DEVELOPING A MECHANISM FOR LEARNING IN ENGINEERING ENVIRONMENTS

Martin Ziarati, David Stockton, MIEE Osman Nuri Ucan

Dogus University/De Montfort University/Istanbul University

Abstract: The concept of learning has invariably been related to a classroom environment and/or industrial seminars, workshops, etc. The recent development in Artificial Intelligence, particularly in Neural Network applications offer interesting opportunities in developing continuous learning mechanisms for industrial applications in specific sectors. This paper gives information about neural models and an application example elucidating how a learning system can be developed for determining and forecasting parts quantities in a supply chain. If a continuous system can reliably predict numbers of parts required at the right time and at the right place, then the entire production schedule throughout the entire supply chain and within each organisation within it can be planned. All information flow routes and material flow paths can be optimised. The possibilities are very promising. The challenge, however, is as to how these learning systems can be validated and used with Computerised Enterprise Resource Planning (CERP) packages already used in industry

Keywords: Learning Systems, Artificial Neural Network (ANN), Material and Information flows in an organisation

Introduction

The existing Enterprise Resource Planning (ERP) packages such as SAP and Oracle do not have a learning mechanism. The example given in this paper offers an interesting opportunity to develop a learning system for these ERP packages hence leading to more reliable predictions and forecasts.

The problem of determining the required number of parts in a supplier chain system is well known. The Economic Order Quantity (EOQ) approach invariably is employed for prediction of required quantities by many businesses particularly supplier chains[1-3]. To find the 'exact' quantities, the EOQ approach is often complemented by a series of "rule of thumb" expressions. These rules are applied on a basis of the historical learning and hence to reduce the effect of the deficiency of the EOQ method.

The problem of deciding on a required number of parts are further complicated by seasonal variations. This paper offers an alternative approach to the EOQ approach by adopting a neural network model. The neural networks are primarily suited to identifying trends and patterns, particularly when there is a large amount of data. The predictive and forecasting ability of the neural network are of particular interest in parts supply and sales.

The down-side of these networks are the initial stage of application. Adequate data needs to be initially available for training of the network. Then the training phase needs to be followed by testing, verification and the latter two phases need to consider stability problems inherent in neural networks.

1. Neural Network – General

The neural models are basically based on the perceived work of the human brain. The artificial model of the brain is known as Artificial Neural Network (ANN) or simply Neural Networks (NN). Neural Networks are acquiring a surprising amount of human-like qualities. Their qualities and abilities can be seen in the following areas of interest:

- Pattern Recognition
- Knowledge poor environment functionality
- Decision making
- Learning

Neural Networks have been developed and used in many applications from recognising crowd levels to determining seasonal differences through to robots learning to walk and even systems being able to speak. Their ability to learn seemingly large amount of abstract data and to inter-relate different sets of information makes them ideal tools for application in many educational and industrial applications.

Generally, however, the ANN is a cellular information processing system designed and developed on the basis of the perceived notion of the human brain and its neural system. The network is composed of large numbers of neurons and their intra-and inter-connections[4-6].

1.1 The Biological Model

The brain is highly complex, non-linear and parallel information processing system. It has the capability to organise its structural constituents known as neurons so as to perform certain computations many times faster than the fastest digital computer in existence today. There exists more than 100 billion neurons of different types highly interconnected with each other via synapses of which there are more than a 150 billion.

Neurons are specialised cells that serve as the functional and structural units of our nervous system. The nervous system itself can be divided into two separate components: The central nervous system, which consists of the brain and spinal chord, and the peripheral nervous system, which connects the central nervous system with the rest of the body. In turn, the peripheral nervous can be broken down into different divisions, one of which is the sympathetic nervous system. Sympathetic neurons generally act without any conscious control and they participate in many of our physiological responses to stress. The increase in heart rate, sweaty palms, and churning stomach are the result of our sympathetic neurons.

The cell body contains the nucleus of the cell, a warehouse for manufacturing cell machinery. The dendrites radiate outward from the cell body and, in general, receive stimuli from external sources, including other neurons. Once the neuron is stimulated, an electrical impulse travels from the dendrites to the cell body and finally into the axon. The axon propagates the impulse to the synaptic terminal and stimulates the release of chemicals called neuro-transmitters. These chemicals can stimulate the dendrites of surrounding neurons if the cellular body accumulates enough electrical potential to overcome a certain threshold, the action potential, and if they do so, the cycle is renewed in the neuron's neighbours. The influence of one neuron and on another changes by changing the effectiveness of the synapses and so that learning occurs. Also note that the rapid, efficient propagation of electrical and chemical impulses is the distinctive characteristic of neurons and the nervous system in general. It generates memories, emotions, and imagination.

1.2.Artificial Neural Network

The neurons operate collectively and simultaneously on most for all data and inputs, which performs as summing and non-linear mapping junctions. In some cases they can be considered as threshold units that fire when total input exceeds certain bias level. Neurons usually operate in parallel and are configured in regular architectures. They are often organised in layers, and feedback connections both within the layer and toward adjacent layers are allowed. Each connection strength is expressed by a numerical value called a weight which can be modified to find an optimum solution. Also they are characterised by their time domain behaviour which is often referred as dynamics.

In general, the neuron could be modelled as a non-linear activated function of which the total potential inputs into synaptic weights are applied[4]. It is assumed that synapses can impose excitation or inhibition but not both on the receptive neuron. Also axons are modelled as transmission lines and dendrites are the receptive zones and the synapses are elementary structural and functional units that mediate the interaction between neurons. From the biological view, the artificial model of neuron should consist of three elements as stated below and shown in Figure 1.

1. A set of synapses or connection links, each of which is characterised by a weight or strength of its own. Specially, a signal x_j at the input of synapse *j* connected to neuron *k* is multiplied by the synaptic weight w_{kj}. Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values.

2. An adder for summing the input signals, weighted by the respective synapses of the neuron.

3. Activation function or transfer function for limiting the amplitude of the output of a neuron.

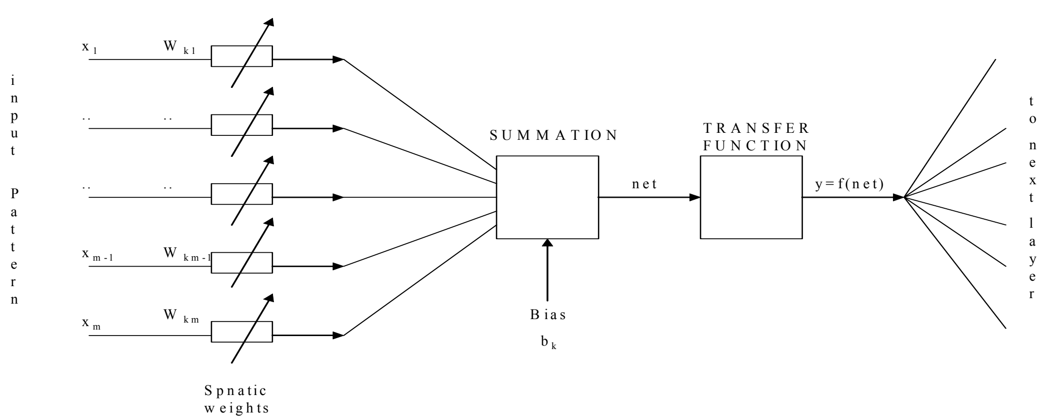

Figure 1. General Block Diagram of a Neuron

The neuron model could also include an externally applied bias, denoted by b_k. The bias b_k has the effect of increasing or lowering the net input of the activation function depending on whether it is positive or negative, respectively. Where $x_1, \ldots, x_m$ are the input signals; $w_{k1}, \ldots w_{km}$ are the synaptic weights of neuron *k*. The activation function, denoted by f(net), defines the output of a neuron which considerably influences the behaviour of the network. Three basic types of activation function are shown in Figure 2.

Mathematically, the neuron *k* can be defined by the following equations:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1}$$

$$net = u_k + b_k \tag{2}$$

$$y_k = f(net) \tag{3}$$

where $x_1, \ldots, x_m$ are the input signals; $w_{k1}, \ldots w_{km}$ are the synaptic weights of neuron *k.* The activation function, denoted by f(net) defines the output of a neuron which considerably influences the behaviour of the network. Three basic types of activation function are given below:

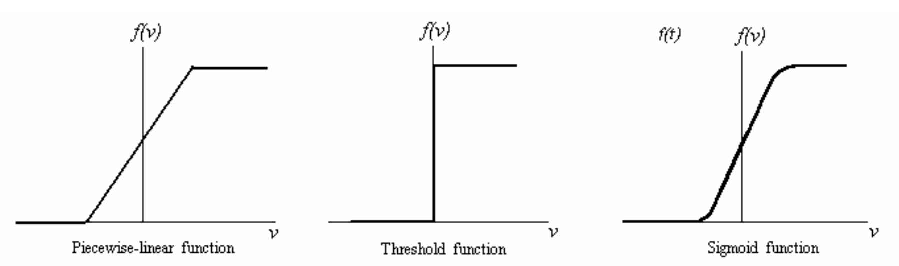

Figure 2. Activation Functions

Piecewise-linear function:

$$f(v) = \begin{cases} 1 & v \geq \frac{1}{2} \\ v & \frac{1}{2} > v > -\frac{1}{2} \\ 0 & v \leq -\frac{1}{2} \end{cases} \tag{4}$$

Threshold function:

$$f(v) = \begin{cases} 1 & \text{if} \quad v \geq 0 \\ 0 & \text{if} \quad v < 0 \end{cases} \tag{5}$$

Sigmoid function:

$$f(v) = \frac{1}{1 + \exp(-av)} \qquad (6)$$

where a is the slope parameter of the sigmoid function.

2. Application of ANN in Forecasting

In this paper, demand is forecasted for a real supply chain problem using an ANN approach. The data gathered on the purchases by six motor car dealers from a 'parts' supplier during a given period was used as input to the artificial neural network described above. Under consideration were 69 different parts supplied to 6 dealers at different time periods and quantities. The ordering of parts by dealers were arbitrary and were based on previous trends in demand for a given part or immediate request from a customer. It has been difficult for the parts supplier to establish a 'just in time' approach and often their existing 'just in case' method had lead to excessive parts being stored in their central and regional warehouses.

The objective of the current investigation is not to concentrate on the nuts and bolts of how companies in a parts supply chain operate, but to investigate the applicability of ANN in forecasting auto part requirements within the chain. It is also of interest to see if a just-in-time approach can be established between the parts supplier and the dealers on the one hand and the dealers and their customers on the other. Such an approach will lead to the timely manufacture and delivery of parts to the parts suppliers.

In this paper a Back Propagation Artificial Neural Network algorithm has been employed. Our structure has 69 input layers, corresponding to all possible input item numbers of the supplier chain. There are 71 hidden layers and 69 outputs (Figure 3). Generally hidden neuron number is chosen greater than input neuron number.

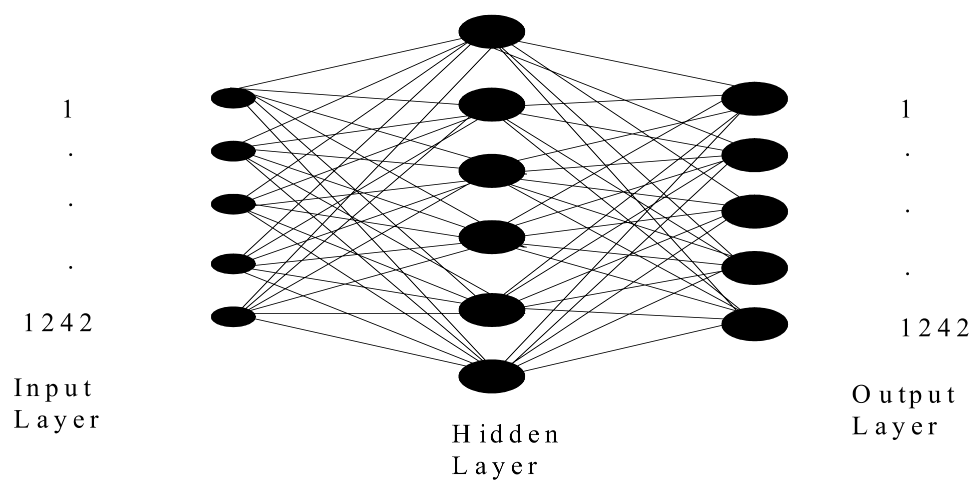

Figure 3. The proposed ANN model for the forecasting problem.

Since the research work reported here is based on forecasting problems of a real supplier chain, the number of the input and output neurons are the same. The Equations (1-6) have been used assuring that car dealers sell 69 different items, each corresponding to a given part. The data for the first two periods (3-weeks each) were used to train the ANN system. After reaching desired training (squared sum of error value of 20.77), the model has been used to find future requirements using weight coefficients computed by the ANN model (Figure 4). To solve our optimisation problem, sum squared error is calculated where all pixel values of output and target matrix are substracted and squared. Thereby, a global parameter can be evaluated

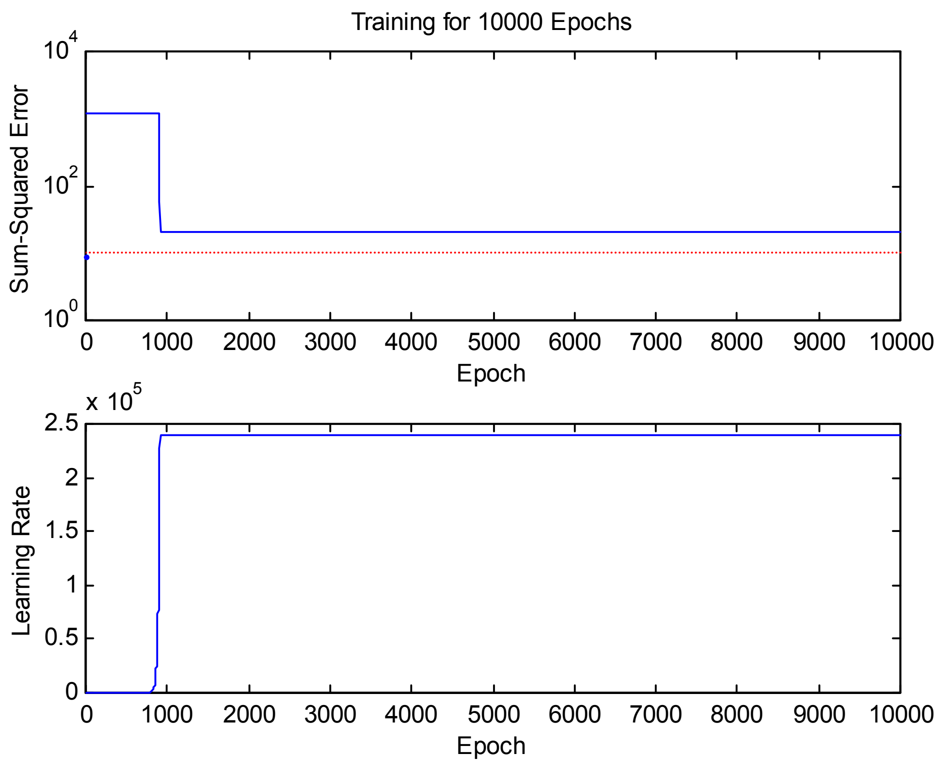

Figure 4. Sum-Squared Error and Learning Rate during training procedure of the ANN model for forecasting problem.

After training procedure is finished with satisfactory results as shown in Figure 4, the following 3-week data were used as input and forecast the forecoming data. As shown in Figure 5 shows without any training and and thus working in real time, a satisfactory squared sum of error of 19.97 can be found. Thus it can be concluded that the ANN model is a good learning mechanism for forecasting parts requirements in a given supplier chain.

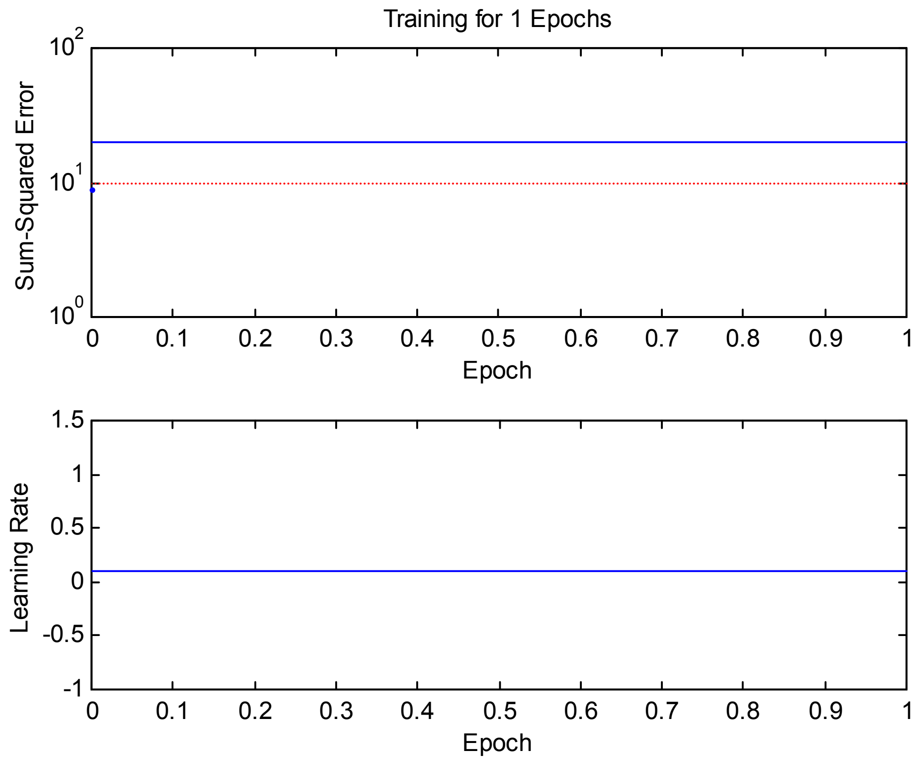

Figure 5. Sum-Squared Error and Learning Rate for real data

3. Conclusion

In this paper, a Back Propagation-Artificial Neural Network model has been developed as a learning mechanism initially to optimise component quantities and the movement of associated materials. The ability of neural models to learn, particularly their capability of handling large amounts of data simultaneously as well as their fast response time, are invariably the characteristics desired for developing learning systems for applications in industry.

The model was tested using actual data in a given supplier chain. The predictions as shown are very promising. The model can easily be adapted to have far larger inputs.

Neural networks are generally applied where there is insufficient information and expert systems have applications in areas where there is a great deal of information. The system proposed in this paper could form the basis for development of expert systems in information poor areas.

The neural network model in this paper is based on a threshold concept working in a similar way to a transistor in a computer hence the concept of learning offered here has a potential in applications where conventional computation techniques have already made an inroad.

It is also feasible to consider other forms of Neural Networks. The authors are investigating ways in which specific aspects of genetics and cellular structure concepts can be incorporated; initial outcomes are very promising[7].

4. Bibliography

1. Ziarati, M. “Improving the Supply Chain in the Automotive Industry Using Kaizen Engineering” MPhil transfer report, De Montfort University, UK, 2000

2. Stockton, D.T., Quinn, L. “Identifying Economic Order Quantities Using Genetic Algorithms” International Journal of Operations and Production Management, V3, 11, 1993

3. Ziarati, M., Ucan, O.N. “Optimisation Of Economic Order Quantity Using Neural Networks Approach”, Dogus University Journal Number, Number 3, 128-140, 2001

4. Haykin, S. “Neural Networks”, John Wiley Pub., 1998.

5. Bose, N.K., Liang, P. “Neural Network Fundamentals with Graphs, Algorithms, and Applications”, McGraw Hill, 1996.

6. Wang, Q. “Improving the Cost Model Development Process Using Neural Networks”, Thesis, De Monfort University, November 2000

7. Ziarati, M. “Design and Development of Material and Information Flow for Supply Chains using Genetic Cellular Neural Network”, Dogus University Journal Number, Number 5, 2002

Biography

Martin Ziarati was born in the city of Bath, UK and before entering University was given a Year In Industry Award. He graduated from Nottingham Trent University in 1995 and obtained an honours degree in Business Economics. He commenced his work for Birmingham Manufacturing Centre in 1996 sponsored by the European Union and published his report on competitiveness in September 1997. In 1997 he was appointed as a researcher at Dogus and later as a Specialist in the Computer Engineering Department. He concluded his Mphil studies at De Montfort University and currently is studying for a PhD at the same university.

Professor Stockton is the Director of the Centre of Lean Engineering at De Montfort University, UK and leads a flourishing research group which conducts high quality fundamental and applied research, within the disciplines of manufacturing engineering & operations management, that is innovative and relevant to the needs of global manufacturing industry. His current research interests are in the areas of value stream design, lean engineering, cost engineering and the design and operation of multi-component flexible manpower lines.

Osman Nuri Uçan was born in Kars in January, 1960. He received the B.S.E.E., M.S.E.E. and PhD. degrees in Electronics and Communication Engineering Department from the Istanbul Technical University (ITU) in 1985,1988 and 1995 respectively. During 1986-1997 he worked as a research assistant in the same university. In 1996 he became technical coordinator at an important Turkish firm. He also worked as supervisor at TUBITAK-Marmara Research Center in 1998. He is now associate Professor and Vice President of Electrical & Electronics Engineering Department of Istanbul University (IU), Head of Telecommunications Division . He is computer network director of Avcilar campus of IU. He is organization committee member of "IEEE Signal Processing and Applications Conference (SIU 2000), chief editor of "International Conference on Electronics and Earth Sciences (ICEES)", Technical committee chairman of “Turkish Artificial Intelligence and Neural

Network Conference (TAINN)". He is member of "Publications and Science Committee" of IU and editor in chief of Istanbul University-Journal of Electrical & Electronics.
His current research areas include: information theory, jitter analysis of modulated signals, channel modelling, cellular neural network systems, random neural networks, wavelet, turbo coding, space-time coding and Markov Random Fields applications on real geophysics data, satellite based 2-D data, biomedical and underwater image processing.