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Artificial Neural Networks' Applications in Management

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Abstract: Finding more effective solution and tools for complicated managerial problems is one of the most important and dominant subjects in management studies. With the advancement of computer and communication technology, the tools that are using for management decisions have undergone a massive change. Artificial Neural Networks (ANNs) are one of these tools that have become a critical component of business intelligence. In this article we describe the basic of neural networks as well as a review of selected works done in application of ANNs in management sciences.

Key words: Artificial Neural Networks · Networks' Applications · Management · Marketing

INTRODUCTION

Artificial Neural Networks (ANNs) are distributed information-processing systems and powerful general-purpose software tools, composed of many simple computational elements interacting across weighted connections. Inspired by the architecture of the human brain, ANNs exhibit certain features such as the ability to learn complex patterns of information and generalize the learned information [1] and are used for a number of data analysis tasks such as prediction, classification and clustering. They are based on abstract simplified models of neural connections.

Simulated artificial neural networks (also referred to as parallel distribute processing models, adaptive systems, connectivity models, or simply neural networks) seek to simulate the human brain structure, human thinking and human learning in a machine. They are computer-based representations of mathematical models that are composed of a large number of simple, highly interconnected units, called processing elements [2].

In structure, a neural network is made up of many processing nodes called neurons, which accept values from other neurons through input arcs. The neurons process these inputs using a transfer function and then release the output to other neurons using output arcs [3].

General Introduction to Neural Networks: An ANN consists of many single processors, which interact through a dense web of interconnections. A neuron or processing element (PE) has primarily two things to do. One is that it computes output, which is sent to the other PE's or outside the network. The neuron or PE determines its output value by applying a transfer function. Secondly, it updates a local memory, i.e. weights and other types of data called data variables. The neurons are organized into layers. The first layer is called the input layer and the last layer is the output layer. The inner layers, one or more, are known as hidden layers. The input neurons receive input values from outside the ANN's environment, whereas the output neurons send their output values there. A hidden or an output neuron receives input signals from the incoming connections and values from its local memory. Figure 1 illustrates a neuron and a typical neural network.

Neural Networks Can Be Used To:

- learn to predict future events based on the patterns that have been observed in the historical training data;
- learn to classify unseen data into pre-defined groups based on characteristics observed in the training data;

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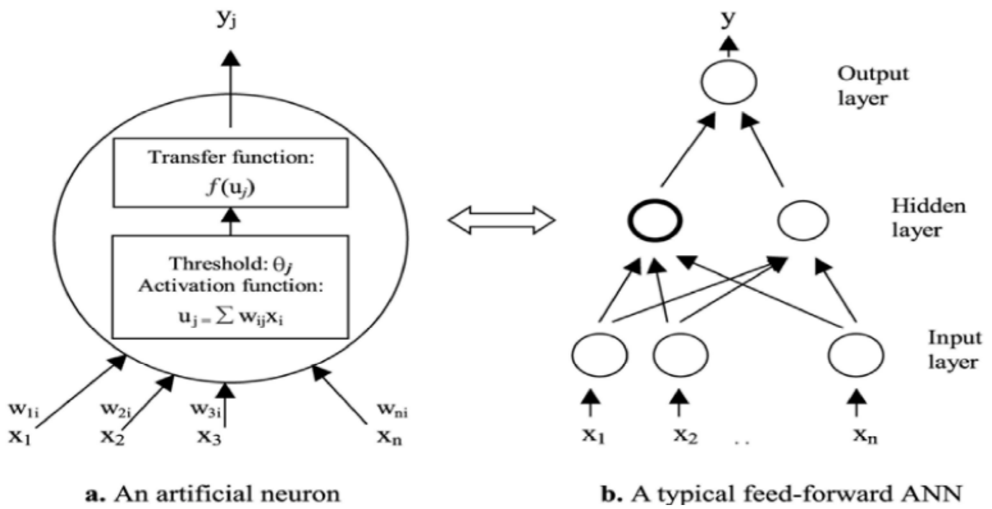

Fig. 1: A Neuron and Artificial Neural Network

- learn to cluster the training data into natural groups based on the similarity of characteristics in the training data [4].

Based on the connection method among the neurons and the different information directions in the network, neural network model can be divided into two kinds. Firstly, feed forward neural networks that have only forward information transfer but no feedback information. Second one is a feedback neural network that has not only forward transfer of information but also reverse transfer (feedback) information [5].

In general, feed forward neural networks are made up of one input layer, hidden layers and one output layer. The neurons of each layer only accept output information coming from the neurons of the forward layer. In a feed forward network, information always moves one direction and never goes backwards.

According to Simon Haykin (2009), there are three fundamentally different classes of network architectures: single-layer feed forward networks, multilayer feed forward networks and recurrent networks. In the simplest form of a layered network, it consists of a single layer of output nodes and the inputs are fed directly to the outputs via a series of weights. Such a network is called a single layer network as shown in figure 2.

The second class of feed forward neural network distinguishes itself by the presence of one or more hidden layers as shown in figure 3. By adding one or more hidden layers, the network is enabled to extract higher order statistics from its output. The function of hidden neuron is to intervene between the external input and the network output in some useful manner. In a multilayer feed forward networks, “fully connected” means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. Feed forward means that the values only move from input to hidden to output layers. No values are feed back to earlier layers. All neural networks have an input layer and an output layer but the number of hidden layers may vary.

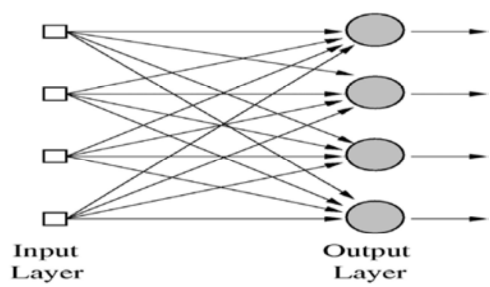

Fig. 2: Feed forward network with a single layer

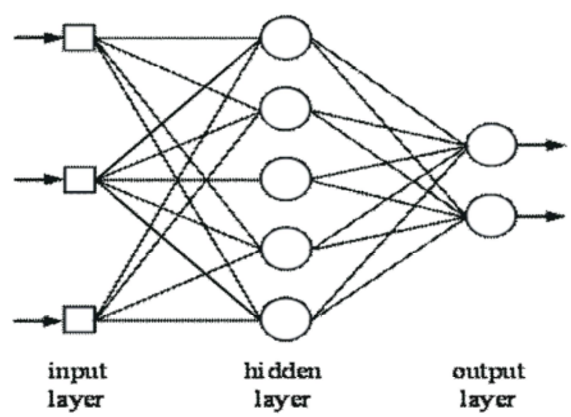

Fig. 3: Multilayer feed forward network

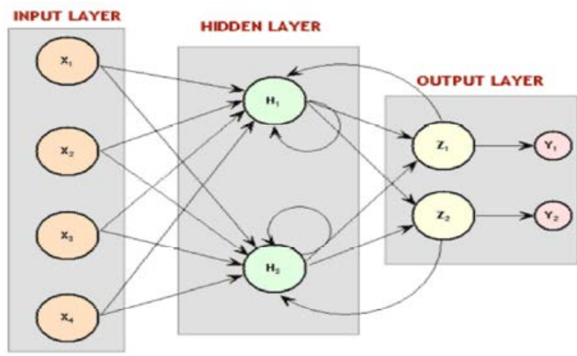

Fig. 4: Recurrent network

The structures, in which connections to the neurons of the same layer or the previous layers are allowed, are called recurrent networks. Recurrent network distinguishes itself from a feed forward neural network by at least one feedback loop (Figure 4). A recurrent network is a class of neural network where connections between units form a directed cycle. This creates an internal state of the network which allows it to exhibit dynamic temporal behaviour. Unlike the feed forward networks, recurrent network can use their internal memory to process arbitrary sequences of inputs.

Another important definition in the specification of an ANN is its learning algorithm. Learning algorithms are closely related with neural architectures. The "Delta" learning algorithm, used to train the single-layer "Perceptron", cannot be applied to a network with one or more hidden layers. The "perceptron" is considered the simplest kind of feed-forward neural network and it is an arrangement of one input layer neurons feeding forward to one output layer of neurons.

For feed forward networks the most common learning algorithm is the back-propagation (BP) algorithm (Figure 5), a method of training artificial neural networks how to perform a given task [6].

Methods used to "train" neural networks for learning are usually divided into two classes: unsupervised and supervised. With unsupervised training models, the training set consists of input vectors only and the outputs are determined by the networks during the course of the training. On the other hand, for supervised neural networks, after the inputs are applied, the desired responses of the system are provided and the networks are "rewarded" for accurate classifications and associations or are "punished" for yielding inaccurate responses [7].

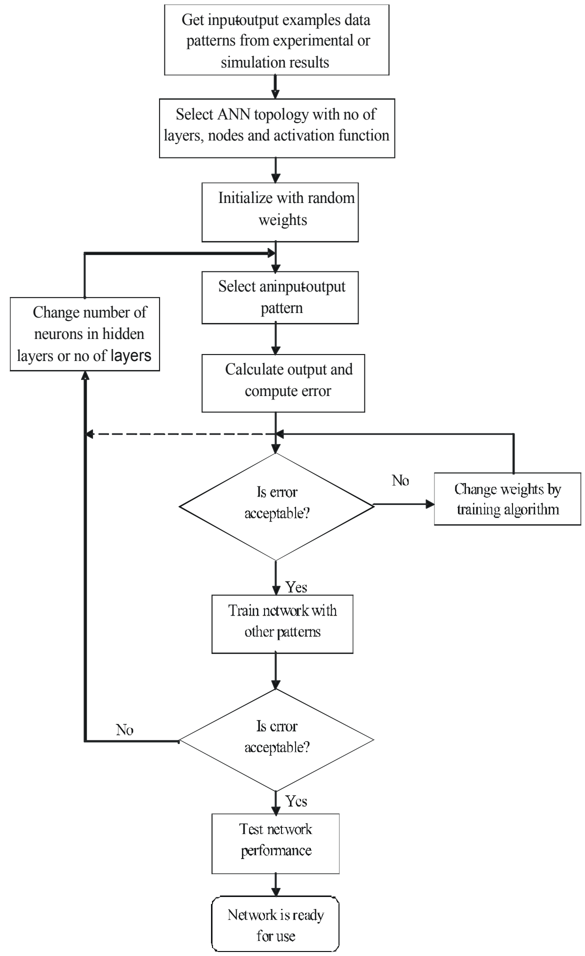

Fig. 5: The Back Propagation (BP) Algorithm

Reported Applications of Artificial Neural Networks: At present there are probably about 30 different families of ANN being used in research and/or applications as a whole [8]. This diversity makes it very difficult to evaluate alternative ANN, the more since up to now no standard reporting scheme has emerged [9]. So we try to present the general applications of ANNs in management sciences. We apply a classification by business disciplines and arrive at a subdivision into the areas of marketing, finance, manufacturing and strategic management.

ANN Applied Within the Field of Marketing: ANN can be applied to many marketing decision making problems which could be tackled previously by multivariate statistical analysis only. Typical problems turn out to be market segmentation tasks and more dominantly market response modelling, classification of consumer spending patterns; new product analysis; identification of customer characteristics; sale forecasts, targeted marketing; and modelling the relationship between market orientation and performance.

Most of cited papers explicitly compare ANN-approaches to traditional methods including primarily discriminante analysis for classification tasks and estimations of market response functions by multiple regression analysis. The most crucial point for research activities in the field of marketing is the lack of applications on the individual level data. These kinds of problems are encountered in the context of purchase decision modelling and should lead to ANN representations of purchase behaviour in the tradition of stochastic models of consumer behaviour [9]. Table indicates some of selected researches that have used ANN in marketing and sales area.

ANNs Applied Within the Field of Finance: ANNs are now frequently used in many modelling and forecasting problems, mainly thanks to the possibility of the use of computer intensive methods. Recently, they have been increasingly applied in financial time series analysis as well [45]. The main advantage of this tool is the ability to approximate almost any nonlinear function arbitrarily close. Particularly in financial time series with complex nonlinear dynamical relationships, the ANN can provide a better fit compared with parametric linear models. On the other hand, usually it is difficult to interpret the meaning of parameters and ANNs are often treated as "black box" models constructed for the pattern recognition and prediction. Further, excellent in-sample fit does not guarantee satisfactory out-of-sample forecasting [46].

The essential topics in finance are forecasts of changes in the value of financial assets under the form of stocks, indices and currencies (i.e., forecasting) and analysis of strength of historical (or pro forma) financial statements (i.e., classification). Table 2 presents some of the selected studies on recent applications in finance.

ANN Applied Within the Field of Manufacturing and Production: According to Krycha and Wagner [9], Forecasting (production costs, delivery dates, etc.), quality control and optimization predominate in production problems. As quality control problems correspond to classification, the appropriateness of ANN-approaches is supposed to be as good as in the respective studies in the fields of marketing and finance. Table 3 shows some selected studies on application of ANN in manufacturing and production fields.

ANN Applied Within the Field of Strategic Management and Business Policy: The empirical research in strategic planning systems has focused on two areas: the impact of strategic planning on firm performance and the role of strategic planning in strategic decision making [110].

Table 1: Reported Application of ANNs in Marketing and Sales

Business Area	Problem type	reference
Marketing and Sales	Forecasting costumer respond	[10-12]
	Market development forecasting	[13]
	Sales forecasting	[14-19]
	Price elasticity modelling	[20]
	Target marketing	[15, 21-22]
	Customer satisfaction assessment	[23]
	Customer loyalty and retention	[24-26]
	Market segmentation	[27-30]
	Customer behaviour analysis	[31-32]
	Brand analysis	[27, 33]
	Market basket analysis	[34]
	Storage layout	[35]
	Customer gender analysis	[36]
	Market orientation and performance	[6]
	Marketing strategies, strategic planning and performance	[3, 37-39]
	Marketing data mining	[40]
	Marketing margin estimation	[41]
	New product acceptance research	[42]
	Consumer choice prediction	[43]
	Market share forecasting	[44]

Table 2: Reported Application of ANNs in Finance and Accounting

Business Area	Problem type	Reference
Finance and Accounting	Financial health prediction	[3, 47-49]
	Compensation assessment	[50-51]
	Bankruptcy classification	[52-57]
	Analytical review process	[58-59]
	Credit scoring	[60-62]
	Signature verification	[48, 63]
	Risk assessment	[64]
	Forecasting	[65-66]
	Stock trend classification	[67-69]
	Bond rating	[70-71]
	Interest rate structure analysis	[72]
	Mutual found selection	[73]
	Compensation assessment	[50-51]
	Credit evaluation	[74-79]

Table 3: Reported Application of ANNs in manufacturing and production

Business Area	Problem type	Reference
Manufacturing and production	Engineering design	[80-84]
	Quality control	[85-89]
	Storage design	[35]
	Inventory control	[90-92]
	Supply chain management	[93-95]
	Demand forecasting	[96-100]
	Monitoring and diagnosis	[101-105]
	Process selection	[80,106-109]

Table 4: Reported Application of ANNs in Strategic management and business policy

Business Area	Problem type	Reference
Strategic management and business policy	Strategic planning and performance	[3, 37, 39, 111-114]
	Assessing decision making	[114-120]
	Evaluating strategies	[7, 121-122]

Neural networks as efficient tool have utilized for determining and clarifying the relationship between strategic planning and performance and also assessing the decision making. Table 4 shows some of selected reported studies in these areas.

Advantages: We can say that neural network approaches differ from traditional statistical techniques in many ways and the differences can be exploited by the application developer. They are powerful alternative tools and a complement to statistical techniques when data are multivariate with a high degree of interdependence between factors, when the data are noisy or incomplete, or when many hypotheses are to be pursued and high computational rates are required.

With their unique features, both methods together can lead to a powerful decision-making tool. Studies and investigations are being made to enhance the applications of ANNs and to achieve the benefits of this new technology [123]. Most frequently quoted advantages of the application of neural networks are:

- Neural network models can provide highly accurate results in comparison with regression models.
- Neural network models are able to learn any complex non-linear mapping / approximate any continuous function and can handle nonlinearities implicitly and directly.
- The significance and accuracy of neural network models can be assessed using the traditional statistical measures of mean squared error and $R2$.
- Neural network models automatically handle variable interactions if they exist [2].
- Neural networks as non-parametric methods do not make a prior assumptions about the distribution of the data/input-output mapping function.
- Neural networks are very flexible with respect to incomplete, missing and noisy data/ NNs are fault tolerant.
- Neural networks models can be easily updated. It means they are suitable for dynamic environment.

- Artificial neural networks overcome some limitations of other statistical methods, while generalizing them [28].
- ANNs have associative ability. That is, once developed, an ANN is generally robust to missing or inaccurate data.
- The multicollinearity does not impact on the ANN's performance as it does on the performance of least-squares regression.
- ANN is a reliable tool for predicting the determinants of relationship quality.[124].

Disadvantages: Limitations of neural networks distinguish them from statistical techniques. For instance, formulae have been developed to determine the sample size for a given desired accuracy in statistical techniques. But there is no hard-and-fast rule in determining the sample size for training neural networks. A sample of larger size would lead to high accuracy, whereas a smaller sample would lead to low accuracy. When there is a severe constraint on sample size, it is suggested that one should increase the number of "epochs" (iterations) to improve efficiency. Likewise, other limitations of neural networks are the lack of explanation qualities and lack of a formal method to decide the network configuration for a given task [123].

- No method has yet been devised to determine the significance of independent variables (inputs) in a neural network directly.

- It is difficult to state the results in a simple precise analytical model statement, Further, neural network weights cannot be interpreted in the same manner as regression coefficients. In a way, the weights indicate the "importance" of an input, but complex interactions in the hidden layers make such an analysis difficult, if not impossible.
- It is difficult to determine when the best solution has been found. Although there are techniques for avoiding local minima, there is no assurance that the best parameters for defining a neural network have been found. Although the three-and four-layer neural network models described in this research predict better than the regression model, even better solutions may exist, however, all complex nonlinear models have this problem.
- Model selection and training is still an art; not a science. Because neural networks are much more complex than ordinary least-squares regression, which is solved analytically and directly, neural network architecture, training algorithms and other parameters must be determined through experimentation. However, by following a careful, methodological approach to network design, one can be confident that a good, if not the best, model configuration can be found.
- If the environment changes, then the neural network must be reconstructed and retrained. However, any model developed to describe a situation in a dynamic environment suffers in this regard.
- Neural networks learning process can be very time consuming.

Comparison: The ability of neural networks to identify patterns in the data could be utilized in market research, especially in areas which were once reserved for multivariate statistical analysis. For this reason, neural networks are often considered to be statistical methods [1].The neural network models exhibited better performance in terms of both mean squared error and $R2$ than the regression model [2].

It was decided for several reasons that a neural network analysis, rather than a more complex non-linear multivariate analysis, would now be the best way to proceed. Firstly, the input data was judgmental rather than factual, so there was some "fuzziness" in the data-the numbers used in the analysis was indicators of feelings or perceptions rather than exact observed values. It was more important to look for overall patterns in the data than to try to formulate equations relating inputs to outputs. Secondly, there was a high degree of correlation between the different inputs-this does not impact on the performance of neural network or the validity of its results as it would on a regression analysis [124].

Finally, the use of a neural network allows the labeling of hidden layer nodes-thus conjunctions of factors contributing to each hidden node could be examined to see if they indicated an underlying management philosophy which would impact either positively or negatively on performance [38].

CONCLUSION

In this paper we have tried to survey most reported works in the area of applications of ANN to different problems in Management Science. Although still regarded as a novel methodology, neural networks are shown to have matured to the point of offering real practical benefits in many of their applications. But there is a clear deficit of more complete work describing neural net models; in particular nearly all quoted papers lack documentation of the applied ANN. Replication of these studies under diverse conditions, in order to validate them, must be encouraged and the application of new "generations" of neural network models is set to provide a sound statistical background to reinforce their performance and overcome some of their frequently drawbacks.

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