Artificial Neural Networks in Auditing: State of the Art

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Abstract

Very many things in our business and auditing environment are changing at an increasing rate. One central theme in auditing is how information technology developments affect the nature of the audit process and the audit skills. Auditors have to ask how to operate in new environments. New information technology support systems for monitoring and controlling operations could be useful. Artificial neural network (ANN) based information systems are proposed as one possible solution as a support tool for auditors. This article introduces the ANN technology and reviews the literature on auditing ANN applications. The review showed that the main application areas in auditing were material errors, management fraud, and support for going concern decision. ANNs have also been applied to internal control risk assessment, audit fee, and financial distress problems. In addition the paper summarises modeling issues of the ANN applications pertaining to auditing problems. Finally, the paper outlines possible tasks were ANN based support systems could be used within auditing.

Keywords: analytical auditing, artificial neural networks

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1. Introduction

Very many things in our business and auditing environment are changing at an increasing rate. Increased competition and the need for faster and better information for decisions mark today’s business environment. In addition, systems are complex and many times on-line. This complexity means that auditors have more and different kinds of work to do than they had earlier. For example, a new dimension in today’s auditing is that a large amount of audit material, e.g. receipts and accounting records, is increasingly displayed only in electronic form. Naturally, this kind of information also has to be audited. Another dimension is that auditors are living in the "expectation gap". This means that their work is regulated to the past in the auditing law and at the same time quite a few interested parties are looking forward to see how the audited company is going to survive in the future. This "expectation gap" is one of the most popular reported auditing topics in the annual congresses of the European Accounting Association 1992-1998 (Pirinen 1998).

The American Institute of Certified Public Accountants (AICPA) Committee has outlined one possible future of financial statement audit (AICPA 2001). AICPA believes that major changes are currently underway involving both the kinds of information with which auditors are involved and the nature of that involvement. They describe this as a shift from an old audit paradigm to a new audit paradigm. This shift is also known as a transformation from audit to assurance. Assurance services are defined by AICPA as "independent professional services that improve the quality or context of information for decision-makers". Furthermore, companies are reporting their financial outcome quarterly and more and more companies are moving their financial information on to a public network. Sometimes the speed at which these reports are made makes one wonder whether all the relevant information is audited and reliable. The complexity of systems, quality and context of information, and speed of reporting are some reasons why auditors need more, or maybe different kinds of, support systems. At the same time as the development of information technology makes the audit environment more complex it provides auditors with new methods and tools to cope with their work (Ratzaee and Reinstein 1998, Bierstaker et al. 2001). The adaptation of new tools may create a competitive advantage for auditors and auditing firms. Figure 1 illustrates the expanding audit environment.

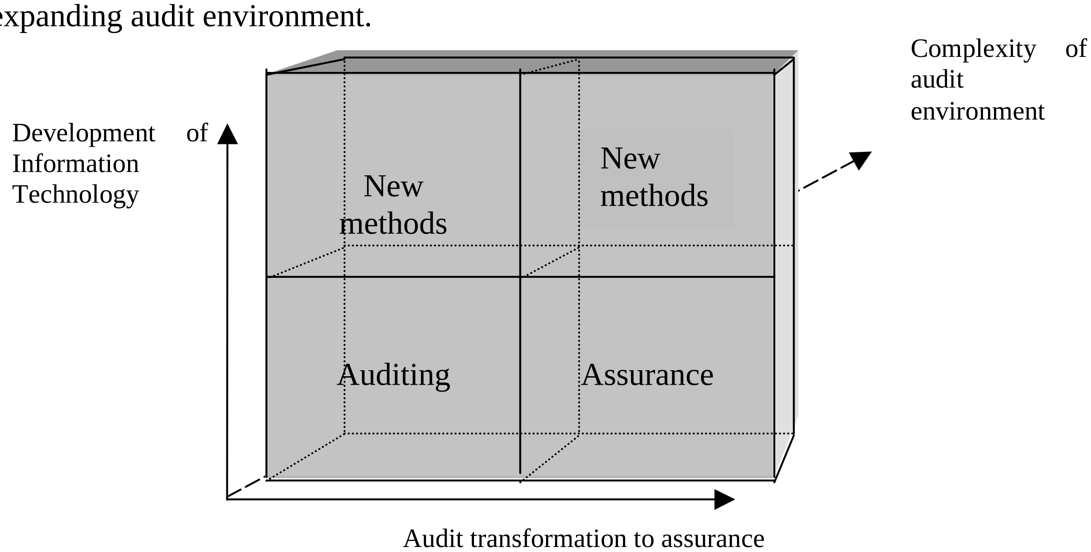


Figure 1: Expanding audit environment

The bottom left corner in Figure 1 illustrates traditional auditing which is defined in the auditing law. The bottom right corner illustrates auditing as an assurance service. The upper corners illustrate the situations where auditors use new information technology methods and tools to support their work. This paper falls in these upper corners by proposing artificial neural network (ANN) based information systems as possible support tools for monitoring and controlling operations in auditing.

Toiviainen (1991) has developed four stages of information technology utilisation in auditing. Table 1 presents these stages. At stage one standard off-the shelf software applications are used. At stage two some databases, e-mail, and graphics are also adapted. At stage three several different external and internal databases, audit software applications and company models are in use. At stage four expert systems, decision support systems and special audit software for continuous auditing are utilised. ANN-based support tools fit into stage four or possibly into the next stage. At this, the fifth stage the software applications are advanced methods like ANN-based systems and the utilisation is assurance services.

Table 1: The five stages in development of utilisation of IT
(Source: Modified from Toiviainen 1991)

STAGE	SOFTWARE APPLICATION	UTILIZATION
I	word-processing, spreadsheets	Documentation, auditor's report, financial analysis and calculations
II	graphics, external databases, electronic mail	Audit planning, comparison of financial information, company analysis
III	company models, audit databases, IS audit software applications	Testing of information systems, database inquires
IV	expert systems, decision support systems, special software for continuous audit	Expert analysis for finding important tasks for audit
V	Advanced method, ANN-based systems	Assurance services

The utilisation stage of information technology varies among auditors and auditing firms. Tiittanen (1998) investigated Finnish auditing firms in 1997 and found that many small auditing firms were at the first stage and big auditing firms were at the second or at the third stage and only very few were at the fourth stage. However, Toiviainen (1999) reported one year later in a study conducted in 1998 among both internal and external auditors in auditing firms, public administration, finance and insurance, services and commerce, and industry on the use of Computer Assisted Audit Tools (CAATs) in Finland. Now 23 of 50 or more than half of the auditors answered that they used at least one support tool specialised in auditing (stages III and IV). ACL (Audit Command Language) and IDEA (Interactive Data Extractions and Analysis) were market leaders among CAATs in the PC-environment. It seems that internal auditors use CAATs more than external auditors. The statement of Glower and Romney (1998), who in 1998 made a survey among internal auditors from Switzerland, Canada, the Philippines, Thailand, Malaysia, Spain, South Africa, and the United States, strengthened this conclusion. They said technology has become an integral part of internal auditing. One explanation for this might be that because internal auditors are inside the company they have deeper knowledge of the organisation and therefore they may utilise CAATs more effectively. Glower and Romney (1998) stated that a relative large percentage of auditors have not adopted the support tools specialised in auditing. However, according to them the use of audit software is likely to become increasingly widespread among external auditors as the use of advanced information systems becomes more prevalent among their clients. Glower and Romney (1998) classified the utilisation of information technology in auditing slightly differently than Toiviainen. They categorised software packages into five groups according to audit areas: 1) data extraction and analysis, 2) fraud detection, 3) internal control evaluation, 4) electronic commerce control, 5) continuous monitoring.

This paper focuses on the ANN-based support systems as a possible future tool in auditing. ANNs have been considered one of the emerging technologies in this millennium (Halal et al. 1998). ANNs have already been applied and have proven their usefulness in many different business areas (Wong et al. 1995, Wong and Selvi 1998, O'Leary 1998, Zhang, Patuwo et al. 1998, Vellido et al. 1999, Coakley and Brown 2000). Moreover, Hill et al. (1996) observed that neural networks did significantly better than traditional statistical and human judgement methods when forecasting quarterly and monthly data in financial time-series. ANNs are suitable for tasks that require prediction, control, and classification capabilities. ANNs can learn, remember, and compare complex patterns. Moreover, ANNs are able to recognise patterns in data even when the data are noisy, ambiguous, distorted, or variable. Furthermore, ANNs continue to perform well even with missing or incomplete data, and they are capable of discovering data relationships. These features make ANNs suitable for many decisions, which require auditing expertise.

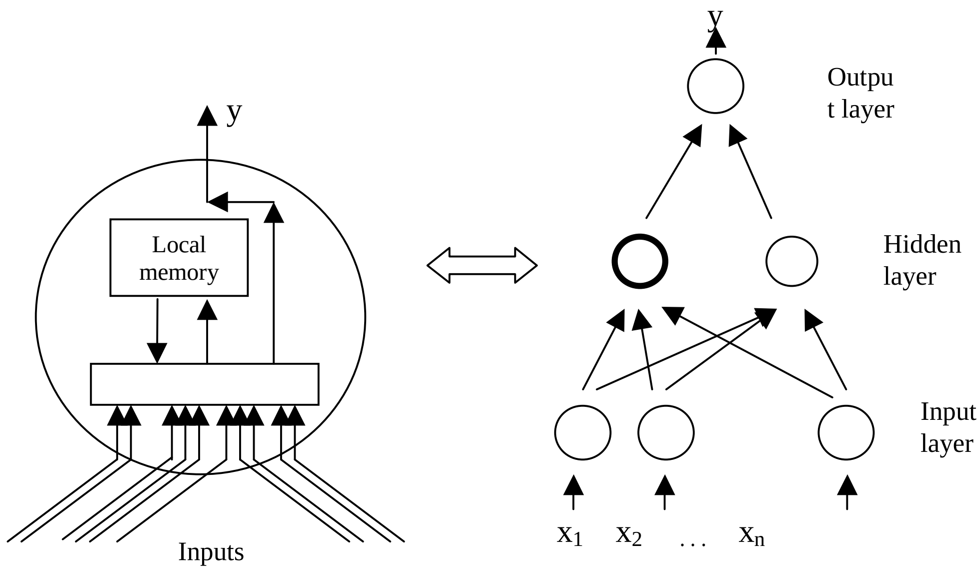
The rest of the paper is organised as follows. Firstly, the basic principles of the ANN technology are introduced. The paper continues by introducing auditing tasks where ANNs have been applied. Furthermore, possible auditing tasks were ANN-based support systems could assist auditing are described.

2. Basics of ANN

In this section a description of the elements of ANNs, the learning paradigms and algorithms, and the architectures are provided. An ANN consists of many single processors, which interact through a dense web of interconnections. This processor has many names, such as a processing element, a node, a unit, a cell, an artificial neuron, or just a *neuron* (Figure 2a).

A neuron has two tasks. It computes one output y, which is sent to the other neurons or outside the network. The neuron determines its output value by applying a *transfer function* (Freeman and Skapura 1991). Then it updates a *local memory*, i.e. weights and other types of data called *data variables* (Hecht-Nielsen 1990).

The neurons are organised into *layers* (Figure 2b). 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.



a) A neuron b) A typical feed-forward ANN

Figure 2. A neuron and artificial neural network

2.1. Learning

An important and attractive feature of an ANN is its learning capability, which allows the network to adapt to its environment. Learning or training means that an ANN tries to find an appropriate set of weights, which allows the network to carry out the desired task (Rumelhart et al. 1994). An ANN learns from training examples that are provided from the environment. The weights of the network change after every training example. The learning consists of different learning paradigms and algorithms/rules. The taxonomy of the learning process shown in Figure 3 is adapted from Haykin (1994). A-priori knowledge of the task and the data influences the selection of learning paradigms when modeling an ANN. A *learning paradigm* refers to a model of the environment in which an ANN operates (Haykin 1994). The most common learning paradigms are supervised learning, reinforced learning, and unsupervised learning.

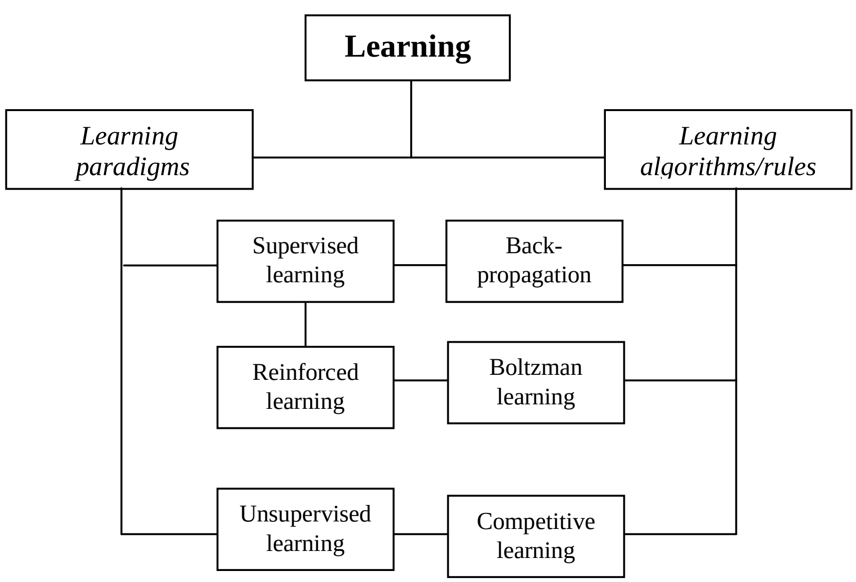


Figure 3. A taxonomy of the learning process

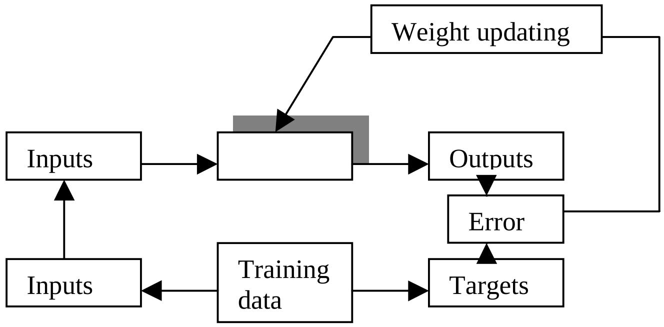


Figure 4. Supervised learning (Source: Modified from Koikkalainen 1994)

In *supervised learning* a teacher has some knowledge of the environment that is unknown to an ANN (Figure 4). The teacher expresses this knowledge with training examples, which consist of input variables together with desired target values (Hecht-Nielsen 1990). The network processes its output values from the input variables and compares them with the target output values. If an error, i.e. a difference between outputs and targets exists, the network adjusts the weights by a small amount in some direction in a step-by-step manner until the error is at an acceptable level. Supervised learning is an *instructive feedback system*. After the network has been trained, it will be able to deal with the environment alone. One disadvantage of this paradigm is that it cannot learn new strategies without a teacher and new training examples (Haykin 1994).

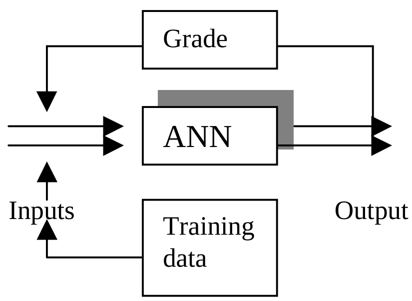


Figure 5. Reinforcement learning (Source: Modified from Koikkalainen 1994)

In *reinforcement or graded learning* the training examples are given to a network without any desired outputs (Figure 5). In addition to the training data inputs, the network occasionally receives a grade, a performance score, from its environment. This grade tells how well the network has done overall since it was last graded (Hecht-Nielsen 1990). The reinforcement learning is on-line learning without a teacher. This paradigm is an *evaluative feedback system*, since it evaluates the system's behaviour. However, it does not indicate if an improvement is possible or the way that the system should change its behaviour (Haykin 1994). The reinforcement learning is a special case of supervised learning (Hertz et al. 1991).
In *unsupervised learning* neither a teacher nor a grade oversees the learning process (Figure 6). Therefore, the network is given only the training data inputs from which the network organises itself into some useful configuration (Hecht-Nielsen 1990). The input vectors are classified according to their degree of similarity. The similar input vectors activate the same output cluster. The user is responsible for giving an interpretation to the clusters.

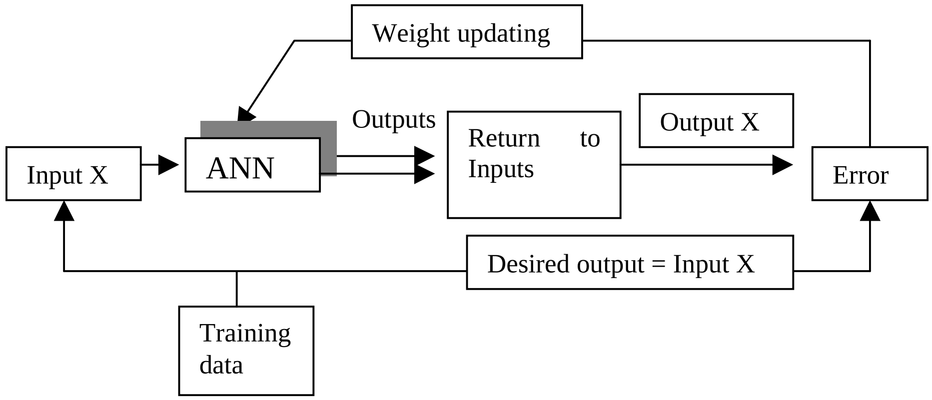


Figure 6. Unsupervised learning (Source: Modified from Koikkalainen 1994)

The hybrid use of learning paradigms may provide a better solution than one paradigm alone. For example, when similar input vectors produce similar outputs, it may be rational to categorise the inputs first with unsupervised learning and use that information for the supervised learning (Hertz et al. 1991).

A *learning algorithm* is a set of well-defined rules for the solution of a learning problem. Several alternative learning algorithms exist and they all have their own advantages. The differences between them are based on various weight adjustments (Haykin 1994). Three different learning algorithms, which suit the three different learning paradigms described above, are presented below.

Backpropagation algorithm has become the most popular one for prediction and classification problems (Sohl and Venkatachalam 1995). This algorithm is used in the supervised learning paradigm (Haykin 1994) and it operates on a multi-layered perceptron network. For a given input vector, it generates the output vector by a forward pass. Then, the difference between the output vector and the desired target vector, the *root mean square error (RMSE)* is backpropagated through the ANN to modify the weights for the entire neural network.

Bolzman learning may be described with a Bolzman machine. The neurons in it constitute a recurrent or feedback structure with symmetric weights. It learns its weights in order to determine an appropriate value for them at the stable state (Holmström and Kohonen 1993). This algorithm is suitable for reinforcement learning.

In *competitive learning*, all the output neurons compete against each other. One of them will be a winner in accordance with a chosen metric and only it will be activated. The winner's weight vector is updated to correspond more closely to the input vectors. This algorithm can discover features that may be used to classify a set of input vectors. This algorithm is suitable for unsupervised learning (Haykin 1994).

2.2. Architectures of ANNs

The ANN *architectures* may be divided into three categories, which are based on a different philosophy (Kohonen 1990): 1) *Signal transfer* (feedforward or nonrecurrent) *networks*, e.g. *multi-layer perceptrons*. 2) *Competitive learning networks*, e.g. *Kohonen's self-organizing map*. 3) *Dynamic state transfer* (feedback or recurrent) *networks*, e.g. *Hopfield networks*. The architecture of the ANN defines how the neurons in a network are interconnected. Each of the architectures has a unique mix of, e.g. information-processing capabilities, domains of applicability, techniques for use, required training data, and training methods (Hecht-Nielsen 1990). The different architectures do not compete against each other; rather, they represent various specialisations in solving different types of problems. Indeed, the architecture strongly influences e.g. what the network can do (Hertz et al. 1991).

A multi-layer perceptron with an input layer, output layer and one hidden layer was depicted in Figure 2b. When the relationship between the input and output variables is non-linear, a hidden layer helps in extracting higher level features and facilitates the generalisation of outputs. This network architecture could include more hidden layers but it has been proven that one hidden layer can approximate even complex functions quite well (Holmström and Kohonen 1993). The network can also include several output neurons. Each neuron in the hidden or output layer is connected to all of the neurons in the layer below it and a weight is associated with each of the incoming connections of the neuron. When a neuron receives inputs, it computes its output value and sends it to the neurons on the next layer above. Thus, the inputs are fed forward through the entire network until they reach the output layer.

The supervised learning paradigm with the backpropagation algorithm is mostly used in business applications (Wong et al. 1995, Wong and Selvi 1998). Classification and prediction tasks, which require some modeling, are especially suitable for this architecture (Klimasauskas 1991, Lehtokangas et al. 1994). Hence, a multi-layer perceptron ANN can be considered for e.g. forecasting where statistical methods like Box-Jenkings are used (Klimasauskas 1991). This architecture is also possible to control because many control applications are on-line process controls or adaptive controllers.

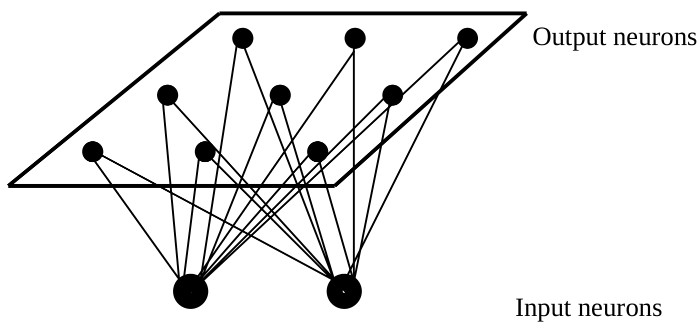


Figure 7. The structure of Kohonen’s self-organising maps
(Source: Modified from Dutta 1993)

Kohonen’s self-organising map (SOM) has an input layer and an output layer (Figure 7). All output neurons are connected to all input neurons with a scalar weight. These scalar weights of one output neuron’s incoming connections form a weight vector for this output neuron. The input neuron sends a signal to all the output neurons through the connections. First, the output neurons compete against each other for the input. The output neuron, whose weight vector is most similar to the input vectors, wins. Afterwards, this winner neuron and its surrounding neurons are updated in a way that their weight vectors approach the present input vector slightly (Kohonen 1997). These self-organising training trials continue until the weight adjustments become small and the network has formed a topology-preserved map. This means that two input items, which are close in the input space, are mapped into the same or neighbouring neurons on the map. Output neurons create groups, which together form a map of the input neurons. SOM is a clustering, visualisation, and abstraction method and the purpose is to show the data set in another representation form (Kohonen 1997).

The two network architectures described above are feedforward networks because they feed the outputs to the neurons on the next layer. *A Hopfield network* differs from them since it represents a feedback network. In a common form, the Hopfield network has n neurons. The network in Figure 8 has three neurons. The input neurons define the initial activity state of a feedback system. It is then changed with sequential state transitions up to the final state that is identified as the output of the network. The network calculates its output based on the inputs and feeds it back in order to modify the inputs. In stable feedback networks, the changes will be smaller until the output become constant (Li 1994). The network will always converge to some stabile state because only a finite number of states exist and the so-called energy function decreases every time when the state changes (Holmström and Kohonen 1993).

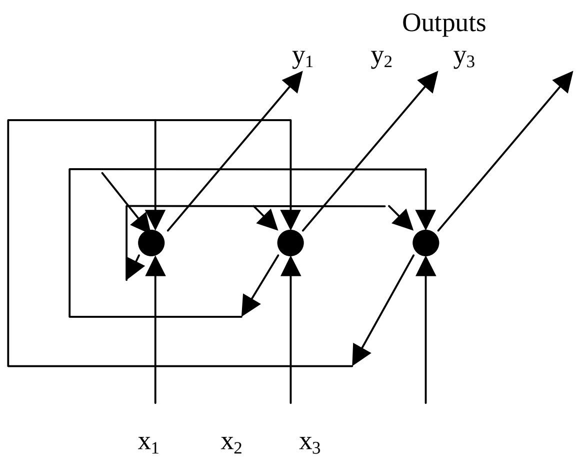


Figure 8. A simple Hopfield network (Dutta 1993)

A Hopfield network may be used as an associative memory where the stable network output gives the complete stored pattern. When they are used as, for example, a classifier, the output is compared to the different example patterns to find the possible match (Dutta 1993). The Hopfield network is usually proposed for optimisation problems (Hertz et al. 1991). In these cases, the function that should be optimised with its limits is illustrated with an energy function of an appropriate network and the dynamic of the network performs the optimisation (Holmström and Kohonen 1993).

3. Auditing with ANNs

In this section a description of auditing tasks where ANNs have been applied is given. This article takes a broad scope of auditing and encompasses both internal and external auditing. The paper includes ANNs that tackle traditional auditing and also those that tackle the use of auditing in new ways and for different purposes. This is in line with traditional auditing research. The data in the paper was mainly collected form journal articles on ANNs applied to business situations, from journal and business magazine databases, namely ABI Inform/Proguest, Ebscohost, Emerald, JTORS, and Elsevier with search words "audit and neural", and from Proceedings of Expert Systems Symposium 1991, The World Congress on Expert Systems 1991, European Conference on Information Systems 2001, and Intelligent Systems in Accounting and Finance 1996. The electronic table of contents of Intelligent Systems in Accounting, Finance & Management, Expert Systems with Application, and Auditing: A Journal of Practice and Theory journals were also reviewed in order to find those articles that were not found in other way.

A number of articles have surveyed journal articles on ANNs applied to business situations. Wong et al. (1995) and Wong and Selvi (1998) surveyed articles from 1988-1996 and classified the articles among others by application areas. One article was categorised into auditing discipline. O'Leary (1998) analysed 15 articles that applied ANNs to predicting corporate failure. He provided information on data, ANN models, software, and architecture. Zhang, Patuwo et al. (1998) surveyed 21 articles that addressed modeling issues when applying ANNs for forecasting. They compared the relative performance of ANNs with traditional methods in 24 cases. None of these articles pertained to auditing problems, however, the paper provides insights into modeling issues by summarising suggestions. Vellido et al. (1999) surveyed 123 articles from 1992 to 1998. Six articles pertained to auditing problems. Besides modeling issues they summarise the most frequently cited advantages and disadvantages of the ANN models. Coakley and Brown (2000) surveyed accounting and finance ANN applications and classified them by research question, type of output (continuous versus discrete), and parametric model.

Twenty-one articles either focusing on or connected to the auditing environment were found. All these articles fit into analytical review (AR) procedures. AR procedures are techniques used to improve the efficiency of audits. Basically, in an AR procedures one compares expected relationships among data items to actual observed relationships. Most existing AR procedures investigate ratios and trends of financial data.

3.1. Applications in the Analytical Review Procedures

The main ANN-application areas in auditing are material errors (Coakley and Brown 1991a, Coakley and Brown 1991b, Coakley and Brown 1993, Wu 1994, Coakley 1995, Koskivaara et al. 1996, Busta and Weinberg 1998, Koskivaara 2000a, Koskivaara 2000b), management fraud (Green and Choi 1997, Fanning and Cogger 1998, Feroz et al. 2000), and support for going concern decision (Hansen et al. 1992, Lenard et al. 1995, Koh and Tan 1999, Anandarajan and Anandarajan 1999, Etheridge et al. 2000). ANNs have also been applied to internal control risk assessment (Davis et al. 1997, Ramamoorti et al. 1999), audit fee (Curry and Peel 1998), and financial distress problems (Fanning and Cogger 1994). Going concern and financial distress are very close or can even be included in bankruptcy studies. This study focuses only on those applications that are conducted from an auditing perspective.

3.1.1. Material Errors

The major ANN-application area in auditing is material errors. Material error applications direct auditors' attention to those financial account values where the actual relationships are not consistent with the expected relationships. An auditor has to decide whether and what kind of further audit investigation is required to explain the unexpected results. Material error ANN-models either predict future values or classify data.

Coakley and Brown (1991a) tested ANN technology for recognising patterns in financial ratios. They predicted future values with an ANN. The financial accounts were selected so that they provided information about a company's solvency and the movement of accounts receivable and inventory. The model was trained with an auto-association process, which means that the input pattern and the desired output pattern were the monthly account balances. Thus each pattern was associated with itself. They also performed a simulation to evaluate the effectiveness of the model. Their preliminary results indicated that the use of ANNs for pattern recognition across related financial data sets might be viable.

Coakley and Brown (1991b) and Coakley and Brown (1993) tested whether an ANN offered improved performance in recognising material misstatements. This ANN-model was based on trend prediction. The researchers selected fifteen income statement and balance sheet accounts or aggregates to represent the major balance sheet categories. The inclusion of all accounts values was not feasible due to the impact of the number of neurons on the time it takes to train an ANN. The researchers compared a presumed lack of actual errors and seeded material errors to evaluate the ANN's performance. The results of the study were divided into findings based on: financial ratios, comparison of methods (financial ratio, regression, ANN), effect of error size, effect of statistical level of confidence, effect of source of material error and applying methods to base period. The results were compared to the results achieved with financial ratio and regression methods, and the ANN demonstrated better predictive ability with less overall variation in the predicted values. However, the fluctuating nature of the financial data within this study limited the effectiveness of all the AR procedures.

Wu (1994) applied the ANN system to classifying tax cases to ascertain whether further audit is required or not. The 180 sample examples were gathered from an expert tax auditors' audit case file. The cases consisted of information about a firm's business income tax behaviour. The classification accuracy for the neural network was 94 per cent with a two-layer neural network and 95 per cent with a three-layer neural network.

Coakley (1995) continued the development of the ANN to be applied to analysing the complex patterns of related fluctuations across numerous financial accounts and identifying the presence and plausible source of a material monetary error in the accounts. The results suggested that the use of the pattern analysis methods as a supplement to traditional analytical procedures offer improved performance in recognising material misstatements within the financial accounts.

Koskivaara et al. (1996) modeled intelligent systems based on ANNs for auditing with the subset of Coakley and Brown (1991a) accounts. They introduced a one-step-ahead prediction model to observe the non-linear dynamics and the relationships between accounts based on monthly income statements and in that way monitored if there were unusual fluctuations.

Busta and Weinberg (1998) used an ANN to distinguish between "normal" and "manipulated" financial data. They examined the digit distribution of the numbers in the underlying financial information. The data analysis is based on Benford´s law, which demonstrated that the digits of naturally occurring numbers are distributed on a predictable and specific pattern. They tested six ANN designs to determine the most effective model. In each design, the inputs to the ANN were the different subsets of the 34 variables. The results showed that the ANN was able to correctly classify 70.8 per cent of the 800 data set. However there were differences between the ANN designs the range being 67 per cent to 100 per cent.

Koskivaara (2000a) illustrated a business line ANN-model to compare information of a firm with similar information for the industry in which the organisation operates. Furthermore, the four different alternative models investigated the effect of the year and company on the ANN's performance. The ANN model used in this study was built by using the financial statements of 31 manufacturing companies over four years. The values of the accounts were regarded as a time-series. The researcher selected sixteen income statement accounts to represent the major financial statement categories; also the average number of staff was included in the model. The account values included financial assets and short-term liabilities, which were taken into the model in order to calculate quick ratio. The data were pre-processed linearly in four different ways: all together, on a yearly basis, on a company basis, and on a yearly and company basis. The results differed depending on what pre-processing method was used. The best results were achieved when all the data were scaled either all together or on a yearly basis.

Koskivaara (2000b) illustrated how an auditor may use an ANN model to support the planning of auditing monthly balances by a graph on the computer screen that either signals that “no further audit is required” or “further audit is required”. The accounts were chosen with the help of a CPA-auditor in the way that they presented the major and the most interesting monthly balance categories. This study has similarities to Wu (1994) study. In the study two models were presented. Model 1 operates inside the quartile and Model 2 has previous quartile data as input variables. The latter model gave slightly better results.

3.1.2. Management Fraud

Auditors cannot assume that the management is honest or dishonest. They should take a hard, cold look at the possibility of management misrepresentation at the start of the audit and re-examine the likelihood of management misrepresentations as the audit progresses. Management fraud (MF) can be defined as deliberate fraud committed by the management that injures investors and creditors through materially misleading financial statements.

Green and Choi (1997) developed an ANN fraud classification model employing endogenous financial data. They used five ratios and three accounts as input variables. The selection of variables was determined by both practical and empirical research. The fraud sample consisted of SEC (Securities and Exchange Commission) filed financial statements that had been subsequently found to contain fraudulent account balances. Financial statements of the nonfraud sample received unqualified auditor opinions for the year of selection. They were selected directly from COMPUSTAT and matched the fraud sample on the basis of year, size, and industry (four digit SIC). The results showed that ANNs have significant potential as a fraud investigative and detection tool.

Fanning and Cogger (1998) used an ANN (AutoNet) to develop a model for detecting management fraud. They compared the results of an ANN with linear and quadratic discriminant analysis as well as logistic regression. The variables were selected by AutoNet and they were the outsider director, having a non-Big Six auditor, the geometric growth rate, accounts receivable to sales, net plan property and equipment to total assets, debt to equity and the trend variables for accounts receivable and gross margin. The result of their models suggested there is potential in detecting fraudulent financial statements through analysis of public documents. They also suggested that ANNs offer better ability than standard statistical methods in detecting fraud.

Feroz et al. (2000) illustrated the application of the ANNs in order to test the ability of selected SAS (Statements of Auditing Standards) No. 53 red flags to predict the targets of the SEC investigations. They used both financial ratios and non-financial turnover red flags mentioned in SAS No. 53. The ANN models classified the membership in target (investigated) firms versus control (non-investigated) firms with an accuracy of 81 per cent. The testing was biased because they used only those red flags that can be constructed from publicly available information. However, authors said they believed that the sampling choice was sound given the data constrains in that particular case.

3.1.3. Going Concern and Financial Distress

Although studies on going concern (GC) and financial distress (FD) remain bankruptcy studies, research as an application area of ANNs has been minimal. This study only focuses on those applications that are conducted from the auditing perspective, e.g. the likelihood of an auditor being sued. An auditor gives a GC an uncertainty opinion when the client company is at risk of failure or exhibits other signs of distress that threaten its ability to continue as a GC. The decision to issue a GC opinion is an unstructured task that requires the use of the auditor's judgement.

Hansen *et al.* (1992) samples consisted of 80 FD companies; 40 that received the GC audit report, and 40 that did not receive the GC audit report, and of 98 firms involved in litigation. They had two models with different variable settings. The Audit opinion - model had either twelve ratios from financial statements or other closing of the books information as variables. Litigation-model had nine variables, which were client, auditor or engagement specific ones. The results indicated that in the case of predicting audit opinions, the qualitative-response models perform at a competitive level with the machine-learning models. Theoretical results inferred that this might be especially true when the training sets were relatively small. The authors stated that qualitative response models might be a desirable alternative when the training samples are relatively small and there is a need to incorporate additional parameters such as prior probabilities and error costs.

Lenard et al. (1995) studied the generalised reduced gradient (GRG2) optimiser for ANN learning, a backpropagation ANN, and a logit model to predict which firms would receive audit reports reflecting a GC uncertainty modification. The sample for the study was drawn from the 1988 Disclosure II Database. The selection of variables was intended to determine whether the GC decision could be made from publicly available financial statement information. The ANN model formulated using GRG2 had the highest prediction accuracy of 95 per cent. The GRG2 based ANN was proposed as a robust alternative model for auditors to support their assessment of GC uncertainty affecting the client company.

Anandarajan and Anandarajan (1999) compared ANN, expert system (ES) and multiple discriminant analysis models to facilitate the decision on the type of GC report that should be issued. The experimental sample of the study was drawn from the 1992 Disclosure database. The data consisted of 14 ratios calculated from the financial statements of 61 companies. The validity of the models was tested by comparing their predictive ability of the type audit report, which should be issued to the client. The results of the study indicate the ANN model has a superior predictive ability in determining the type of GC audit report that should be issued to the client.

Koh and Tan (1999) predicted a firm's CG status from six financial ratios with an ANN model. Their data set contained 165 non-GCs and 165 matched GCs. On an evenly distributed hold-out sample, the trained network model correctly predicted all 30 test cases. They compared the GC results of the ANN to the probit model and the audit opinion. Their results suggested that the ANN was at least as good as both the auditors and the probit model for predicting the GC status of firms from financial ratios.

Etheridge et al. (2000) compared the performance of three ANN approaches: Backpropagation (BPN), Categorical Learning Network (CLN), and Probabilistic Neural Network (PNN) as classification tools to assist and support the auditor's judgment about a client's continued financial viability in the future (GC status). The data was provided by a Big Six CPA firm and consisted of 57 financial ratios for the years 1986-1988 for 1,139 banks in various regions of the U.S. They had three, two, and one year prior to failure models. When only the overall error rate was considered, the probabilistic ANN was the most reliable in classification, followed by backpropogation and categorical learning ANN. When the estimated relative costs of misclassification were considered, the categorical learning ANN was the least costly, followed by backpropogation and probabilistic ANN.

Fanning and Cogger (1994) examined the efficiency of a generalised adaptive neural network algorithm (GANNA) processor in comparison to earlier model-based methods, a backpropagation ANN, and logistic regression approaches to data classification. The research used the binary classification problem of discriminating between failing and non-failing firms to compare the methods. All the models had three inputs: the mean adjusted cash flow divided by its standard deviation, the firm's adjusted cash position divided by its standard deviation, and the number of years prior to failure for the failed year. This number of input variables might limit the predictive ability of an ANN. However, the results indicated the potential in time savings and the successful classification results available from a GANNA processor.

3.1.4. Control Risk Assessment and Audit Fee

An auditor considers a huge amount of data when assessing the risk of the internal control (IC) structure of an entity failing to prevent or detect significant misstatements in financial statements. The relationships between IC variables that must be identified, selected, and analysed often make assessing a control risk a difficult task. Therefore, control risk assessment (CRA) is a systematic process for integrating professional judgements about relevant risk factors, their relative significance and probable adverse conditions and/or events leading to identification of auditable activities (IIA, 1995, SIAS No. 9).

Davis et al. (1997) presented a construction of a prototype, which integrated an ES and an ANN. The rules were contained in the ES model basic CRA heuristics, thus allowing for efficient use of well-known control variable relationships. The ANN provided a way to recognise patterns in the large number of control variable inter-relationships that even experienced auditors could not express as a logical set of specific rules. The ANN was trained using actual case decisions of practising auditors. The input variables were judgement cues/variables from general environment, computer processing, general computer and accounting controls. The ANN model provided the auditor with information on how close a risk category border was.

Ramamoorti et al. (1999)) used both quantitative (26 variables) and qualitative (19 variables) risk factors as input variables in the models. The risk was defined in an internal auditing context. The models were in the context of a public state university. The quantitative data were downloaded from the University of Illinois Financial and Administration System. The qualitative risk factor values were elicited from audit staff using a pre-defined scale from 0 to 9. The eventual number of variables selected to construct the models were in the 7 to 18 range. The research project included a Delphi study and a comparison with statistical approaches, and presented preliminary results, which indicated that internal auditors could benefit from using ANN technology for assessing risk.

Curry and Peel (1998) provided an overview of the ANN modeling approach and the performance of ANNs, relative to conventional ordinary least squares (OLS) regression analysis, in predicting the cross-sectional variation in corporate *audit fees* (AF). The data was derived from a sample of 128 unquoted UK companies operating in the electronic industrial sector. The audit fee, the dependent variable in the study, must be disclosed (under UK company law) in a note to a company's annual statements. The input variables were related to auditee size, audit complexity, audit risk, auditee profitability, and auditor size. The ANN models exhibited better forecasting accuracy than their OLS counterparts, but this differential reduced when the models were tested out-of-sample.

3.1.5. Audit ANN in Praxis

Credit-card companies use ANN technology to reveal fraudulent clients (Mulqueen 1996, Fryer 199, Fisher 1999). KPMG Peat Marwick has already developed an ANN for bankruptcy prediction (Etheridge and Brooks 1994). Probably because these applications contain business secrets the models are kept secret.

3.2. Issues in ANN Modeling for Auditing

Table 2 summarises the modeling issues of ANN literature pertaining to auditing problems in a chronological order. Auditing ANN research started in the beginning of the nineties. The *application area* in Table 2 is abbreviated as follows: material error (ME), going concern (GC), financial distress (FD), control risk assessment (CRA), management fraud (MF), and audit fee (AF). In all, nine ME-, five GC-, and three MF-applications were found. Two CRA-applications were found and one FD- and AF-application each.

Both quantitative and qualitative *data* were used as input variables in the applications. Financial statement values and ratios and monthly account values were mostly used as quantitative input variables. Number of staff was also included in quantitative input variables. Qualitative data included both opinions and observations of auditors or red flag data defined by SAS.

A *training* and a *test* sample are typically required for building an ANN model. The training sample is used for ANN model development and the test sample is adopted for evaluating the model. The training and testing set size depends on the problem domain and on available data. Sometimes a third one called the validation sample is utilised to avoid the overfitting problem or to determine the stopping point of the training process. However, it is common to use one test set for both validation and testing purposes particularly with small data sets. All but two applications reviewed in this survey had quite small data sets. The analytical review ANN-model of Busta and Weinberg (1998) was based on digits of numbers, and therefore it had bigger data sets than others. Etheridge et al. (2000) had a data set of financial ratios from 1,139 banks provided by a Big Six CPA firm applied in GC application. In our view, it is common in the early developing phase of ANN models to use small data sets. It is critical to have both the training and test set representative of the population or underlying mechanism. The selection of the training and test set may affect the performance of an ANN.

The selection of numbers of *input nodes*, *hidden layers and nodes* and *output nodes* is problem dependent. For example, all the income statement account values could be selected as input variables in many applications. However, too many input variables in combination with too few observations could have affected the ANN ability to learn. Therefore, some selection of variables might help an ANN to get better results. In our view this is true with the supervised learning paradigm in prediction models. The hidden nodes in a hidden layer allow ANN to detect the feature, to capture the pattern in the data, and to perform complicated nonlinear mapping between input and output variables. Linear relationships between the variable are very often a simplification of the natural financial data. The number of output nodes is relatively easy to specify as it is directly related to the problem under study. The majority of these auditing ANN-applications under study had one output node. This is common in classification models whereas prediction models might have one or more nodes in the output layer.

All but one study used the supervised *learning* paradigm. Fanning and Cogger (1998) used the self-organising learning paradigm in management fraud application. Most studies used the straightforward MLP networks with a backpropagation algorithm while others employed some variants of MLP. A sigmoid or a modified sigmoid *transfer function* was used in the twelve studies, a logistic function was used in three studies. Six applications used some other transfer function. The *performance measurement* of the models varied a lot. Root mean square error, prediction accuracy, and average error were mostly used. In some cases also a comparison to the traditional statistical methods was used.

Table 2: Summary of modeling issues of auditing ANN

Researcher Area	Data type	Train/ test set	# input nodes	# hidden layers/ nodes	# output nodes	Transfer function	Learning algorithm	Performance measure
Coakley & Brown (1991a) ME	Monthly account values	48/48	11	2:	10	Sigmoid	BP	Average error, standard deviation
Coakley & Brown (1991b) ME	Monthly account values, aggregates	36/12	42	1:15	15	Modified sigmoid squashing	BP	MSE (mean square error)
Hansen et al. (1992) GC	Ratios, non-financial variables	30*40 /40	12 9	NA.	1	Hybrid of steepest gradient, Newton-Raphson	BP	MSE Average error statistical models
Coakley & Brown (1993) ME	Monthly account values, aggregates	36/12	42	1:15	15	Modified sigmoid	BP	MSE
Fanning & Cogger (1994) FD	Liquidity, cash-flow ratios	75/ 115	3	2:6-7	1	Quadratic Sigmoid logistic	GANNA BP	% accuracy
Wu (1994) ME	Income tax behavior data	90/90	16	1:8 0:0	1	Sigmoid	BP	Predictive accuracy
Coakley (1995) ME	Monthly financial ratios	48/	5	2:11-11	3	Hyperbol. Tangent activation	BP	SSE (sum of square error)
Lenard et al. (1995) GC	Financial statements' ratios and values	80/80	8(4)	1:5 (1:3)	1	General. Reducent gradient optimizer	BP	% accuracy logit model
Koskivaara et al. (1996) ME	Monthly income statement values	54/12	30	1:16	9	Sigmoid	BP	RMSE
Davis et al. (1997) CRA	IC risk data, ob-servations of auditors	32/32	210	1:30	1	Sigmoid	BP	RMSE Pearson's coeffic., accuracy %
Green & Choi (1997) MF	Financial statements' ratios and values	49/46	8	1:4	1	Sigmoid logistic	BP	SPCNN PSYDNN ISYDNN
Busta & Weinberg (1998) ME	Digits of numbers	800/ 800	34 24 15 5 1 1	1:4 1:6 1:6 1:6 1:4 0:	1	Logistic	BP	accuracy %
Curry & Peel (1998) AF	Financial, non-financial data	96/32 86/42 64/64	25	1:2 1:3 1:4	1	Sigmoid	BP	MSE
Fanning & Cogger (1998) MF	Financial statements' accounts, ratios	150/5 4	8	NA.	1	Simple quadratic, quadratic	"AutoNet"	Prediction accuracy % Log./DA

Anandarajan & Anandarajan 1999	Financial statements' ratios	37/24	14	NA.	3	Sigmoid	BP	accuracy %
Koh & Tan (1999) GC	Financial Raitios	300/ 30	6	1:13	1	Sigmoid	BP	accuracy %
Ramamoorti et al. (1999) CRA	Qualitat. quantitat. Risk factor	70%/ 30%	10	NA.	1	NA.	BP	R-squared %, Delphi overlap
Etheridge et al. (2000) GC	Financial ratios	749- 776+ 114- 116/ 192+ 23	57	NA.	1	NA.	BP, categorial l. probabalis tic l.	OER Pearson's coefficient
Feroz et al. (2000) MF	7 SAS No. 53 red flag data	24/14 60/30 60/6 30/3	7	1:14	1	Binary sigmoid	BP	OER (overall error rate) MSE
Koskivaara (2000a) ME	Financial statements' account values Non- financial values	25/6	37	3:32- 26-16 1:27 4:33- 29-25- 26 1:27	16	Sigmoid	BP	RMSE QR
Koskivaara (2000b) ME	Monthly balance account values	60/12	30 48	2:27- 18 4:40- 32-26- 18	9	Sigmoid	BP	RMSE
Researcher Area	Data type	Train/t est set	# input nodes	# hidden layers/ nodes	# output nodes	Transfer function	Learning algorithm	Performance measure

4. Conclusions and the Future

As information technological changes occur at an increasing rate, auditors must keep pace with these emerging changes and their impact on their client's information processing systems as well as on their own audit procedures. This paper reviewed the current state of the ANN-applications connected to auditing purpose. The review is comprehensive but by no means exhaustive, given the fast growing nature of the literature. The main findings are summarised as follows:

The main application areas were material errors, management fraud, and support for going concern decision. ANNs have also been applied to internal control risk assessment, audit fee, and financial distress problems. New application areas like authority checking and analysing minutes with an ANN could be considered. Commercial ANN pen-based systems and natural language interfaces are currently available. To develop an ANN to serve as either a hand-written character or speech recognition device and to integrate the ANN with existing software (for example, word processor, spreadsheet, etc.) might be useful for authority checking. An auditor may analyse minutes and other documents of the entity with an ANN (e.g. Moore et al. 1995, Visa et al. 2001). This can be done either alone or simultaneously together with financial accounts' values. The ability to forecast a company's earnings may be useful in assisting management in developing an operating strategy or in evaluating the budgeting.

Most studies used the straightforward MLP networks with a backpropagation algorithm while others employed some variants of MPL. Therefore, an alternative ANN architecture, like Kohonen's self-organising map or the Hopfield network, may further enhance the effectiveness of auditing e.g. in the pattern analysis procedure or in optimising audit fees. Any technique that reduces the probability of major, undetected fraud or fault should assist boards of directors and decrease auditor exposure to litigation.

All but two applications reviewed in this survey had quite small data sets. In our view, it is common in the early developing phase of ANN models to use small data sets. However, it is critical to have both the training and test set representative of the population or underlying mechanism to get reliable results with ANNs. ANNs can be more appropriate for large data sets. The selection of the training and test set may affect the performance of an ANN.

ANNs offer a promising alternative approach to AR procedures. There are many research questions and problems in this area. The future of ANNs in auditing is open and will be even brighter as more and more research efforts are devoted to this area.

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