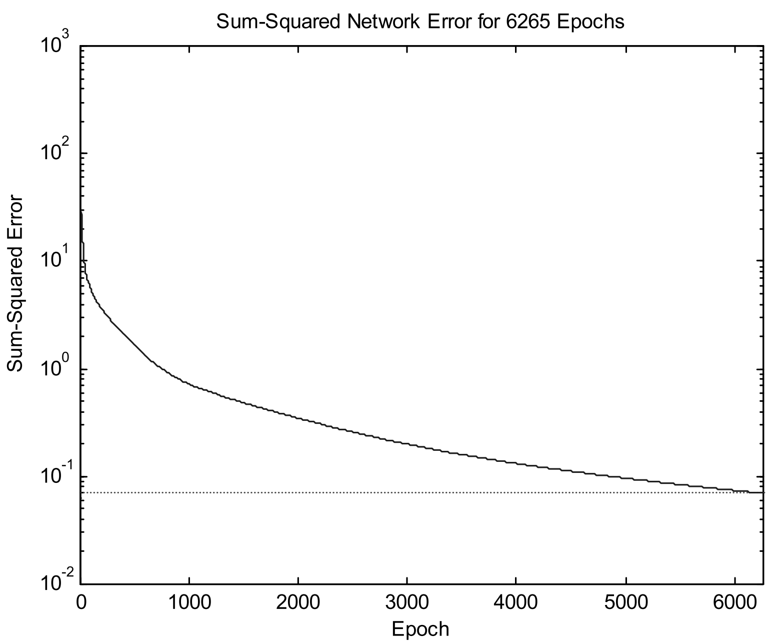

Figure 5. Evolution for a training network usin 16-8-5 (I-H-O).

to 1. However, due to difficulty in detecting the directional invariance property using a sigmoid function, the hyperbolic tangent with output values in the range -1 to 1 will be used as a transfer function in this algorithm. The hyperbolic tangent function will provide equal weight to low and high end values.

6.6. *Train network*

During the training procedures, a learning coefficient of 0.01 was used. The magnitude of this coefficient determines the pace of weight adaptation. Usually, a overly large coefficient causes the convergence behaviour to oscillate and possibly never to converge. On the other hand, an overly small coefficient causes the learning process to progress slowly but has better chances to avoid local minimum. After several simulations of this network, the learning coefficient with a value 0.01 was the appropriate in this application.

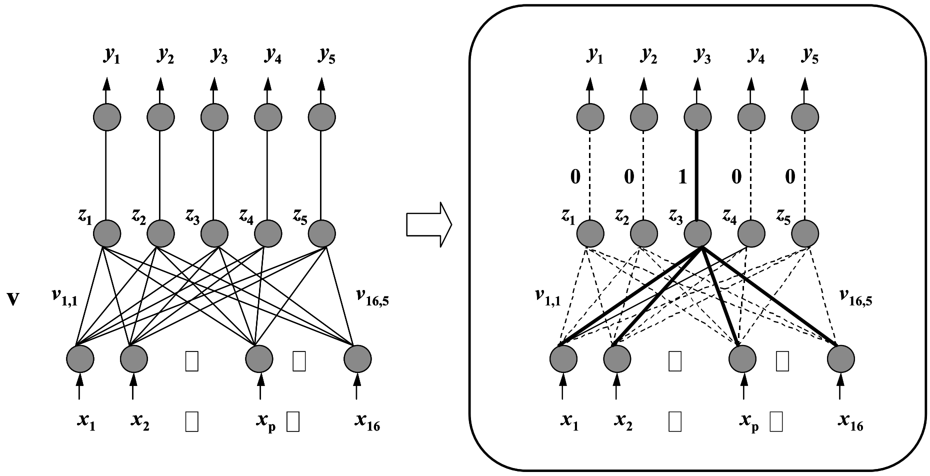

Figure 6. Training procedure of the proposed network.

Each pattern will be randomly and independently generated in the training set. In addition, all patterns are equally represented in the training dataset to make performance comparisons among the pattern class. The weights for the network will be adjusted until the network converges to a prespecified condition. The following steps will be used to train the network.

Step 1. Initializing weight vectors: At the beginning of training, the initial weights for both hidden layer and output layer are set randomly between −0.1 and +0.1.
Step 2. Presenting input vectors with desired vectors: Each input vector with the associated desired vector must be randomly selected and put in the network.
Step 3. Updating weights: Modify weight matrixes by using equations (2) and (3).
Step 4. Stopping criterion: Repeat Steps 2 and 3 until all patterns are correctly classified or the required SSE has been researched.

Figure 6 shows the example of the training layout of the proposed network. If any hidden layer wins the competition, the output vector is set to 1 and other values are set to 0. Then the network will only modify weights for winning nodes.

6.7. *Performance evaluation*

The performance evaluation was conducted to validate the usefulness of the proposed algorithms. There are nine combinations of parameters for each pattern to test the classification ability of the network. Table 2 provides a detailed look at the classification results for each non-random pattern. Each combination has 100 different datasets with 16 observations.

The proposed algorithms can classify upward and downward trends with more than 90% accuracy in the detection of right classes. When the slops of both upward and downward are large enough (more than 0.3 or less than −0.3), the algorithm has almost 100% accuracy to clarify correctly regardless of the size of random noise. The performance on cycles clearly depends on the amplitude of the cycle and the associated random noise. The detection of a cyclic pattern becomes poor when the amplitude of the cycle and the associated random noise are relatively small. This

S: slop SD: random noise	Natural	Upward Trend	Downward Trend	Cycle	Systematic
Upward trends					
$S = 0.2,\ \mathrm{SD} = 0.1\ (100)$	10	90			
$S = 0.2,\ \mathrm{SD} = 0.2\ (100)$	4	96			
$S = 0.2,\ \mathrm{SD} = 0.3\ (100)$		100			
$S = 0.3,\ \mathrm{SD} = 0.1\ (100)$		98			
$S = 0.3,\ \mathrm{SD} = 0.2\ (100)$		100			
$S = 0.3,\ \mathrm{SD} = 0.3\ (100)$		100			
$S = 0.4,\ \mathrm{SD} = 0.1\ (100)$		100			
$S = 0.4,\ \mathrm{SD} = 0.2\ (100)$		100			
$S = 0.4,\ \mathrm{SD} = 0.3\ (100)$		100			
Downward trends					
$S = -0.2,\ \mathrm{SD} = 0.1\ (100)$	8		92		
$S = -0.2,\ \mathrm{SD} = 0.2\ (100)$	2		98		
$S = -0.2,\ \mathrm{SD} = 0.3\ (100)$			100		
$S = -0.3,\ \mathrm{SD} = 0.1\ (100)$	1		99		
$S = -0.3,\ \mathrm{SD} = 0.2\ (100)$			100		
$S = -0.3,\ \mathrm{SD} = 0.3\ (100)$			100		
$S = -0.4,\ \mathrm{SD} = 0.1\ (100)$			100		
$S = -0.4,\ \mathrm{SD} = 0.2\ (100)$			100		
$S = -0.4,\ \mathrm{SD} = 0.3\ (100)$			100		
Cycle					
$M = 1.5,\ \mathrm{SD} = 0.1\ (100)$	22			74	4
$M = 1.5,\ \mathrm{SD} = 0.2\ (100)$	2			98	
$M = 1.5,\ \mathrm{SD} = 0.3\ (100)$				100	
$M = 2.0,\ \mathrm{SD} = 0.1\ (100)$	1			99	
$M = 2.0,\ \mathrm{SD} = 0.2\ (100)$				100	
$M = 2.0,\ \mathrm{SD} = 0.3\ (100)$				100	
$M = 2.5,\ \mathrm{SD} = 0.1\ (100)$				100	
$M = 2.5,\ \mathrm{SD} = 0.2\ (100)$				100	
$M = 2.5,\ \mathrm{SD} = 0.3\ (100)$				100	
Systematic					
$A = 1.5,\ \mathrm{SD} = 0.1\ (100)$	19				81
$A = 1.5,\ \mathrm{SD} = 0.2\ (100)$	2			1	97
$A = 1.5,\ \mathrm{SD} = 0.3\ (100)$					100
$A = 2.0,\ \mathrm{SD} = 0.1\ (100)$	3				97
$A = 2.0,\ \mathrm{SD} = 0.2\ (100)$					100
$A = 2.0,\ \mathrm{SD} = 0.3\ (100)$					100
$A = 2.5,\ \mathrm{SD} = 0.1\ (100)$					100
$A = 2.5,\ \mathrm{SD} = 0.1\ (100)$					100
$A = 2.5,\ \mathrm{SD} = 0.2\ (100)$					100
$A = 2.5,\ \mathrm{SD} = 0.3\ (100)$					100

Table 2. Testing results for each pattern with various parameters.

is obvious because a smaller random noise-contaminated cycle will be a more likely natural pattern. Similarly, some systematic patterns with a small random noise can be classified as a natural pattern. For other cases, the performance of a systematic pattern for the algorithm is quite consistent with various pattern parameters. Based on the overall results of the performance evaluations, it can be concluded that the proposed algorithm is capable of detecting the predetermined non-random patterns successfully. The following case study will show how this algorithm can be applied and integrated with knowledge-based diagnosis in an automotive assembly process.

7. Case study

7.1. *Data collection*

As a case study for the proposed neural run chart, the underbody assembly is presented. During body assembly operations there are several pallets that carry the automotive bodies from the station to the station in the assembly line. Usually three holding pins support and position the underbody on the pallet. After the underbody is loaded onto a pallet, the pallet clamps are closed to fix the position of the underbody on the pallet. Then the underbody moves into each assembly station to be welded with the subassembly parts. From the body shop assembly line, data were collected, $n = 419$ per each measurement (32 measurements), by the OCMM from the underbody assembly process.

7.2. *Identify non-random pattern*

To apply the proposed algorithm, we used the concept of 'moving windows of data'. See more details on the concept in Hwarang and Hubble (1993), Hwarng (1995) and Cheng (1995). From the process control point of view, since the most recent data have more important information for process control, the trained network will start to check a non-random pattern based on the most recent 16 observations. If any non-random patterns are not detected, the network will try to check a non-random pattern based on the second most recent 16 observations. For example, as we have 419 observations in this case study, the first classification attempt will be applied to observations $\{x_{404}, x_{405}, x_{406}, \ldots, x_{419}\}$ and the second attempt will be applied to $\{x_{403}, x_{404}, x_{405}, \ldots, x_{418}\}$, etc. As soon as data are preprocessed, each window of data is filtered through the trained network and one of the predefined pattern classes (natural, upward/downward trends, cycle or systematic pattern) is determined.

As a result of checking data by the proposed network, the systematic patterns were found on three points (UR2, UK1, UK2) around the left locker of the underbody. Figure 7 shows the measurement locations of the three points with the run chart. Specifically, systematic pattern were detected on UK2 during $\{x_{150}, x_{151}, \ldots, x_{149}\}$ and others were classified as natural. Similarly, UK1 had systematic pattern during $\{x_{80}, x_{81}, \ldots, x_{226}\}$ and $\{x_{272}, x_{273}, \ldots, x_{419}\}$. In addition, systematic patterns were found on UK2 during $\{x_{143}, x_{144}, \ldots, x_{216}\}$ and $\{x_{258}, x_{259}, \ldots, x_{419}\}$.

From the knowledge base for non-random variation pattern described in the Section 3, a systematic variation pattern can be from assembly fixtures or locating holes in the assembly process. Thus, this pattern suggests that the possibility of variation came from in-part positioning. After investigation of the pallets, it was found that three holding pins on the pallet were worn out. They were replaced as a corrective action. After the corrective action, new 216 samples were collected at the same measurement locations and then checked by the proposed algorithm. The network classified the variation patterns for all three points as natural. Figure 8 shows run charts for the same measurement points after corrective action. Therefore, we conclude that all three points were in control.

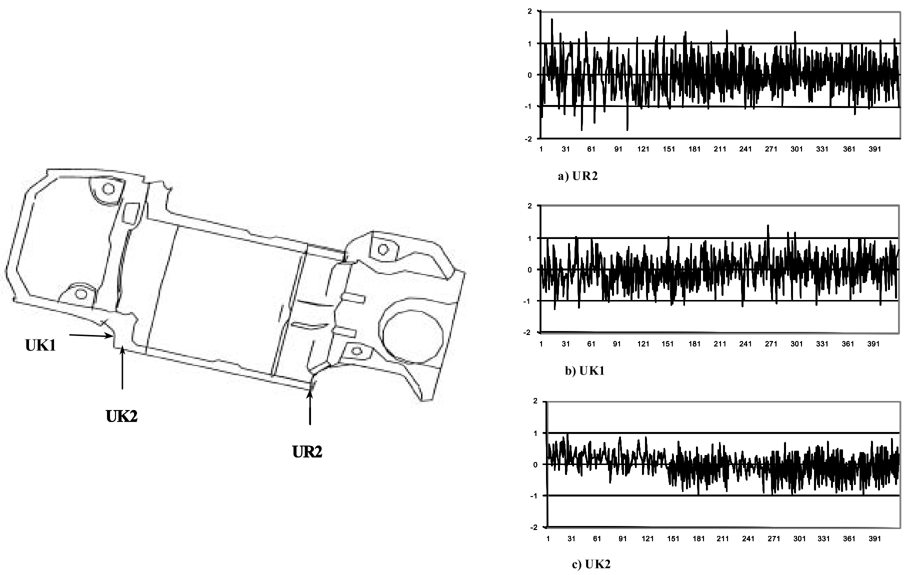

Figure 7. Location of three points detected systematic patterns.

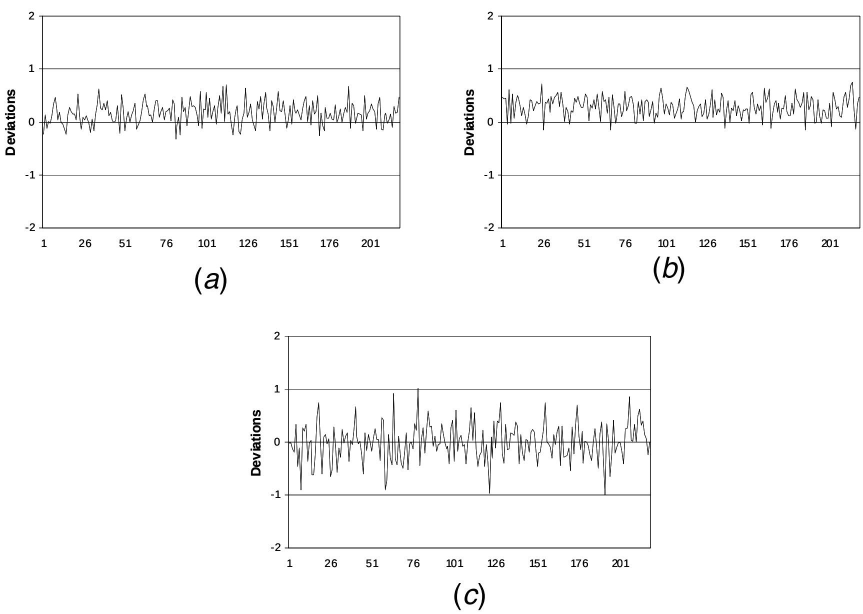

Figure 8. Run charts after corrective action: (*a*) UK1; (*b*) UK2; (*c*) UR2.

This case study shows clearly how the proposed neural network can detect and identify the predefined non-random variation pattern. Once these non-random patterns occur again on the run chart, the root causes of dimensional variations can be loaded systematically by investigating each possible cause based on the knowledge of the assembly process. Therefore, it can be expected that the run chart with this proposed pattern recognition algorithm will play a more important role as a systematic diagnosis tool rather than as a only statistical monitoring tool.

8. Summary and conclusion

A control chart pattern recognition methodologies based on the LVQ algorithms has been presented. To train the networks, a pattern generator was used to generate the dataset with various combinations of shape parameters and their performances were evaluated in terms of a classification test. An extensive evaluation indicates that the proposed algorithm will provide effective methodologies for monitoring non-random variation patterns to help in the correction of assignable causes.

The proposed pattern recognition algorithm integrated with the process knowledge basis was designed not only to detect variation patterns, but also to address the identification of unacceptable variation manifested by non-random, or unnatural, patterns on the run chart. With this approach, the process can be monitored by a computer-based pattern recognition algorithm without the need of human intervention. Once any non-random patterns occur on the control chart, the root causes of dimensional variations can be located systematically by investigating each possible cause based on the knowledge of the assembly process. This information will help to make process modifications that reduce dimensional variability for automotive body assembly process in real time. Therefore, it can be expected that the control chart with the proposed pattern recognition algorithm will play a more important role as a systematic diagnosis tool rather than only as a statistical monitoring tool.

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