

DECISION-MAKING BASED ON MACHINE LEARNING TECHNIQUES: A CASE STUDY

Pouabe E.P.S., Pretorius J-H. C., Pretorius L. *

Abstract: Decision-making in companies is often based on the managers' personal experience. However, their consequences can have an impact on the development of the daily activities. To illustrate the managerial impact of decision-making, the biggest African power utility company based in South Africa will be analyzed. Various data such as annual productivity and energy sales were extracted over 15 years from his annual reports and two artificial neural network techniques named Levenberg-Marquardt and Scaled Conjugate Gradient used to analyze them. It emerged from the results obtained that between 2018 and 2020 the company experienced good growth which could extend until 2025 in the best-case scenario or else will drop again to reach its 2020 well-being state. Thus, the obtained results could be used to reinforce the decision-making and to determine the moment when decisions should be taken to prevent the demise of the company.

Keywords: decision-making, strategic management, machine learning techniques

DOI: 10.17512/pjms.2023.28.1.14

Article history:

Received August 24, 2023; *Revised* September 13, 2023; *Accepted* October 14, 2023

Introduction

Professional experience is nowadays at the center of all recruitment even when it comes to work that does not require a particular professional qualification. Any company would like to have the best person in the desired position to increase the company's performance. Another motivator for companies to recruit only the best is due to the fact that company managers invest very little in the training of newly recruited staff (Antonio, et al., 2003). So, even if those managers are going to invest in training of new employees, they will prefer to train an employee who has already acquired some experience in the position he will occupy.

Throughout his professional career, the employee will acquire a certain amount of knowledge and gradually evolve from his employee position to a decision-maker position. This is how the majority of employees grow in their work environment all over the world. The problem arises when it comes to making major decisions for the

*Patrick S. Pouabe Eboule, Dr, University of Johannesburg, South Africa;

✉ corresponding author email: patrickpe@uj.ac.za,

ORCID: 0000-0002-2007-1055

Jan-Harm C. Pretorius, Prof., University of Johannesburg, South Africa;

✉ email: jhcpretorius@uj.ac.za,

ORCID: 0000-0002-2023-749X

Leon Pretorius, Prof., University of Johannesburg, South Africa;

✉ email: pretoriussystems@gmail.com,

ORCID: 0000-0002-2842-3596

company's development such as the entry of a company to the stock market, the launch of a new product, the creation of a new department, the ordering, and storage of a raw material whose cost is highly fluctuating or the dismissal of a director. For example, in 2017 the South African currency lost around 5% of its value after the dismissal of the finance minister (Onishi and Chan, 2017). The decision-making in such situations becomes critical for the company's well-being. It can contribute to gaining considerable profits and therefore developing the company or to losing enough assets to contribute to the company's demise. As a result, many companies are investing in decision-making support tools to limit the damage caused by the implementation of consecutive bad decisions. With the proliferation of artificial intelligence (AI) applied in several fields of engineering, it may be wise to determine if it is feasible to use its algorithms to predict the behavior of a company regardless of its structural size.

The main objective of this study is to use two machine learning techniques to analyze the state of a company. The specific objectives of this study are firstly to identify a suitable data set and machine learning techniques which can be applied in decision-making; secondly to show that machine learning can help to forecast the state of a company. The third specific objective is to compare the obtained results of two artificial neural network (ANN) time series machine learning techniques, the Levenberg-Marquardt (LM) and the Scaled Conjugate Gradient (SCG) techniques with the advantages of these ANN techniques of being fast, robust and easily applicable in different engineering fields notwithstanding data type. The aim of comparing these two techniques is to establish which of the two is more efficient for this purpose.

The novelty this study offers refers to the application of machine learning techniques which are often used in engineering domains such as image recognition, fault detection and classification as well as data processing in decision-making. These machine learning techniques will be applied to the data of one of the biggest industries in Africa which is based in South Africa and annually greatly contributes to South Africa's economic growth.

The analyses made in this study may contribute to reinforcing the country's economy, can lead to job creation and increase the yield of the company because the impact of good decision-making leads to financial growth. Moreover, this study could be used as a baseline for machine learning's applications in the academic environment. This paper is structured as follows: Section II covers the literature review; Section III discusses the experimental setup such as the data used for this study and emphasizes the proposed machine learning techniques. In Section IV the simulation results and discussion are presented followed by Section V with the conclusions and recommendations.

Literature Review

In order to reduce errors in decision-making, research has been conducted in the area of quality management. In 2021, (Jiju and Sony, 2021) presented an empirical

qualification and skills study of quality management experts in contemporary organizations. This study is based on a global survey and agenda. The objective of this research was to explore the skills and qualifications of quality management experts in many organizations at a comprehensive level. A survey was conducted over 22 weeks in 46 countries over six continents and 336 responses were obtained from managers in roles such as quality directors, quality managers and quality engineers. It emerged from this study that 37% of quality managers never had a university degree for their position, and up to 40% of quality engineers and managers have had less than a week of training. However, information sharing was identified as one of the major problems (Gao, et al., 2020). It is possible to reduce this lack of information sharing by adopting responsible behavior. A study was conducted in this regard (Love, et al., 2020) that aimed to establish how a new organization can reduce and limit errors in its projects and mitigate rework and failures. The method consisted of having semi-structured interviews with employees involved in the construction companies. It emerged that the primary culture of new organizations focused on error prevention, which obstructed its aptitude to learn and decrease rework in projects. Organizations often deliberately endorsed a trade-off between quality and safety.

In 2020, (Sofiyabadi and Valmohammadi, 2020) evaluated the impact of knowledge management practices on innovation performance. The primary objective of this research was to study the influence of knowledge management practices on the innovation performance of a top Iranian private bank. The method consisted of distributing a questionnaire of 52 questions among 237 experts and managers of the bank. Exploratory and confirmatory factor analyzes were used to analyze the research data and it emerged from this study that independent factors such as better communication positively impact innovation performance. However, in the engineering domain designed principles and system operation techniques should be developed to increase the stakeholders' value. (Specking, et al., 2021) proposed a framework for engineering managers to better communicate with stakeholders' operators to strengthen the company's resilience. The technique developed is based on the principles-means-ends diagram for resilience-engineered systems. Various resilience terms were identified from previous publications and classified. It was found that engineering managers and systems engineers need to standardize resilience terminology to communicate better between them and other stakeholders. Thus, to increase companies' resilience, some research emphasized the mindset of stakeholders and proposed AI techniques (ANN approach) to evaluate the psychology and system-related barriers. (Wong, et al., 2021) proposed a block chain for operation management study where one-hundred-seventy-eight responses from manufacturing were collected and analyzed using ANN. Nonlinear relationships of the barriers toward operation management resistance were found compared to linear relationships usually obtained by other researchers in this domain. Researchers have estimated that one of the top influencing factors was the working environment, such as top-quality colleagues. They also proposed to intensify practice in the

management engineering field which integrates management and engineering knowledge. This is nowadays necessary to overcome many challenges encountered in various corporates and to improve quality efficiency.

The basis of all innovation is the competitiveness desire. The majority of companies promote innovation as their main objective to stay competitive despite any challenges encountered. Thus, the innovation also starts with the managerial side. Companies should base their competitiveness on a value chain and end-to-end business process optimization rather than only on profit (Vermeulen, et al., 2012). In this case, the functionalities or serious organization factors are used to quantify their willingness to implement a business process capability and assist organizational leaders, executives, and employees in judgmentally analyzing of the current business processes through gap investigation whereby organizational emergencies have to be analyzed and to be compared against the existing practice performances. In 2021, (Hena-García and Montoya, 2021) inspected the relationship between technological innovation, management innovation, and performance. A survey was conducted, and a regression model was applied to analyze the obtained data from the Columbian manufacturing sector. The analysis indicated that the introduction of management and technological innovation does not guarantee the company's performance. But this performance could be achieved by applying effective technical solutions in the problem process and from solid support and engagement of all organizations and involved staff (Xiong, et al., 2021). However, the proposed technique is based on the staff's total commitment and engagement knowing that humans are dynamic.

In 2020, (Prentice, et al., 2020) proposed a developed strategic management framework to support the improvement of the stratagems for increasing the commercialization rate of multi-technology renewable energy systems, and applied it as a case study to concentrating solar power in South Africa. For the same perspective, (Maruster and Alblas, 2020) proposed a data-driven approach based on data mining techniques and innovative text analytics to tailor the engineering design process. The method applied consisted of embarking on an automatic analysis to extract specific events from an unstructured event log. It emerged that the accuracy obtained associated with specific engineering change types is high, assuring the method's applicability. These studies concurred to develop the strategy for sustainable economic growth and could be applied in small-scale mining operations (Singh, et al., 2018). The impact of this change management is the decreasing overall project cost and schedule. This has been highlighted in (Serapelo, et al., 2017). It often happens that the efficiency of an innovation in a corporate is contested due to bad practices. In this regard, the quality efficiencies are investigated in (Vermeulen, et al., 2015). Moreover, nowadays it is unfair to talk about innovation without taking into consideration the new and powerful AI techniques.

Several investigations are now done in management based on AI techniques in order to solve complex constraint work tasks such as outage management of nuclear power plants (Gomes, et al., 1997) and to make strategic decisions (Demirkan, et al., 2020).

Such investigations will help to determine hubristic decisions taken by the top managers to influence the market performance of their companies before these decisions could be implemented. In 2020, (Muhlroth and Grottke, 2020) presented an AI-based data mining model that helps companies spot emerging issues and trends at a higher level of automation than previously possible. Three case studies were analyzed and the authors showed that their model is used to identify new technologies before their first publication in the Gertner Hype Cycle for emerging technologies. The data were trained in supervised learning and tested in an unsupervised manner. The results show that the model developed can achieve the highest possible degree of automation compared to the existing approaches in this field. In the new technological era, we have electric vehicles where (Inuzuka, 2019) used reinforcement learning to predict real-time energy management. The method consists of predicting the future vehicle speed and planning the necessary power to achieve it. It was shown that deep reinforcement learning could well be used for energy management because it can increase the expected discounted reward based on its own knowledge.

In 2019, (Alsheryani, et al., 2019) studied the improvement of asset management systems based on AI techniques. Even for some traditional industries such as in (Chai, et al., 2019), AI techniques were investigated to support the business management of power-grid companies and to explore how entrepreneurship is seen in the areas of engineering, compared with how it is offered in other contexts (Schuelke-Leech, 2020). It emerges that specific topics are covered differently in engineering entrepreneurship than in other types of entrepreneurship because in engineering, courses are less likely to emphasize financial management, managing ventures and entrepreneurial processes. Another AI technique often used for predictive management is fuzzy logic. This technique was used in 2020 (Chen, et al., 2020), to study a new driving cycle technique for the energy management strategy of a battery energy storage system. Based on the results obtained, the management could extend the battery's life. This technique has also been used to investigate the investment decision of optimum repair of multiple metro vehicles. The damage level of an existing distress metro vehicle by specific indicators was determined and the annual fund investment for maintenance and repair was evaluated. The research concluded that due to the approximate characteristics of the vehicle repair problematic, the choice of its investment needs human intelligence because fuzzy AI techniques have been used for decision-making for uncertainty problems.

Experimental Setup

Debates over the causes of Africa's largest power utility company decline are in the news. Load shedding increase to stage six (6000 MW power shortage) has a huge negative impact on the sub-region's economy and especially on that of South Africa. Some political actions have been taken to boost the production of this company or to split the company into three minor companies in order to reduce the impacts of failure. The proposed solutions have no scientific basis study and could also

contribute to increase the failure. Therefore, it may be wise to use advance scientific techniques such as machine learning to analyze the current situation and propose solutions which can contribute to raising its economy. The experiment was set up to analyze a company's annual reports published online in order to identify some parameters that have an influence in the decision-making. It was also investigated if their impact can be used to determine the well-being of a power generation and transmission line company. The extracted data over a 15-year period from 2005 to 2020 were used as the input data. For a better analysis, this input data was divided into five groups which are:

1) Data related to the company's annual energy productivity (Date, Energy sales in South Africa, International sales, Total sales). The size of this data is 15 rows times 5 columns for a total of 75 datasets.

2) The use of all data related to the productivity (Date, Energy sales in South Africa, International Sales, Total sales, with a data size of 15x3); related to the income earned (Revenue in South Africa and International revenue, with a data size of 15x3), related to the energy demand and the number of customers connected to the grid (peak demand, customer number, with a data size of 15x3), and related to the transmission line parameters (total length of the lines, level of CO₂ pollution, total transmissible power generated, generating capacity, with a data size of 15x5) for a total data size of 15x12.

The expected output was determined and set by allocating a binary number "0" or "1" (Wanto, et al., 2017) (Tayeb, 2013) if CEOs' dismissal or resignation status is respectively negative or positive for the studied years. Knowing that a good utility management could be evaluated by the level of load shedding for the electricity sector, the binary allocation process was based on the level of load shedding and the reasons why a chief executive officer was maintained, dismissed or had resigned during the studied time frame. In a year such as 2017 where negative decisions were involving in the CEOs' changing, a binary number "0" was allocated for the expected output.

Nevertheless, it is possible to have some dismissals not be performance-related. For example, despite the improving financial ratio, McDonald's CEO Steve Easterbrook was fired for consensual relationship with a subordinate (Selyukh, n.d.). If this situation has to be allocated a binary number as an output, "1" should have been given since this study focuses on companies' well-being neither a human resources' emotions. However, if this same situation financially or technically impacted the yield of the company, a "0" should have been given as output. Having the input and output data, two of the ANNs time series machine learning techniques, namely ANN-LM and ANNSCG, were used based on their capacity to analyze nonlinear data and to predict the result over time. Moreover, a set of 10, and 50 were given to the number of hidden neurons used to perform the simulations. This was done to determine the impact of some parameters that influence the machine learning performances. A time series response is plotted to analyze the results obtained. In

time series, a response takes a target time series (t) and an output time series (y) and plots them on the same axis showing the errors between them (MathWorks, n.d.).

Data Collected

The annual report is a precious source of information where much data can be obtained. From 2005 till 2020, the data extracted from these reports to perform this study were the energy sale in GWh at international and domestic levels; the total energy produced yearly; the revenue gained from international and domestic sales; the peak demand in MW; the number of consumers; the total length of the transmission lines in km; the yearly level of CO₂ pollution in Mt and the total power generated in MW. These data were determining factors to establish the well-being of an electricity generation company.

To perform the simulation, a target output has to be set. Thus, the list of CEOs with the reasons given for their dismissal as shown in Table 1 was analysed in-depth. Various reasons were given to justify their stepping down and those reasons were respectively converted into a “good’ using “1’ or “bad’ using “0’ managerial decisions taken by the dismissed during this function. Thus, the decisions taken have either contributed to improve or reduce the company’s well-being.

Table 1: List of a South African company’s CEOs Performance over 10 years (Businesstech, n.d.)

| CEO | Years of Function | Status | Reasons |
|-----|-------------------|-------------------------------------|---|
| 1 | 2000-2007 | Term ended | End of the contract |
| 2 | 2007-2009 | Resigned | Pretend to have been dismissed illegally Court’s decisions in favor of the company’s board |
| 3 | 2009-2010 | Acting term ended | Served as acting CEO |
| 4 | 2010-2013 | Resigned | Personal reasons |
| 5 | 2013-2014 | Acting term ended | Served as acting CEO |
| 6 | 2014-2015 | Dismissed | Load shedding investigation, and the reason the company could not prevent it |
| 7 | 2015-2016 | Resigned | Claimed he retired after allegation of being involved in State Capture |
| 8 | 2016-2017 | Acting, dismissed and then resigned | Facing allegations of nepotism, leaking confidential information and misleading |
| 9 | 2017 | Acting term ended then resigned | To follow private business interests |
| 10 | 2017-2018 | Acting, dismissed and then resigned | Associated to State Capture, while facing charges of misleading relating to Trillian and a Hong Kong company. |
| 11 | 2018- Now | Actual, CEO | / |

Machine Learning Techniques Used

The development of machine learning techniques is based on human brain behaviour. The first ANN technique was proposed by Hebb in early 1949 (Bansal, 2015). To solve complex problems with nonlinear data, the association of many neurons give the general structure of an ANN architecture as shown in Figure 1.

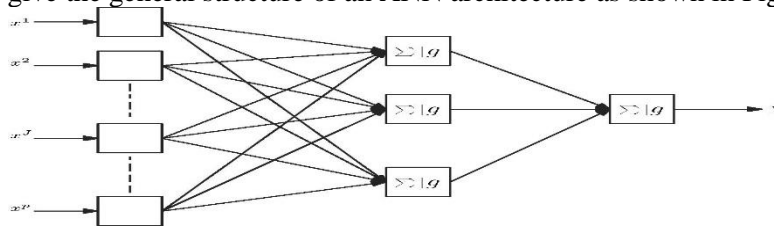


Figure 1: Typical General Architecture of an ANN Technique

When the expected output data are set to be binary numbers, the input data should be normalized. The formulas used to normalize an input data is shown in Equation 3 (Wanto, et al., 2017) (Tayeb, 2013).

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_n is the normalized value, X_{max} represents the maximum value, X_{min} is the minimum value and X represents the value to be normalized.

The applications of ANN techniques are varied and diversified. However, according to the kind of problem to be solved, a specific configuration should be used among three main categories which are:

- 1) Nonlinear Auto-regressive in which the external inputs are used as a part of the input data and this is mostly applied in control. This is presented in Figure 2a.
- 2) Nonlinear Auto-regressive in which the external output is used as the input such as in image recognition. Its structure is presented in Figure 2b.
- 3) Nonlinear Input-Output in which there is no direct relationship between the inputs and the desired outputs of the system as shown in Figure 2c. This is mostly used in fault classification and will be used in this case study.

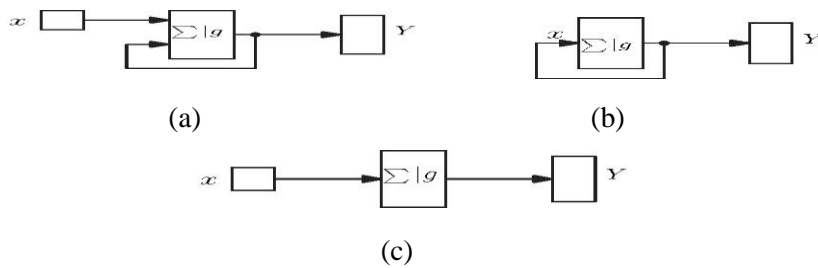


Figure 2: Specific ANN Architectures

To optimize the results obtained, ANN techniques are endowed with a function of back-propagation of the error. It is used to evaluate the obtained output 'y' compared to that desired and to determine the error and this error could now be backpropagated. Thus, determining an output value and backpropagating the error to have a new input is called epoch. This procedure can be done n -times. However, a limit of epoch should be set to avoid increasing the mean squared error (MSE). This is why current machine learning determines the MSE value at each epoch and compares it against other obtained values. If a decreasing MSE value changes its initial direction and starts to increase, the system will automatically stop the computation. During the simulation using MATLAB, various steps have to be followed such as: Import input and output data from an Excel file; Choose the right percentages for training; Validation and testing with the default percentage being respectively 70%, 15%, 15%; Choose the suitable architecture of your machine learning technique (the number of hidden layers and the value of the delay); Choose the suitable type of Machine learning algorithm (SCB or LM) for the analysis and train the system, and Interpret the obtained results.

Simulation Results and Discussion

In this section, the robustness of the proposed ANN techniques is demonstrated through the simulation study with real data collected from annual reports of the largest African company located in South Africa. Data were processed using the machine learning techniques of MATLAB R2016a, installed on an i5 computer that has 8GB memory. The training was performed with various sets of data as shown in the experimental setup section for each of the two implemented techniques. This was done to determine the most appropriate approach to obtain the best results. For each setup training was done, and the performance of the system, the training state, the error histogram as well as the time-series responses were analyzed. A training session was successful only if the regression values that measured the correlation between outputs and targets were obtained closest to “1” in absolute value. If this regression value was closest to ‘0”, then the system was retrained to meet the conditions and the MSE was then collected. Using the ANN-LM technique, Figure 3 shows the MSE obtained at different epochs for the training, validation, and testing using the default percentages. The data related to the company’s annual productivity were used as the inputs of the machine learning. The best validation was obtained when MSE was equal to 0.09 at epoch 5. Thus, 5 epochs were necessary to complete the full training of the system because the MSE obtained was the smallest.

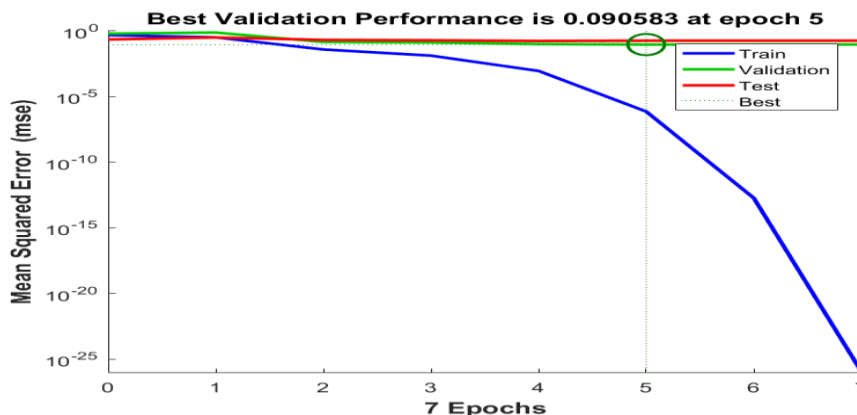


Figure 3: ANN-LM Performance with 10 Hidden Layers

The error of the system in Figure 4 was determined by computing the difference between the expected outputs and the obtained outputs. It shows that the error obtained is higher for the training compared to the validation and test and the error of the test in “red” is also higher in absolute value at the beginning of the training. The time-series response obtained is shown in Figure 5. This response shows that the error is higher with data used at the beginning of the computation followed by

the last data which respectively represents the data collected earlier in 2005 and 2020 even though these errors are the smallest.

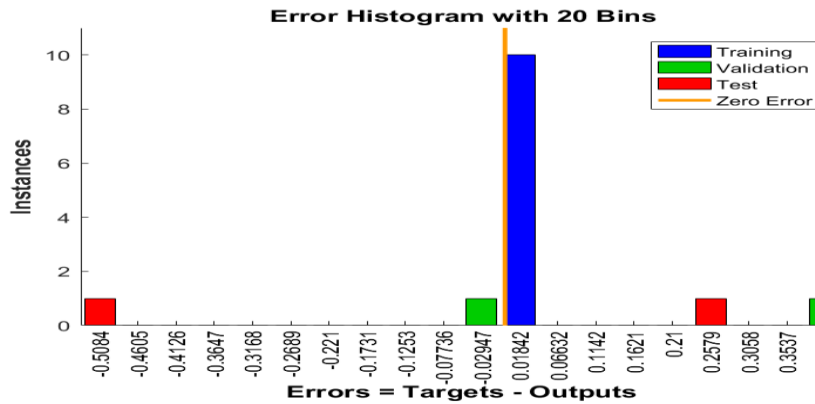


Figure 4. ANN-LM Errors Histogram with 10 Hidden Layers

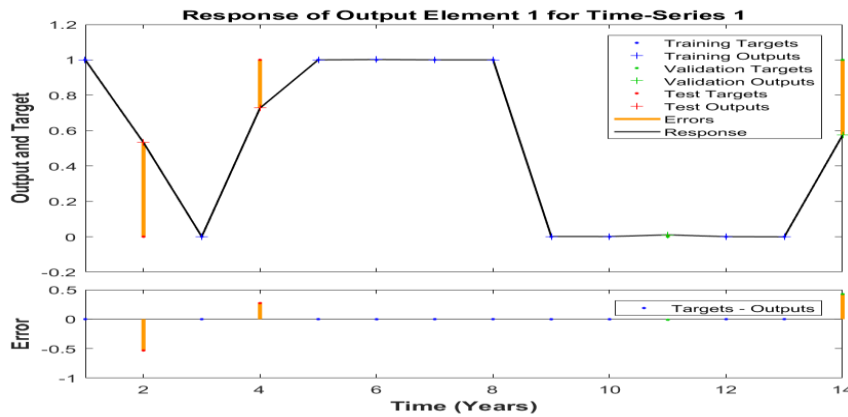


Figure 5. ANN-LM Time-Series Response with 10 Hidden Layers

Table 2. MSE obtained using ANN-LM

| Input Variables | Hidden Neuron Used for Training | MSE Obtained | | | Epoch for Best validation |
|---------------------|---------------------------------|--------------|------------|---------|---------------------------|
| | | Training | Validation | Testing | |
| Energy Productivity | 10 | 7.26E-7 | 9.05E-2 | 1.78E-1 | 5 |
| | 20 | 2.75E-25 | 2.65E-1 | 1.9E-1 | 5 |
| | 30 | 6.34E-3 | 5.08E-1 | 8.1E-2 | 1 |
| | 40 | 2.6E-2 | 6.84E-1 | 1.17 | 1 |
| | 50 | 3.2 | 9.55E-2 | 1.57 | 0 |
| Income Earned | 10 | 7.58E-2 | 1.19E-1 | 2.76E-1 | 5 |
| | 20 | 7.74E-2 | 5.67E-2 | 2.11E-2 | 3 |

| | | | | | |
|--|----|----------|---------|---------|---|
| | 30 | 7.79E-2 | 6.01E-2 | 5.42E-1 | 4 |
| | 40 | 3.85E-2 | 6.16E-1 | 6.01E-1 | 1 |
| | 50 | 5.91E-2 | 1.86E-1 | 8.54E-1 | 1 |
| Number of Consumers and Energy Demand | 10 | 1.25E-16 | 8.95E-2 | 8.01E-1 | 6 |
| | 20 | 9.12E-7 | 5.05E-3 | 1.17E-7 | 3 |
| | 30 | 6.62E-1 | 4.09E-1 | 1.09E-1 | 0 |
| | 40 | 8.65E-4 | 4.63E-2 | 1.38 | 2 |
| | 50 | 3.4E-5 | 3.07E-2 | 4.5E-1 | 2 |
| Lines' Length and Pollution Level | 10 | 1.54E-2 | 3.29E-3 | 7.52E-1 | 3 |
| | 20 | 3.12E-2 | 6.14E-2 | 3.08E-2 | 2 |
| | 30 | 1.87E-4 | 2.08E-1 | 4.73E-2 | 2 |
| | 40 | 4.74E-4 | 1.89E-1 | 1.03E-1 | 2 |
| | 50 | 6.81E-3 | 5.5E-3 | 6.14E-2 | 1 |
| All Variables | 10 | 2.78E-28 | 2.23E-2 | 2.03E-1 | 6 |
| | 20 | 5.51E-6 | 2.13E-1 | 1.63E-2 | 2 |
| | 30 | 5.64E-5 | 1.52E-1 | 2.61E-1 | 2 |
| | 40 | 1.03E-5 | 1.64E-1 | 1.35E-2 | 2 |
| | 50 | 1.26E-2 | 1.06E-1 | 3.5E-4 | 1 |

As shown in Table 2, the input variables used with the allocated hidden layers vary with the epoch for best validation and subsequently, the MSE obtained. The increasing number of hidden layers leads to an increase in the MSE obtained, but reduces the total epoch for best validation. This can be observed in all input variables utilized. However, this does not affect the overall results that much due to the fact that these errors are the smallest.

The ANN-SCG technique was also applied to evaluate its capability to solve nonlinear problems i.e. its robustness. The MSE obtained defines the performance of the system at different epochs for the training, the validation and the test as is shown in Figure 6. This performance was evaluated when 30 hidden layers were utilized with the income earned by the company as the inputs of the machine learning. The graphs of the validation in "green" color and test in "red" color indicate that the training and the best validation performance of the system were obtained when the number of epochs equaled 11. This demonstrated that this machine learning technique learns better when the number of data sets is low.

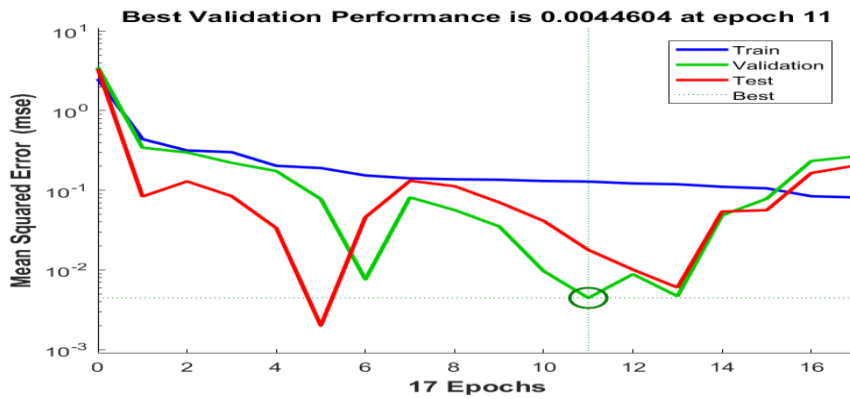


Figure 6: ANN-SCG Performance with 30 Hidden Layers

The obtained error of the system shown in Figure 7 demonstrates that, even though the validation and the test errors are fewer compared to the training errors, the obtained values are higher compared to the ANN-LM technique. That is why the system continued to increase the number of epochs in order to reduce these errors. Thus, the time-series response in Figure 8 shows that the value of the errors varies from one target to another and increases with the increase of the hidden layer numbers as shown in Table 3 where all the data sets with their corresponding MSEs obtained are presented. This Table 3 shows that if all variables are used, the best system configuration is when 40 hidden layers are used since this gives the smallest number of epochs.

Table 3. MSE obtained using ANN-SCG

| Input Variables | Hidden Neuron Used for Training | MSE Obtained | | | Epoch for Best validation |
|---------------------|---------------------------------|--------------|------------|---------|---------------------------|
| | | Training | Validation | Testing | |
| Energy Productivity | 10 | 1.25E-3 | 5.83E-2 | 3.02E-1 | 22 |
| | 20 | 7.04E-7 | 1.57E-2 | 3.78E-1 | 3 |
| | 30 | 6.11E-2 | 1.93E-1 | 1.41E-3 | 2 |
| | 40 | 5.54E-6 | 1.2E-2 | 5.7E-1 | 2 |
| | 50 | 1.25E-18 | 9.3E-2 | 5.17E-2 | 4 |
| Income Earned | 10 | 8.79E-2 | 1.95E-1 | 2.55E-1 | 13 |
| | 20 | 7.09E-2 | 2.01E-1 | 8.49E-1 | 11 |
| | 30 | 1.28E-1 | 4.46E-3 | 1.78E-2 | 11 |

| | | | | | |
|--|----|---------|---------|---------|----|
| | 40 | 8.92E-1 | 1E-2 | 2.58E-2 | 0 |
| | 50 | 1.33E-1 | 1.46E-2 | 1.02E-1 | 5 |
| Number of Consumers and Energy Demand | 10 | 3.19E-2 | 6.34E-3 | 2.19E-1 | 11 |
| | 20 | 7.60E-3 | 1.01E-2 | 2.74E-1 | 10 |
| | 30 | 1.95E-2 | 9.68E-2 | 2.29E-1 | 7 |
| | 40 | 1.16E-2 | 8.33E-3 | 6.93E-2 | 8 |
| | 50 | 3.73E-2 | 8.02E-2 | 1.11E-1 | 5 |
| Lines' Length and Pollution Level | 10 | 6.02E-2 | 1.3E-1 | 5.35E-2 | 8 |
| | 20 | 4E-2 | 8.62E-2 | 9.2E-1 | 5 |
| | 30 | 2.08E-2 | 1.8E-2 | 2.26E-1 | 6 |
| | 40 | 2.04E-2 | 4.02E-3 | 4.18E-2 | 5 |
| | 50 | 2.24E-2 | 1.83E-4 | 5.81E-3 | 9 |
| All Variables | 10 | 5.41E-3 | 9.62E-3 | 1.78E-1 | 15 |
| | 20 | 2.85E-2 | 3.21E-3 | 2.10E-1 | 5 |
| | 30 | 2.34E-2 | 1.45E-2 | 1.19E-1 | 7 |
| | 40 | 2.42E-2 | 9.75E-2 | 1.91E-1 | 3 |
| | 50 | 5E-4 | 9.56E-2 | 6.79E-2 | 12 |

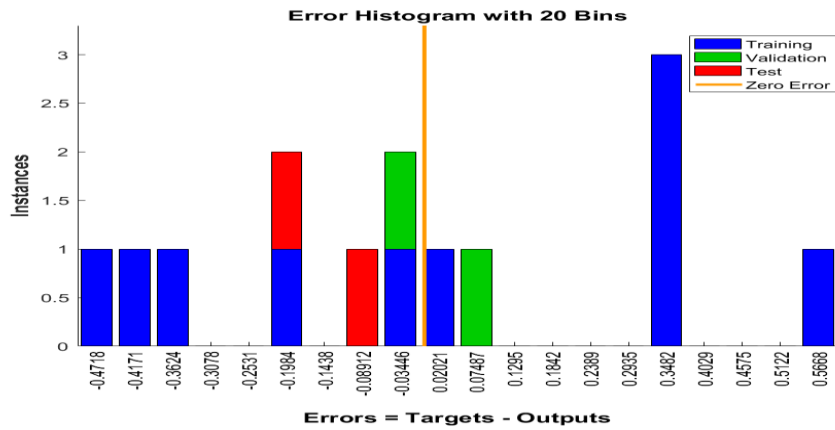


Figure 7: ANN-SCG Errors Histogram with 30 Hidden Layers

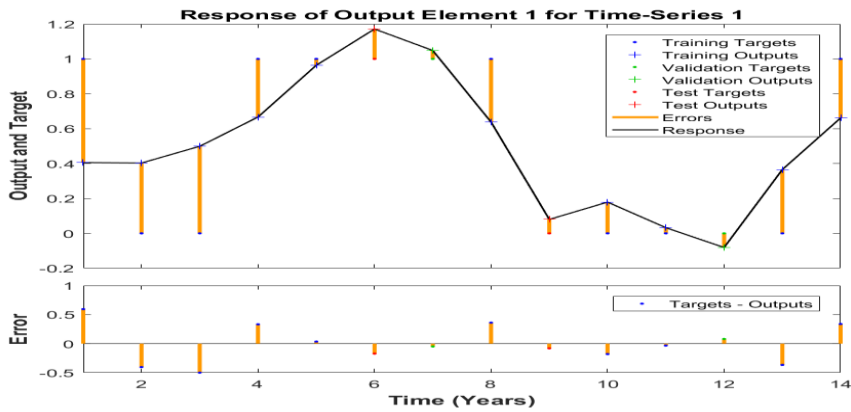


Figure 8. ANN-SCG Time-Series Response with 30 Hidden Layers

The results obtained with the machine learning techniques demonstrated that the learning, test, and validation procedures provide excellent results due to the short number of epochs used to obtain the lesser MSE thus, to validate the results. Therefore, the two techniques used are well chosen and can be used for decision-making. These techniques have been used to predict Figure 9, Figure 10, Figure 11 and Figure 12. Analysis and recommendations provide with the obtained figures will be based on the slope of the response curve in black color.

In Figure 9 the prediction output is made using the ANN- LM technique with the annual energy productivity. From the slopes at various areas on the curve, a projection could be done in "y" axis to have the corresponding date and perform some analysis. It is shown that despite the load-shedding which was instituted in the year 2010, this did not affect the company growth much. This was due to the fact that energy growth continued despite the poor state of the studied company.

However, this growth proceeded very slowly and at any time could have turned negative maybe because of a power unit collapse or a lack of raw material.

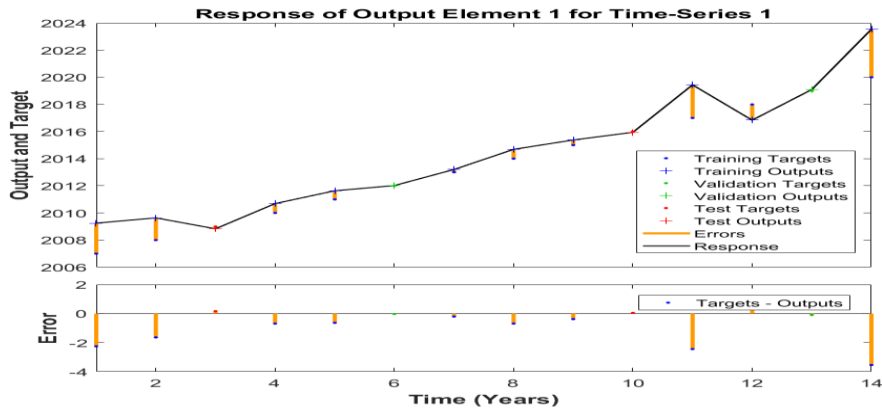


Figure 9: Prediction Output using ANN-LM with the Annual Energy Productivity and 10 Hidden Layers.

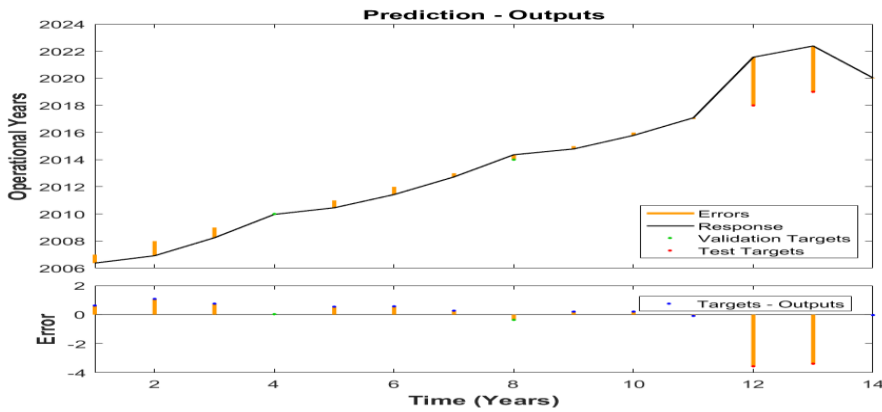


Figure 10: Prediction Output using ANN-LM with all Data and 50 Hidden Layers

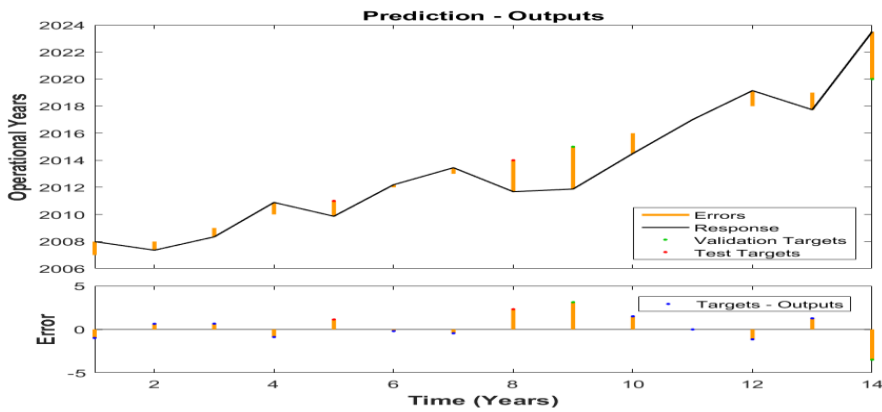


Figure 11: Prediction Output using ANN-SCG with the Annual Energy Productivity and 10 Hidden Layers

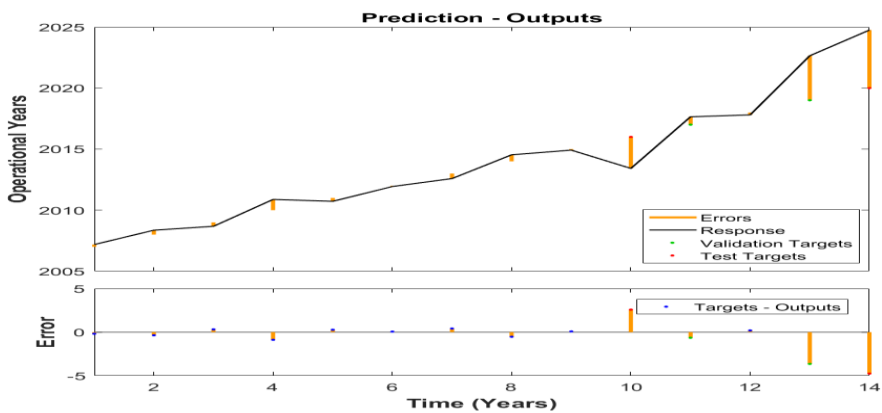


Figure 12: Prediction Output using ANN-SCG with all Data and 50 Hidden Layers

In 2012, the well-being of the company improved consistently until 2015 before seeing its growth reduce in 2017 comparing to previous years. Figure 9 also indicates that in 2016, the measures taken to turn around the company had an impact on the following years with strong growth which has be weakened between 2019, since a negative slope was predicted. However, from 2020, the system predicted a positive slope. Nevertheless, This Figure 9 also shows that in 2020, the training outputs predicted has the highest error compared to the target, this could be due to the system’s setup such as the number of hidden layers used.

The same observation is made in the Figure 10 where we see an almost similar evolution with a jump between 2016 and 2020, but with a predicted slight decrease in the company’s well-being from 2020 to 2022. Thereafter a decrease is expected in the following years. Figure 11 tell us that the company has experienced downturns for several years but a strong increase occurred between 2014 and 2019 materialized by the positive slopes. However, in 2019, a decline was felt which brought back the

company to its 2018 state before the measures taken to revitalize it allowed it to gain momentum which will be maintained in the years to come with a positive GDP economic contribution up to 2025. In Figure 12, some downturns are also observed up to 2017 before a strong increase in the company's state since a positive slope is predicted. Beyond 2022, a positive slope is still observed but compared to the previous one, a small decrease will be observed up to 2025.

In view of the results obtained and predicted by the machine learning techniques used and the current situation in the country, it can be seen that the techniques implemented have faithfully reproduced the company's state during its last years except for Figure 10 up to 2020 and Figure 11. These predicted a growing state between 2014 and 2016 while the company was going through a difficult time. However, these two developed techniques indicate a good evolution between 2016 and 2018, but without denying good growth in the coming years. But beyond 2022, according to the current situation, Figure 10 seems to have the better prediction of a decrease in the company's state. This can be observed with the level of loadshedding currently implemented in the country even though Figure 12 also predicts a slight decrease. It should be noted that Figures 9 and 11 base their results only on annual energy productivity data. This in itself is not a limited factor to assess the state of a company's well-being because there is a direct relationship between energy productivity, demand and accrued revenues. In Figures 10 and 12 their predictions are based on a set of parameters which takes into account the total energy produced, revenues, electricity demand, number of consumers, length of the transmission lines, the total power generated, and the quantity of CO₂ generated which enables one to have a more realistic idea of the studied situation. It is clear that the company in the year 2020 has a net increase in its well-being compared to previous years, but may see this pull up in 2022 to its state before the year 2020 according to Figure 10. Nevertheless, this well-being may continue up to 2024 according to Figure 9, 11 and 12.

In view of the results obtained, all objectives have been addressed. It is now scientifically demonstrated that the state of this company analyzed is unsatisfactory. It may therefore be wise to take essential measures which are known to be excellent for rectifying the curve. Some of the measures that can be implemented to influence the state of this company are known such as the training of qualified engineers in a particular training school for the maintenance of power plants; A competitive salary policy to retain the most qualified employees in the company; An anticipation of energy demand according to the economic policy set up; The strengthening of the measures taken in years 2018 to permanently supply electricity since all predictions have shown an increase during that time.

ANN technique has been used in several studies to estimate one of the top influencing factors in the working environment (Wong et al., 2021) but has not yet been used in decision-making. Nevertheless, (Muhlroth and Grottke, 2020) used AI-based data mining to spot emerging issues and trend in automation. Usually,

decision-making studies are based on survey (Juju and Sony, 2021), (Love et al., 2020). This study allows to expand the application of ANN in the literature.

Conclusion

The objective of this study was to develop a decision-making support system based on two machine-learning techniques. To do this, data from the largest African power utility company based in South Africa were analyzed using ANN-LM and ANN-SCG. These techniques have been chosen due to their simplicity and the kind of data utilized in this research (binary numbers). The first step consisted of determining the company's internal parameters which have an impact on the increasing evolution of its activities and can be used to materialize its well-being. According to the annually published data in its reports, it was noted that the data relating to energy production, annual income, energy demand, number of consumers, and length of transmission lines and level of pollution are most important. Thus, this data was used as the input data for the machine learning techniques. The second step was to determine the expected outputs of machine learning techniques based on the state of the studied company for 15 years. Based on the reasons for CEOs' dismissals or resignations, a binary number '0' or '1' was assigned to each operational year. The third step was to determine if the two machine learning techniques used can well analyze the data obtained and create a faithful relationship between the input and output data in order to use their learning power to assess the level of well-being of the company.

Both techniques have been shown to be excellent in learning the data provided regardless of the number of hidden layers used. Thus, all objectives have been met. The results obtained have shown that the company which highly supported the country's GDP in the years from 2005 has been doing relatively badly since 2008. The fluctuating situation saw a succession of 12 CEOs in 10 years of operation and has cost up to US\$35,439,272. However, this change in CEOs did not solve the problems that this company encountered and was going through. Nevertheless, the machine learning techniques used have shown that between 2018 and 2020 the company experienced good growth which could extend until 2025 in the best of the cases if good decisions are taken or else will fall again from 2022 to reach its 2020 well-being state.

Since the input data were assigned output data according to the company's state, it is recommended to increase the production and the length of the transmission lines knowing that the demand is high and the number of customers continues to increase year after year. It was also noted that the CO₂ rate is a function of the amount of electricity produced. This is due to the fact that the vast majority of electricity produced is generated from coal as a raw material. It is, therefore, recommended to increase the production of renewable energy plants such as solar and wind power to reduce this CO₂ rate. Using such data among others allows for a unique set of inputs necessary to accurate the results. Finally, it is recommended to increase the number of international consumers who usually pay their bills in foreign currency such as the US dollar in order to support other local activity sectors. For future research and

in addition to this study, a larger sample size of data will be used and statistical approaches will be implemented to compare with the machine learning techniques. Moreover, k-fold validation will also be deployed and the results obtained from these techniques will be analyzed. In conclusion, modelization does not predict the future but helps to understand the future better and stay prepared to take informed decisions.

References

- Alsheryani, R. M., Alkaabi, S. S., Alkaabi, S. S., Aldhaheeri, A. M., Khouri, F. I., Alharmoodi, S. I. and Alhajeri, A. S., (2019). Applying Artificial Intelligence (AI) for Predictive Maintenance of Power Distribution Networks: A Case Study of Al Ain Distribution Company. *International Conference on Electrical and Computing Technologies and Applications (ICECTA)*, 1-5.
- Antonio, A.-S., Barba-Aragón, I. and Sanz-Valle, R., (2003). Effects of training on business results. *The International Journal of Human Resource Management*, 14(6), 956-980.
- Bansal, R. C., (2015). Optimization methods for electric power systems overview. *International Journal of Emerging Electric Power System*, 2(1).
- Businesstech. (n.d.). *Eskom's 12 CEOs and executives have cost R514 million: Manuel*. Retrieved September 06, 2021, from <https://businesstech.co.za/news/energy/302442/eskoms-12-ceos-andexecutives->
- Chai, B., Zhang, Q., Chen, Q., Zhao, T. and Gao, K., (2019). Research on Applications of Artificial Intelligence in Business Management of Power Grid Enterprises. *4th Advanced Information Technology Electronic and Automation Control Conference (IAEAC)*, 1, 683-.
- Chen, H., Xiong, R., Lin, C. and Shen, W., (2020). Model predictive control based real-time energy management for a hybrid energy storage system. *CSEE Journal of Power and Energy Systems*, 7(4), 862-874.
- Confalonieri, M., Barni, A., Valente, A., Cinus, M. and Pedrazzoli, P., (2015). An AI based decision support system for preventive maintenance and production optimization in energy intensive manufacturing plants. *Technology and Innovation/International Technology Management Conference (ICE/ITMC)*, 1-8.
- Demirkan, I., Demirkan, S. and Kiessling, T. S., (2020). Strategic Decision Making of Top Management: Earnings Management and Corporate Acquisitions. *IEEE Transactions on Engineering Management*, 69(4), 963-975.
- Eskom., (2005). *Eskom Annual Report*. Retrieved September 6, 2021, from <https://www.eskom.co.za/OurCompany/Investors/IntegratedReports/PagesAnnualStatements.aspx>
- Eskom., (2009). *Eskom Annual Report*. Retrieved September 6, 2021, from <https://www.eskom.co.za/OurCompany/Investors/IntegratedReports/PagesAnnualStatements.aspx>. Annual Report 2009.pdf.
- Gao, D., Wang, N., Bin, J., Gao, J. and Yang, Z., (2020). Value of Information Sharing in Online Retail Supply Chain Considering Product Loss. *IEEE Transactions on Engineering Management*, 69(5), 2155-2172.

- Garces, E., Daim, T. U. and Dabi'c, M., (2021). Evaluating RandD Projects in Regulated Utilities: The Case of Power Transmission Utilities. *IEEE Transactions on Engineering Management*.
- Gavin, H. P., (2019). The Levenberg-Marquardt algorithm for nonlinear least squares curve-fitting problems. *Department of Civil and Environmental Engineering, Duke University*, 1-19.
- Gianluca, E., Margherita, A. and Passiante, G., (2020). Management Engineering: a new perspective on the integration of engineering and management knowledge. *IEEE Transactions on Engineering Management*, 68(3), 881-893.
- Gomes, C. P., Smith, D. and Westfold, S., (1997). A transformational approach applied to outage management of nuclear power. *In Proceedings of the Thirtieth Hawaii International Conference*, 5, 658-667.
- Henao-Garc'ia, E. A., Montoya, R. A., (2021). Management Innovation in an Emerging Economy: An Analysis of Its Moderating Effect on the Technological Innovation–Performance Relationship. *IEEE Transactions on Engineering Management*, 70(1), 128-141.
- Inuzuka, S. F., (2019). Reinforcement learning based on energy management strategy for HEVs. (pp. 1-6). *IEEE Vehicle Power and Propulsion Conference (VPPC)*.
- Jabbar, R. A., Junaid, M., Masood, M. A., Zaka, A., Jahangir, H., Rafique, A. and Kaleem, R. I., (2010). Neural network (NN) based demand side management (DSM). (pp. 1-6). *20th Australasian Universities Power Engineering Conference, IEEE*.
- Jiju, A., Sony, M., (2021). An Empirical Study Into Qualification and Skills of Quality Management Practitioners in Contemporary Organizations: Results From a Global Survey and Agenda for Future Research. *IEEE Transactions on Engineering Management*.
- Kao, L.-J., Chiu, C.-C., Lu, C.-C. and Wu, C.-Y., (2021). Identification and Rating of Workforce Competencies for Manufacturing Process Engineers: Case Study of an IC Packaging Process Engineer. *IEEE Transactions on Engineering Management*, 70(1), 196-208.
- Li, X.-q. A.-b., (2010). Application of back propagation neural network on performance evaluation of enterprise informatization. *IEEE 17th International Conference on Industrial Engineering and Engineering Management*, 34-38.
- Love, P. E., Ika, L., Luo, H., Zhou, Y., Zhong, B. and Fang, W., (2020). Rework, Failures, and Unsafe Behavior: Moving Toward an Error Management Mindset in Construction. *IEEE Transactions on Engineering Management*, 69(4), 1489-1501.
- Maruster, L., Alblas, A., (2020). Tailoring the Engineering Design Process Through Data and Process Mining. *IEEE Transactions on Engineering Management*, 69(4), 1577-1591.
- MathWorks. (n.d.). *MathWorks: plotresponse*. Retrieved September 16, 2022, from <https://se.mathworks.com/help/deeplearning/ref/plotresponse.html>
- Muhlroth, C., Grottke, M., (2020). Artificial intelligence in innovation: how to spot emerging trends and technologies. *IEEE Transactions on Engineering Management*, 69(2), 493-510.
- Ogunrinde, O., Shittu, E. and Dhanda, K. K., (2020). Distilling the Interplay Between Corporate Environmental Management Financial, and Emissions Performance: Evidence From US Firms. *IEEE Transactions on Engineering Management*, 69(6), 3407-3435.

- Onishi, N., Chan, S., (2017). *The New York Times*. Retrieved September 6, 2021, from <https://www.nytimes.com/2017/03/31/world/africa/south-africa-pravin-gordhan-jacob-zuma.html>
- Prentice, G. S., Brent, A. C. and de Kock, I. H., (2020). A Strategic Management Framework for the Commercialization of Multitechnology Renewable Energy Systems: The Case of Concentrating Solar Power in South Africa. *IEEE Transactions on Engineering Management*, 68(6), 1690-1702.
- Reynecke, N., Marnewick, A. and Pretorius, J.-H., (2017). Factors influencing research in an engineering faculty. *IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 145-149.
- Schuelke-Leech, B.-A., (2020). Engineering Entrepreneurship Teaching and Practice in the United States and Canada. *IEEE Transactions on Engineering Management*, 68(6), 1570-1589.
- Selyukh, A., (n.d.). *NPR: Silence And Lies': McDonald's Sues Fired CEO, Says He Hid Sexual Relationships*. Retrieved August 27, 2022, from <https://www.npr.org/2020/08/10/900831535/silence-and-lies-mcdonalds->
- Serapelo, T. E., Erasmus, L. and Pretorius, J.-H., (2017). Engineering Change Management Impact on Project Success within a South African Petrochemical Company. (pp. 1-8). *Portland International Conference on Management of Engineering and Technology (PICMET)*.
- Singh, N., Mulaba-Bafobiandi, A. F. and Pretorius, J.-H. C., (2018). Strategy for Sustainable Economic Growth of Small Scale Mining Operations in South Africa. (pp. 1-8). *Portland International Conference on Management of Engineering and Technology (PICMET)*.
- Sofiyabadi, J., Valmohammadi, C., (2020). Impact of knowledge management practices on innovation performance. *IEEE Transactions on Engineering Management*, 69(6), 3225-3239.
- Specking, E., Gregory, S. P., Pohl, E. and Buchanan, R., (2021). Engineering Resilient Systems: Achieving Stakeholder Value Through Design Principles and System Operations. *IEEE Transactions on Engineering Management*, 69(6), 3982-3993.
- Tayeb, E. B., (2013). Faults detection in power systems using artificial neural network. *American Journal of Engineering Research*, 2(6), 69-75.
- Vermeulen, A., Pretorius, J.-H. C. and Kruger, D., (2012). Business processes capability and performance: A South African perspective Proceedings of PICMET'12. *Technology Management for Emerging Technologies*, 547-559.
- Vermeulen, A., Pretorius, J.-H. C., Motjoade, V. and Kruger, D., (2015). Developing and improving quality efficiency in the South African Energy industry. *Portland International Conference on Management of Engineering and Technology (PICMET)*, 1985-1992.
- Wanto, A., Windarto, A. P., Hartama, D. and Parlina, I., (2017). Use of binary sigmoid function and linear identity in artificial neural networks for forecasting population density. *International Journal of Information System and Technology*, 1(1), 43-54.
- Wong, L.-W., Garry Wei-Han, T., Voon-Hsien, L., Ooi, K.-B. and Sohal, A., (2021). Psychological and System-Related Barriers to Adopting Blockchain for Operations Management: An Artificial Neural Network Approach. *IEEE Transactions on Engineering Management*, 70(1), 67-81.

- Xie, Y.-J., Ma, C.-F., (2015). The scaling conjugate gradient iterative method for two types of linear matrix equations. *Computers and Mathematics with Applications*, 70(5), 1098-1113.
- Xiong, G., Wu, H., Helo, P., Shang, X., Qin, G. X. and Wang, F.-Y., (2021). A Kind of Change Management Method for Global Value Chain Optimization and Its Case Study. *IEEE Transactions on Computational Social Systems*, 9(4), 1060-1074.
- Zwikael, O., Gilchrist, A., (2021). Planning to Fail: When Is Project Planning Counterproductive? *IEEE Transactions on Engineering Management*, 70(1), 220-231.
- Xiong, G., Wu, H., Helo, P., Shang, X., Xiong, G., Qin, R., & Wang, F. Y. (2021). A kind of change management method for global value chain optimization and its case study. *IEEE Transactions on Computational Social Systems*, 9(4), 1060-1074.

PODEJMOWANIE DECYZJI W OPARCIU O TECHNIKI UCZENIA MASZYNOWEGO: STUDIUM PRZYPADKU

Streszczenie: Podejmowanie decyzji w firmach często opiera się na osobistym doświadczeniu menedżerów. Jednak konsekwencje tychże decyzji mogą mieć wpływ na rozwój codziennych działań. Aby zilustrować wpływ podejmowania decyzji na zarządzanie, przeanalizowana zostanie największa afrykańska firma energetyczna z siedzibą w RPA. Różnorodne dane, takie jak: roczna produktywność i sprzedaż energii, zostały wyodrębnione z raportów rocznych z 15 lat. Do analizy wyodrębnionych danych wykorzystano dwie techniki sztucznych sieci neuronowych o nazwach: Levenberg-Marquardt i Scaled Conjugate Gradient. Z uzyskanych rezultatów badań wynika, że w latach 2018-2020 firma doświadczyła dynamicznego wzrostu, który w najlepszym przypadku może potrwać do 2025 r po czym spadnie do poziomu z 2020 r. Uzyskane wyniki można zatem wykorzystać do wzmocnienia procesu decyzyjnego i określenia momentu, w którym należy podjąć decyzje zapobiegające upadkowi firmy.

Słowa kluczowe: podejmowanie decyzji, zarządzanie strategiczne, techniki uczenia maszynowego