Accounting Results Modelling with Neural Networks: The Case of an International Oil and Gas Company

Yang Duan[(✉)], Chung-Hsing Yeh, and David L. Dowe

Faculty of Information Technology, Monash University, Clayton,
VIC 3800, Australia
yang.duan@monash.edu

Abstract. Accounting results are crucial information closely monitored by managers, investors and government agencies for decision making. Understanding various endogenous and exogenous business factors affecting accounting results is an essential step in managing them. However, how to model the relationship between accounting results and their business factor antecedents remains an unresolved issue. To address this issue, this paper develops neural network (NN) models for modelling complex interactions between the business factors and accounting results. Based on empirical data from an international leading oil and gas company, 15 original data points, 8 inputs and 6 outputs are used, and 4 NN architectures in 2 training settings are tested. The experiments conducted show satisfactory results. Comparisons of various training settings suggest that a recurrent NN architecture with multiple outputs is best suited for accounting results modelling. The relative contribution factor analysis with the best-performing NN model provides new insights in understanding crucial business factors for the case company and accounting professionals to manage accounting results. As a pilot study, this paper contributes to business, accounting and finance research by providing a promising approach for accounting results modelling.

Keywords: Neural network modelling · Accounting results · Business factors
Oil and gas company

1 Introduction

Accounting results, namely accounting information presented on the statements of the balance sheet, the profit and loss, and the cash flow, are critical information to managers, investors and the government agencies. For public traded companies, published accounting results have significant impacts on their share prices and influences on their ability in funding future operations. Many studies in management, finance and economics use accounting results for performance measurements, asset pricing, bankruptcy prediction and tax fraud detection.

The modern business operates in a complex environment that exogenous factors would have the economic consequences to its accounting results. These exogenous factors have been neglected in traditional accounting research and their complex

non-linear relationships with the accounting results are also overlooked due to the use of traditional statistical models [1]. Numerous endogenous influential factors, such as operational settings, managerial preferences and financial settings, have been well investigated. However, the interactive effects among these endogenous factors and the effects caused by exogenous factors from the corresponding industry, financial market and macro economy are not considered. Complex and fast-changing business environments make accounting results projection an unresolved issue in business, accounting and finance research.

As a pilot study to address this challenging issue, this paper develops a neural network (NN) approach by considering both endogenous and exogenous factors relevant to the selected accounting results for modelling. With empirical data from a leading multinational integrated oil and gas company, we experiment with 4 different NN architectures and training techniques to demonstrate the feasibility of NN modelling of accounting results. The results of the experiments conducted provide new insights in managing accounting results for the case company and general accounting professionals.

In subsequent sections, we first briefly review the accounting result related studies and NN modelling in Sect. 2. We next present our NN modelling approach with application to the case company in Sect. 3. We then discuss the results and implications of this study in Sect. 4. Finally, we conclude and summarize this study in Sect. 5.

2   Related Works

Accounting is a systematic and comprehensive approach to measuring, processing, recording and communicating companies' operation in financial information. Accounting results are crucial information and widely used in business decision making and academic research, such as contracting, performance evaluation, investment decision making, share price prediction, bankruptcy prediction and accounting information quality [1–4].

Accounting results are categorized and reorganized financial information of the business operation. The relationships between accounting results and business operation have been investigated [2, 5]. Companies have the discretion in choosing suitable accounting process for its business operation to achieve better quality accounting results.

Current accounting research examines real-world accounting practice and connects accounting events with economic consequences, which is known as positive accounting research. Mixed views have been developed. Existing studies have concluded that accounting results are the true reflection of the business operation, with empirical data of 260,000 observations over 50 years [6]. Similar conclusions are reached by other studies using accounting results for research and development (R&D) projects and initial public offering (IPO) respectively [7, 8]. By contrast, another view believes that accounting results are driven by the financial demands for meeting or beating analysts' expectations and senior management personal benefits [1, 3, 9, 10]. For instance, accounting choices determine how business operations to be recorded in financial information. As discretionary decisions, they have often been used to

purposefully affect accounting results to smooth or boost accounting results for a variety of reasons, such as personal benefits [11–13], draw funding [14, 15] and tax saving [1, 5, 16, 17]. For instance, senior management would influence the accounting results through the deliberate selection of accounting choice to serve their personal needs, such as bonus and tenure. Therefore, it is believed that we only have limited understanding of the accounting results and the process producing them [18]. Further, conflicting theories cannot effectively support business decision making.

In modelling complex problems, such as business and financial decision making, neural networks (NNs) have been proven to be effective and promising [4]. It requires less theoretical understanding of the problem and high accuracy in performance [19]. Difference NN architectures suit different problems [20]. Selection of relevant features, sufficient data, appropriate NN architectures and limiting data fitting problems are essential to successful NN applications [21, 22].

Despite their wide applications, NNs have not been widely applied in the context of accounting yet. One study that uses NNs in forecasting quarterly accounting earning has yielded less satisfactory results in comparison with linear time series models [23]. The study uses a one-layer feedforward NN model to predict the current period based on the previous 4 periods of quarterly earnings.

3 Neural Network Modelling of Accounting Results

3.1 Accounting Results of the Case Company

The case company, Eni S. p. A., is a leading multinational integrated oil and gas company with 50 billion euros of market capital. It has a complex capital structure that funds multi-section operations, including activities in upstream and mid-downstream. Debt, corporate bond and shares are the main sources of its funding. Its operation spreads among oil and natural gas exploration, field development and production, supplying, trading and shipping of natural gas, liquid natural gas (LNG), electricity, fuels and chemical products worldwide. In addition, the business model, business strategy and corporate governance policies, produced by executives, guide its daily operation, decision making, performance control and improvement.

As Eni operates globally, it is also exposed to the influences of macroeconomic factors, such as oil commodity price, currency exchange rates and interest rates. Those factors are identified as risks and can cause significant fluctuations on the accounting results. For instance, sale prices of crude oil and refinery products are considerably affected by oil future prices, as the mechanism of the oil market is highly integrated with the future market. Thereby, operation revenue and profit are to be affected. Additionally, the effects of currency exchange rates and interest rates would impact the revenue and expense when involving foreign currencies and debts.

Thus, Eni's accounting results are the results of its operation under the influences of several endogenous and exogenous factors, such as capital structure, production, sales, management preference and financial market impacts.

3.2   Selection of Accounting Results as NN Outputs

To determine the most crucial accounting items for modelling, we review a number of Eni's key performance indicators (KPIs) and financial ratios. We choose one set of commonly used financial ratios that are regarded as the basis for comprehending the business performance and evaluating the value and the profitability of a company, in practice. These financial ratios are return on asset (ROA), return on equity (ROE) and financial leverage. The items used for calculating the ratio are thus selected, which are asset, liability, equity and net profit. Moreover, net sale from the operation and net profit attributed to shareholders are also included since sales made by the operation is the essential part that accounting is recording, and the amount of profit attributed to shareholders determines the level of appeal in investing the company. Each accounting item corresponds to a category of item accumulated, as shown in the following:

- Total asset (R1): the resources owned or controlled that are able to provide future economic benefits.
- Total liability (R2): the financial obligations that the company owes to external entities.
- Total equity (R3): the resources brought by the ownership of the company. It also can be defined as the value of the business after its liabilities.
- Net sale from operation (R4): the value of sales after returns, damaging, missing and discounts from its normal operation.
- Operation profit (R5): the profits generated from its normal business operation.
- Net profit attributed to shareholders (R6): the net profit that has been determined to be distributed to shareholders.

3.3   Selection of Business Factors as NN Inputs

Relevant business factors are to be identified for the selected accounting items. Existing accounting literature, Eni's annual reports and industry reports are reviewed and analyzed. Based on the relationships between Eni's operation and accounting items, we classify the identified business factors into four groups, namely, resource-related factors, production-related factors, financial factors, and accounting factors.

First, the resource-related factor is proved oil and gas reserves (B1). Three types of reserves are accounted for, which are liquids (O11), natural gas (O12) and hydrocarbons (O13). They are the most important asset as the source generates future economic benefits. The reserves that can be recovered with a reasonable level of certainty are proved reserves, which might or might not be able to be recovered economically. Thus, not all found proved reserves are assets. Hence, determining whether reserves are to be recorded as asset depends on the project and the conditions of the operation including technology applied, operation and financial efficiency, and managerial preference of control and risk.

Second, the production-related factors are the production volume (B2) and company size (B3). The production volumes of liquids (O21), natural gas (O22) and hydrocarbons (O23) are the values created by the operation. Eni uses its resources to create values for revenue. The number of employee (O31) is considered to approximate the capacity of the production with given other conditions.

Third, the financial factors include the effects brought by company shares (B4), oil commodity (B5), interest rates (B6) and exchange rate (B7). The oil and gas industry is a capital-intensive industry. The share price (O41) and traded share volume (O42) mostly affect the operation funding by investment. The oil future prices (O51) and traded volume (O52) in two world major future markets, the Light Sweet Crude Oil in the ICE West Texas Intermediate future market and the Brent future market, significantly influences the prices of crude oil and refinery products. Eni is located in Europe and uses EURO as the base currency, whereas USD is the primary currency in the international oil and gas market. The interest rates of USD (O61) and EURO (O62) and exchange rate of USD/EURO (O71) can fluctuate their accounting results significantly through USD debts and revenue.

Finally, the accounting factor is the discretionary decision that is related to the accounting process, namely, accounting choice (B8). Despite accounting standards and laws existing to regulate accounting practice, within the accounting process, accounting choice can be made by management discretion. It makes the accounting process more suitable to the circumstance of the company. Eni complies with the International Financial Reporting Standard (IFRS). It has changed one of the critical accounting choices, exploration costing (O81), from Full Cost (FC) to Successful Effort (SE) in January 2016. Its effects on the accounting results are substantial by changing how to record the cost that is related to searching for, acquiring and developing the reserves. FC defers unsuccessful exploration and development costs to be charged to the company as an entity in the future, whereas SE requires unsuccessfully projects to be expensed immediately on a field-by-field basis. Although the accounting results would be the same in the long term, assuming the identical operation result, the FC would report more net income and profit in the early stage of new projects than SE. The effect reverses at a later stage from the information recording perspective without considering other factors.

Therefore, we select 15 business factors to produce 8 NN inputs, shown in Table 1.

Table 1. Business factors for NN inputs

Business factors	NN inputs
Reserves volume: liquids (O11), natural gas (O12), hydrocarbons (O13)	B1: Reserve
Production volume: liquids (O21), natural gas (O22), hydrocarbons (O23)	B2: Production
Number of employees (O31)	B3: Company size
Share price (O41), traded volume (O42)	B4: Company share effect
Future price (O51), traded volume (O52)	B5: Oil commodity effect
Interest rate for USD (O61) and EURO (O62)	B6: Interest rates
Exchange rate for USD/EURO (O71)	B7: Exchange rate
Exploration costing method FC/SE (O81)	B8: Accounting choice

3.4   Data Collection and Pre-processing

The dataset used for NN training consists of 45 sets of 15 quarterly data points from the 4th quarter of 2005 to the 4th quarter of 2016. They are collected and reorganized from two types of sources. Company relevant data, including operational data and accounting data, are sourced from publicly available Eni's annual reports, Eni's Factbooks and U.S. Securities and Exchange Commission (SEC) 20-F filings. Data for exogenous factors, including shares, features and interest rates are sourced from yahoo finance and the economic research data repository of Federal Reserve Bank of St. Louis (FRED).

Three scaling methods are applied to examine the performance of the NN models constructed as the business factors scale differently. These three methods are (a) standard score normalization, (b) feature scaling normalization and (c) decimal scaling, given respectively as

$$X' = (X - \mu)/\sigma \tag{1}$$

$$X' = (X - X_{min})/(X_{max} - X_{min}) \tag{2}$$

$$X' = X/10^i \tag{3}$$

where X' and X are the normalize data and original data respectively. μ, σ, X_{max}, X_{min} and 10^i denote the mean, standard deviation, the maximum of the X, minimum of the X and 10 to the ith power to bring X' into the range $(-10, 10)$ respectively. Decimal scaling has achieved better results. The following experiments and results are reported based on the decimal scaled data.

3.5   NN Architectures and Training

We choose 4 different NN architectures for testing in two settings. First, we construct the NN model with all the inputs and multiple outputs (MO) shown in Fig. 1. Second, we test the NN model with the same inputs but with a single activated output (SO) neuron in training. The 4 NN architectures are

- Single hidden layer feedforward NN with standard backpropagation;
- Two hidden layers feedforward NN with standard backpropagation;
- Recurrent NN with feedback connection from output neurons to input neurons, suiting better to time series data and often being used in predicting financial data; and
- Ward nets with multiple activation functions to detect different features in data.

As shown in Fig. 1, business factors are used to compose the 8 NN inputs for the 6 NN outputs. When training in SO settings, only one neuron is active. To model all 6 selected accounting items, we train 6 separate NN models, each with a single output.
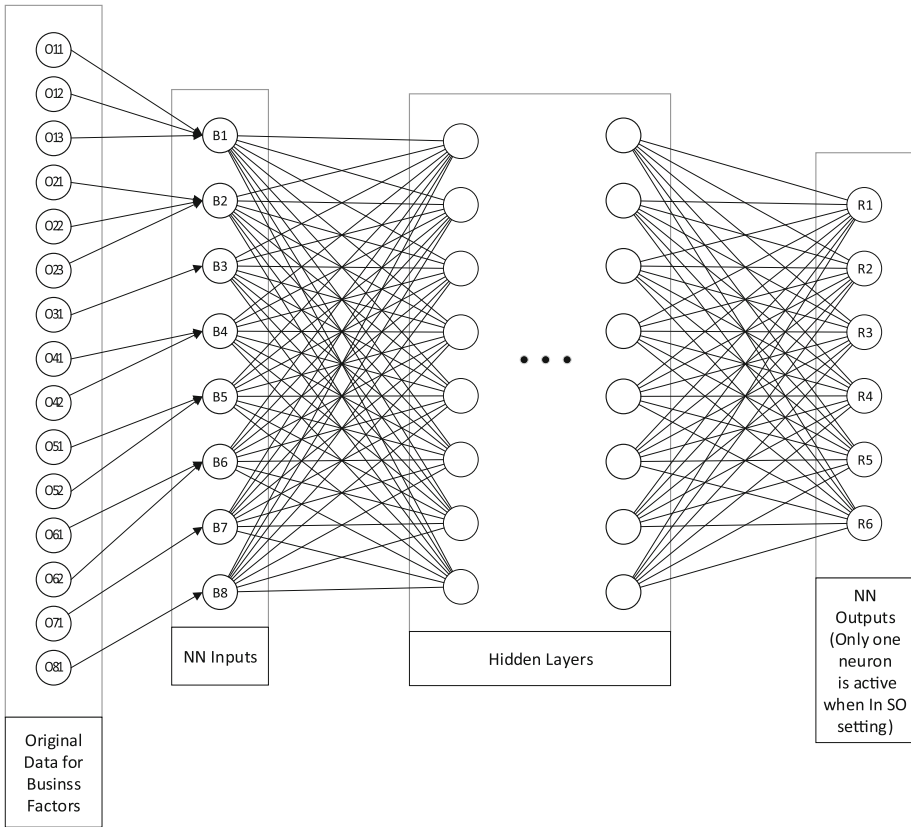
Fig. 1. NN modelling of accounting results

With a 10-fold cross-validation procedure, the test dataset is extracted randomly which consists of 20% instances of the total dataset. The performance of the NN models is measured with the minimum value of the mean squared prediction error (MSPE) which is the averaged of the mean squared error between model prediction and actual output over all of training or testing patterns. Different parameters are tested, including the number of neurons for each hidden layer, initial weights, learning rate and updating momentum. With the best performing parameters, we conduct the experiments for all 4 NN architectures in MO and SO settings with 70,000 learning epochs.

4   Results

First, all the NN models constructed produce satisfactory results. To compare the performance of the NN architectures in SO and MO settings, Table 2 shows their MAEs. The recurrent neural network architecture outperforms other architectures in both settings, which is consistent with the fact that the accounting results problem features the time series data set.

Table 2. Model performance under different NN architectures

NN setting	Dataset	One hidden layer feedforward	Two hidden layers feedforward	Recurrent network	Ward network
SO	Training set	0.0000775	0.0001397	0.0000616	0.0000627
SO	Test set	0.0003808	0.0004755	0.0002799	0.0003238
MO	Training set	0.0000815	0.0001018	0.0000595	0.0000630
MO	Test set	0.0003935	0.0004246	0.0003138	0.0003295

Second, to identify the most influential business factors, we conduct a relative contribution analysis with the best-performing NN model for the 8 inputs in a SO and MO setting. Table 3 shows the result.

Table 3. Relative contribution of NN inputs to outputs

NN output	NN setting	NN Input							
		B1	B2	B3	B4	B5	B6	B7	B8
R1	SO	0.114	0.083	0.128	0.129	0.087	0.109	0.115	0.134
	MO	0.042	0.035	0.068	0.043	0.083	0.103	0.04	0.041
R2	SO	0.075	0.061	0.146	0.08	0.199	0.243	0.073	0.077
	MO	0.048	0.03	0.081	0.042	0.082	0.118	0.042	0.039
R3	SO	0.097	0.076	0.164	0.111	0.089	0.161	0.096	0.117
	MO	0.048	0.025	0.07	0.045	0.08	0.102	0.041	0.036
R4	SO	0.134	0.084	0.122	0.124	0.086	0.079	0.114	0.127
	MO	0.042	0.028	0.059	0.048	0.094	0.064	0.04	0.046
R5	SO	0.107	0.056	0.215	0.094	0.09	0.178	0.092	0.086
	MO	0.045	0.022	0.071	0.047	0.082	0.095	0.043	0.035
R6	SO	0.123	0.06	0.182	0.108	0.081	0.139	0.11	0.094
	MO	0.054	0.022	0.063	0.042	0.081	0.108	0.043	0.041

Table 2 shows mixed results in the relative contribution of the inputs made to individual output. Thus, we consolidate the rankings produced in 6 NNs in SO settings to compare with the ranking in MO settings for further analysis. Table 4 shows the result.

By analyzing individual business factors' contribution to individual accounting items and overall accounting results as shown in Tables 3 and 4, the results produced by MO settings are more consistent with the perceptions of the oil and gas industry and of Eni's analysts and accounting professionals [24]. For instance, as a matured company, Eni's operating profit (R5) is mainly influenced by the total revenue less its variable cost. In addition, for total asset (R1), as Eni explores and develops reserves outside Europe while using EURO as the base currency, the contribution of the exchange rate should surpass company size given Eni's operational settings.

Table 4. Consolidated ranking of contributing factors to overall outputs

NN Setting	Ranking
SO	B3 > B6 > B8 > B1 > B4 > B5 > B7 > B2
MO	B6 > B5 > B3 > B1 > B4 > B7 > B8 > B2

The performance of NN models in SO and MO settings suggests that SO settings, in more cases, produce better accuracy results with the same NN architecture. However, in SO settings, the contributions of the inputs that are to other inactive output neurons may be accounted for the active output in this case. Thus, the results of relative contribution analysis in SO settings are not consistent with the current understanding of the Eni business and accounting results. Whereas, having similar MSPE, MO settings better reflect the accounting information processing. Hence, we conclude that the MO setting is better suited for modelling accounting results in this case study.

Additionally, based on the best-performing NN model in MO settings, the quantitative relative contribution values shown in Table 5 provide new insights into understanding the relative importance of business factors for managing accounting results. The effects of oil futures (B5) and interest rates (B6) can be almost twice as influential as other NN inputs to the accounting results. Specifically, the oil future price (O51), traded volume (O52) and interest rates of USD (O61) and EURO (O62) are among the most important business factors. This result is consistent with the qualitative conclusions made by Eni and industry reports [24], although the trade volume (O52) was not considered in the reports. Moreover, production (B2) is the least contributing factor, whereas company size (B3) seems to have an unexpected high impact on the accounting results. This result offers new evidence to the inconclusive theories regarding the accounting results, production and company size [1, 25]. Lastly, the accounting choices (B8) is as significant as reserves (B1), company shares (B4) and exchange rate (B7) in terms of its impact on accounting results, which has not been investigated quantitatively in previous accounting studies.

Table 5. Relative contribution of NN inputs to overall accounting results

NN Input	B1	B2	B3	B4	B5	B6	B7	B8
Relative Contribution	0.28	0.16	0.41	0.27	0.50	0.59	0.25	0.24

5   Conclusion

Accounting results are crucial, and the projection of the accounting results is a challenging issue. To address this issue, we have proposed an NN modelling approach by considering complex interactions between the business factors and accounting results. We have experimented with 4 NN architectures in SO and MO settings and achieved satisfactory performance. The mixed results by SO and MO settings imply interacting effects among accounting items, although NN models with multiple outputs perform better. The experiments conducted show that a recurrent NN model with multiple outputs is the most appropriate NN architecture in terms of its performance and consistency in relevant contribution factor analysis. In addition, this study provides new insights into understanding the business factors that have high impact on the accounting results for the case company. This study offers a promising approach in modelling accounting results which can be used to predict accounting results based on business factors for business, accounting and finance research. The NN modelling approach proposed in this study has general application for other companies with different accounting settings. In future research, we will investigate the correlations between accounting items and apply the NN modelling approach in alternative accounting problems that are significant for decision making for other companies and industries.

References

1. Fields, T.D., Lys, T.Z., Vincent, L.: Empirical research on accounting choice. J. Account. Econ. **31**, 255–307 (2001)
2. Watts, R.L., Zimmerman, J.L.: Positive accounting theory: a ten year perspective. Account. Rev. **65**, 131–156 (1990)
3. Kim, J.-B., Zhang, L.: Accounting conservatism and stock price crash risk: firm-level evidence. Contemp. Account. Res. **33**, 412–441 (2016)
4. Tkáč, M., Verner, R.: Artificial neural networks in business: two decades of research. Appl. Soft Comput. **38**, 788–804 (2016)
5. Groot, T.d.: Accounting choices of controllers: an insight into controller deliberations. vol. Doctor of Philosophy. Tilburg University. CentER, Center for Economic Research, Tilburg (2015)
6. Dichev, I.D., Li, F.: Growth and accounting choice. Aust. J. Manag. **38**, 221–252 (2013)
7. Aharony, J., Lin, C.-J., Loeb, M.P.: Initial public offerings, accounting choices, and earnings management. Contemp. Account. Res. **10**, 61–81 (1993)
8. Cazavan-Jeny, A., Jeanjean, T., Joos, P.: Accounting choice and future performance: the case of R&D accounting in France. J. Account. Public Policy **30**, 145–165 (2011)

9. Huang, T.-L., Wang, T., Seng, J.-L.: Voluntary accounting changes and analyst following. Int. J. Account. Inf. Manag. **23**, 2–15 (2015)
10. Gietzmann, M., Ireland, J.: Cost of capital, strategic disclosures and accounting choice. J. Bus. Financ. Account. **32**, 599–634 (2005)
11. Watts, R.L., Zimmerman, J.L.: Towards a positive theory of the determination of accounting standards. Account. Rev. **53**, 112–134 (1978)
12. Zhang, W.: CEO Tenure and Aggressive Accounting, vol. 3421490, p. 63. The University of Texas at Dallas, Ann Arbor (2010)
13. Balsam, S.: Discretionary accounting choices and CEO compensation. Contemp. Account. Res. **15**, 229–252 (1998)
14. Oler, M.: Determinants of the length of time a firm's book-to-market ratio is greater than one. Rev. Quant. Financ. Acc. **45**, 509–539 (2015)
15. Friedlan, J.M.: Accounting choices of issuers of initial public offerings. Contemp. Account. Res. **11**, 1–31 (1994)
16. Lennox, C., Lisowsky, P., Pittman, J.: Tax aggressiveness and accounting fraud. J. Account. Res. **51**, 739–778 (2013)
17. Hanlon, M., Slemrod, J.: What does tax aggressiveness signal? Evidence from stock price reactions to news about tax shelter involvement. J. Public Econ. **93**, 126–141 (2009)
18. Hirshleifer, D., Kewei, H., Teoh, S.H., Yinglei, Z.: Do investors overvalue firms with bloated balance sheets? J. Account. Econ. **38**, 297–331 (2004)
19. Gardner, M.W., Dorling, S.: Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmos. Environ. **32**, 2627–2636 (1998)
20. Russell, S., Norvig, P.: Artificial Intelligence: A Modern Approach. Prentice-Hall, Egnlewood Cliffs (2003)
21. Hagan, M.T., Demuth, H.B., Beale, M.H.: Neural Network Design. PWS Pub, Boston (1996)
22. Coakley, J.R., Brown, C.E.: Artificial neural networks in accounting and finance: modeling issues. Int. J. Intell. Syst. Account. Financ. Manag. **9**, 119–144 (2000)
23. Callen, J.L., Kwan, C.C.Y., Yip, P.C.Y., Yuan, Y.: Neural network forecasting of quarterly accounting earnings. Int. J. Forecast. **12**, 475–482 (1996)
24. PwC: Financial reporting in the oil and gas industry - International Financial Reporting Standards (2017)
25. Dechow, P.M., Hutton, A.P., Sloan, R.G.: Economic consequences of accounting for stock-based compensation. J. Account. Res. **34**, 1–20 (1996)