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# Comparing Different Methods in Analytical Procedures Using Real World Data

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## ABSTRACT

*Analytical procedures play an important role in assisting the auditor in determining the nature, timing and extent of their substantive testing, and in forming an overall opinion as to the reasonableness of recorded account values. The present study compares the artificial neural network (ANN) system and traditional analytical procedures on pattern recognition in monthly account values. The results of the study indicate that the ANN-system has a better predictive ability on pattern recognition in monthly account values than the traditional analytical procedures used in this study.*

## 1 INTRODUCTION

The demands in the auditing environment have led to the publication of several standards on analytical procedures (APs) in different countries (e.g. AICPA, 1988; APB, 1995; KHT-yhditys, 2003). The US standard (SAS 56) on AP[1] has generally, in the literature, been considered as an authoritative pronouncement to AP (AICPA, 1988). The emphasis in the SAS 56 definition is on expectations developed by the auditor. It states as follows:

Analytical procedures involve comparing of recorded amounts, or ratios developed from recorded amounts, to expectations developed by the auditor. The auditor develops such expectations by identifying and using plausible relationships that are reasonably expected to exist based on the auditor's understanding of the client and of the industry in which the client operates.

SAS 96 contains amendments adding specific documentation requirements to the SAS no. 56, which at the moment requires auditors to document the factors they considered in developing the expectation for a substantive analytical procedure (AICPA, 2002). Besides, they have to document the expectation if it is not apparent from the documentation of the work that they performed. The auditors also should document (a) the results of their comparison of that expectation to the recorded amounts or ratios that they developed from recorded amounts, and (b) any additional auditing procedures they performed in response to significant unexpected differences arising from the APs, as well as the results of such additional procedures.

APs may be performed:

- in the *client acceptance/retention stage* in order to assist in obtaining a better understanding of the client's business
- in the *audit planning stage* to identify possible problem areas
- in the *substantive testing stage* as a means of gathering substantive evidence in relation to one or more account balances or classes of transactions
- in the *opinion formulation stage*, as a means of gathering evidence as to the consistency of the financial statements with the auditor's knowledge of the business

Auditing researchers have developed a variety of models to assist in the APs Techniques included in these models range from simple comparisons to complex analyses (e.g. Leitch and Chen, 2003; Blocher, et al. 2002; Fleming, 2004). Fraser, Hatherly, and Lin (1997) have identified three types of AP techniques: non-quantitative (NQT) or *judgmental*, such as scanning; simple quantitative (SQT) such as trend, ratio and reasonableness tests; and advanced quantitative (AQT), such as regression analysis. These techniques differ significantly in their ability to identify potential misstatement. Judgmental techniques include auditor's subjective evaluations based on client knowledge and past experience. Trend analysis assesses whether there is a functional relationship between the variables over time. Ratio analysis incorporates the expected relationships between two or more accounts directly. For example, turnover ratios are useful because there is typically a stable relationship between sales and other financial statement accounts, especially receivables and inventory. Although ratios are easy to compute, which in part explains their wide appeal, their interpretation is problematic, especially when two or more ratios provide conflicting signals. Indeed, ratio analysis is often criticized on the grounds of subjectivity, i.e. the auditor must pick and choose ratios in order to assess the overall performance of a client. In a reasonableness test, the expected value is determined by reference to data partly or wholly independent of the accounting information system, and for that reason, evidence obtained through the application of such a test may be more reliable than evidence gathered using only an accounting information system. For example, the reasonableness of the total annual revenue of a freight company may be estimated by calculating the total tons carried during the year and the average freight rate per ton. With a regression analysis model the auditor may predict financial and operating data by incorporating e.g. economic and environmental factors into the model. Sad to say, many of the AQT-based models have not found their way into practice. Most of the AP models used in practice for signaling errors throughout the audit include relatively simple techniques and are not based on any statistical methods (Ameen and Strawser, 1994; Cho and Lew, 2000; Fraser, Hatherly, and Lin, 1997; Lin, Fraser, and Hatherly, 2003).

Needless to say, there is a need for better AP tools and this study argues that ANNs (artificial neural networks) could be a feasible technique to aid auditors in creating expectations, and these expectations can then be compared to actual values automatically (cf. SAS 56). ANNs have many beneficial aspects in comparison to other techniques. They are adaptive tools for processing data. They can learn, remember, and compare complex patterns (Medsker and Liebowitz, 1994). They are useful for recognition of patterns from noisy data and they are able to dynamically adapt to a changing environment (Dutta, 1993). Basically, ANNs learn from examples and then generalize the learning to new observations. Compared to regression analysis we do not need an a priori model because ANNs are data driven. In addition, ANNs are, unlike traditional statistical techniques, capable of identifying and simulating non-linear relationships in the data without any a priori assumptions about the distribution properties of the data. One advantage of the ANN-systems could be that they provide additional information to the decision process. With the help of an ANN an auditor may find something from the data more effectively and efficiently than with conventional APs.

Auditing ANN research started a little more than a decade ago (Koskivaara, 2004). The main ANN-application areas in auditing are detecting material errors, detecting management fraud, and supporting going concern decision. ANNs have also been applied to internal control risk assessment, to determination of the audit fee, and to financial distress problems. Going concern and financial distress are very close or can even be included in bankruptcy studies. All these above mentioned researches fit into APs. Most of the researchers state that the ANNs have the potential to improve APs. This research can be classified under detecting material error, especially illustrating monthly account values, applications. The paper proceeds as follows: Section 2 identifies the research settings; Section 3 presents the results; Section 4 discusses the findings.

## 2 RESEARCH SETTINGS

### 2.1 Sample and data selection

For the study, we have selected three units from a big organization with the help of their executive management. Although it is doubtful from the auditing point of view to let the management of the organization select those accounts that should be audited it is acceptable in a research setting. The management of the organization should know which accounts follow the trends best and are related to each other. Besides, in principle, all the accounts should be audited in one way or another. Therefore, this selection basis might give an idea to the auditor of which accounts would be the most suitable for ANN-assisted auditing. Indeed, researchers have also proposed APs to management accounting for controlling operations (Lee and Colbert, 1997; Colbert, 1994).

We collected eight years' total monthly costs of theses units. The data for year 2002 was held out for testing and all the previous years' data were used for training the ANN. All the values had been audited, and therefore, in theory, they should have been correct.

### 2.2. ANN- model

The ANN-model uses the supervised training method with the *resilient backpropagation* (RPROP) training algorithm with sigmoid function, which is one of the most efficient algorithms for pattern recognition problems (Demuth and Beale, 2000). The forming expectations for account values can be classified into the pattern recognition problem. The purpose of the RPROP training algorithm is to eliminate the effects of the magnitudes of the partial derivatives (Riedmiller, 1994; Riedmiller and Braun, 1993). Only the sign of the derivative is used to determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value. The update value for each weight and bias is increased whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations. The update value is decreased whenever the derivative with respect to that weight changes sign from the previous iteration. If the derivative is zero, then the update value remains the same. Whenever the weights are oscillating the weight change will be reduced. If the weight continues to change in the same direction for several iterations, then the magnitude of the weight change will be increased. There are two more reasons for selecting RPROP for the learning algorithm for the prototype. First, the performance of RPROP is not very sensitive to the settings of the training parameters. Second, RPROP uses a batch training algorithm and is therefore efficient and requires minimal storage. In the batch mode of learning weight updating is performed after the presentation of all the training examples that constitute an epoch. Besides, as the patterns in the system are presented to the network in a time series manner the use of holistic updating of weights makes the search in weight space stochastic in nature. This in turn makes it less likely for the network to be trapped in a local minimum.

Training parameters included in the system are *training cycles*, *weight decay*, *delta0* and *max delta*. Training cycles refer to the number of training runs needed to complete the task. Smaller values can give the prediction results faster, which can sometimes be advantageous. The weight decay, which is used by default, is very useful in the training, as it reduces overlearning and therefore increases the generalization ability. Delta0 and max delta are parameters specific to RPROP. They are the initial step size and the maximum step size, respectively. The optimal parameter values vary depending on the data, the amount of training cycles, and the network architecture.

The achieved optimal network training parameters for the ANN-system are as follows. The training cycles of the ANN-system were 1000, this is not a high value, but neither is the amount of the data in the model. The value of the weight decay was 0.99999 and the delta0 values were 0.1. These indicate the fluctuating nature of the data. Max delta was 50 in all the cases. The construction of the ANN-system is presented more thoroughly in Koskivaara and Back (2003).

The network architecture of the ANN-system of the present study is as follows. The ANN-system has multiple variables as inputs and outputs (i.e. MIMO-system). Additional 12 input neurons indicate the month of the input data. One previous month was given as input. The ANN-architecture has one hidden layer with eight neurons. To summarize, the ANN-system has 15 neurons in the input layer, eight neurons in the hidden layer, and three neurons in the output layer. The data in the ANN-system was equalized with linear scaling of all accounts at a time. Linear scaling has the advantage of preserving the relative position of each data point along the range. This means that with the linear scaling the original and normalized values are one-to-one. Therefore, this scaling does not move any relevant information from the data before it is fed to the ANN.

### 2.3 Development of comparison metrics and hypothesis

To study (with *t* test on paired differences) whether the ANN-system recognize patterns in monthly account values more accurately than traditional APs in the real data environment, requires the selection of the traditional APs and an assumption that the population of differences between the pairs of observations is normally distributed. This was done.

As mentioned in the introduction, research has consistently indicated that auditors prefer simple scanning, reasonableness tests, and ratio analysis to sophisticated statistical or mathematical models in APs. This is true also in the organization that provided us the data for testing the ANN-based system. One explanation for the popularity of simple techniques might be that they are quite straightforward and require only few calculations. As simple techniques play a fundamental role in the APs in practice, they are selected as the basis for the comparison metrics for the ANN-based system. These comparison metrics are based on the guideline for APs in auditing given by Gauntt and Gletzen (1997). The abbreviations in brackets and explanations of the comparison metrics (= traditional APs) used in this study are as follows:

- Previous year's value (PYS) is the same value from the previous year.
- Average of previous years (AVE) is the average of the same account values from all the previous years.
- Average delta prediction (DELTA) calculates an average of the monthly changes from previous years, and makes predictions by adding the change to the account value of the previous month.
- Zero delta prediction (ZERO) values are the same as in the previous month.
- Combined trivial prediction (CTM) combines the above mentioned simple prediction models.

The predictions of these comparison metrics are made immediately when a data file has been loaded in the system. In effect, we have five populations, one population associated with each method (i.e. ANN, CTM, DELTA, AVE, PYS, ZERO). The following hypothesis will be tested:

$H_0$: *There is no significant difference between the prediction accuracy in the monthly account values of the ANN-system and the traditional APs.*

If $H_0$ cannot be rejected, we will not have evidence to conclude that the ANN-system differs from the traditional APs. However, if $H_0$ can be rejected, we will conclude that the ANN-system differs from the traditional APs.

## 3 RESULTS

First we measured the accuracy of the ANN-system and the traditional APs in their expectations forming capability by comparing

*Table 1. Means and standard deviations of the comparison methods*

| | ANN | CTM | DELTA | AVE | PYS | ZERO |
|---|---|---|---|---|---|---|
| MEAN | **279540** | 396297 | 352831 | 752253 | 358826 | 365795 |
| STANDARD DEVIATION | **214154** | 271171 | 273852 | 413668 | 294126 | 301408 |

*Table 2. Prediction accuracy of ANN-system vs APs*

| Paired Samples Test | t-value | df | Sig. (2-tailed) |
|---|---|---|---|
| ANN – CTM | -2,448 | 35 | **0,020** |
| ANN – DELTA | -2,125 | 35 | **0,041** |
| ANN – AVE | -6,416 | 35 | **0,000** |
| ANN – PYS | -1,651 | 35 | 0,108 |
| ANN – ZERO | -2,293 | 35 | **0,028** |

their mean errors and their standard deviations in the holdout sample. Table 1 presents these values of all the methods used in this study. The ANN-system has the lowest average error in money (= the average difference between the actual account value and the account values achieved with some method such as ANN) and the lowest standard deviation of these average errors. The lowest average currency error indicates that the ANN-system has the best average prediction accuracy. The lowest standard deviation illustrates that the ANN-values are less dispersed from the average value. So, the ANN-system forms expectations for monthly account values more consistently than the other methods in the study.

Paired samples t-tests were conducted to assess the significance of the differences of the methods, this was possible, because the population between the differences between the pairs of observations was normally distributed. As shown in Table 2, there is a significant difference between the ANN-model and the traditional APs at the 0.05 level in four (in bold) out of five cases. Therefore, $H_0$ can be rejected in these cases. There was no significant difference between the account values achieved with the ANN-system and with the PYS-method. Although the results are encouraging, it should also be emphasized that the number of variables, which were inputs and outputs in the system, were limited.

## 4 DISCUSSION

The Enron incident and other such scandals also highlight the use and efficiency of APs. Recent research of Lin, Fraser, and Hatherly (2003) conducted in Canada indicates that APs are extensively applied in practice, particularly by larger audit firms, and that their use dominates the completion phase of audit regardless of the firm size. Their results are comparable with those from research conducted in the US (Ameen and Strawser, 1994). One explanation for the greater use of APs by larger audit firms is the client size. Larger clients are more likely to have strong internal controls that facilitate the reliance of accounting data and support documents and data for using APs. An important part of using APs is to select the most appropriate procedures.

Despite investments by larger firms in technology and in audit automation, audit firms of all sizes continue to emphasize judgment-based procedures as compared with those which are more quantitative based. However, the development of IT supports systems makes the use of advanced methods easier and more cost effective. Therefore, auditors must keep pace with the emerging IT changes and their impact on their client's information processing systems, as well as on their own audit procedures. This also means the development of APs.

In this study, an ANN-based system was trained and tested with the real world operating monthly data. The predictive ability of the ANN-system was compared with the predictive ability of the five other AP methods. The results indicate that the ANN-system has a better prediction accuracy than the other AP methods used in the study. One advantage of the ANN-based system such as used in this study is that it can provide auditors with objective information about a client company. Therefore, it can prove to be a persuasive analytical tool when an auditor discusses problems with the clients and recommends changes in the financial account values. The ANN-system could be adapted to the changes in the environment by retraining it with the new audited data. In our opinion the ANN-based system could serve a continuous monitoring and controlling purpose. For example, it could automatically trace, once a month, those accounts that follow a trend and are inside a certain threshold limit. Then the auditor could decide whether and what kind of further audit with these accounts would be needed.

Although the ANN-based systems cannot entirely replace professional judgment, they offer a promising alternative approach to APs. Indeed, ANNs provide a non-linear dimension that captures the underlying representations within the data sets. Therefore, the future of ANNs in auditing is open and challenging, but it will be brighter as more and more research efforts are devoted to this area. Another challenge is to get practitioners to adopt ANN-based or other feasible statistical methods.

[1] Statement of Auditing Standards (SAS) No. 56 of the AICPA (American Institute of Certified Public Accountants). AP first appeared in the authoritative literature of the AICPA in 1972 (Kinney, Jr. and William Jr., 1980).

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