An intelligent system-based approach to accounting method selection

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Abstract

This research develops a new intelligent system-based approach for addressing the accounting method selection problem from a novel decision support perspective. The accounting method selection problem has been regarded as being of significance and long-standing challenges to companies, academic researchers and partitioners. Although existing studies and current best accounting practices hypothesise or theorise why a particular accounting method is selected, the problem of how to make a justifiable accounting method selection remains unaddressed. This is mainly because no specific methodology has been developed for evaluating accounting method alternatives. The intelligent system-based approach represents a novel structured methodology for addressing this important gap in accounting method research in a rational and informed manner. As demonstrated by empirical studies, this research makes an original contribution to knowledge conceptually, methodologically and empirically in addressing the evaluation and selection of accounting method alternatives as a complex decision problem.

The objective of this research is to develop an intelligent system-based approach for evaluating and selecting accounting method alternatives in terms of their performance on a company's strategic goals. To achieve the research objective, four research questions are to be addressed, which are (a) how to model the relationship between business factors and accounting results for a given accounting method type under evaluation? (b) how to obtain the accounting results under an unused accounting method alternative for a given accounting method type? (c) how to evaluate applicable accounting method alternatives and identify the most suitable accounting method for a given accounting method type with respect to a company's strategic goals? and (d) how to evaluate and select the best accounting method combination for multiple accounting method types?

To address the four research questions, the intelligent system-based approach consists of two modules: a neural network (NN) module and a multicriteria decision making (MCDM) module. With an innovative NN modelling process, the NN module predicts the accounting results under an unused accounting method for obtaining the performance ratings of the accounting method alternatives on evaluation criteria. With optimal criteria weighting, the MCDM module evaluates the accounting method alternatives with respect to a company's strategic goals and selects the most suitable accounting method alternative with the highest overall performance value. Empirical studies with a case company in the oil and gas industry are conducted to illustrate how the four research questions are addressed.

To set the context for the empirical studies, the background of the case company is discussed. Relevant business factors, accounting results and strategic goals of the case company are identified. The predication performance and advantages of NN models are compared with commonly used methods for time series forecasting. For a single accounting method type selection, the full cost (FC) and successful efforts (SE) methods for exploration costing are evaluated. With the NN module, the best performing NN model for predicting accounting results is obtained by extensive experiments with four data scaling techniques, four NN architectures and four NN model training techniques. The accounting results under the unused FC accounting method alternative are obtained. With the MCDM module, four group criteria and 16 criteria in line with the strategic goals of the case company are identified. The performance ratings of the SE and FC methods on the evaluation criteria are obtained based on actual and predicted accounting results. The weights of the evaluation criteria are initially assigned by pairwise comparisons using fuzzy numbers. The overall performance value of the FC and SE methods are obtained by fuzzy MCDM with an optimal weighting model. The SE method is selected as the most suitable exploration costing method for the case company.

For the selection problem of two accounting method types, four accounting method alternatives for exploration costing and for inventory are evaluated, which are FC/last-in-first-out (LIFO), FC/weighted average (WA), SE/LIFO and SE/WA. The SE/WA method achieves the highest overall performance value. To examine the interacting effects between the two accounting method types, exploration costing and inventory, the LIFO and WA methods are also evaluated in a single accounting method type selection setting. Significant interacting effects on the accounting results and subsequently the strategic goals are confirmed. The results of the empirical studies are of significance for the case company to gain new insights into understanding the accounting method selection problem.

As a pioneering study in accounting research to empirically examine the time delay effect of business transactions on accounting results, this research develops a new method by training NN models using different time alignments between business factors and accounting results. The empirical result of this research confirms the time delay effect and provides the case company with a useful insight into understanding the amount of time delayed in its accounting results.

The intelligent system-based approach developed in this research has general application for evaluating and selecting accounting method alternatives individually for one accounting method type or collectively for multiple accounting method types. Although the approach is exemplified with a case company in the oil and gas industry, it is applicable to other companies or other industries by adjusting relevant business factors, accounting items and evaluation criteria based on their specific business settings.

Declaration

I hereby declare that this thesis comprises original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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Publications during enrolment

This study has led to the following publications.

Refereed conference papers

Duan, Y., Yeh, C.-H., Dowe, D.L., 2021. Accounting method selection using neural networks and multi-criteria decision making. *Proceedings of the 54th Hawaii International Conference on System Sciences* (HICSS-54), Hawaii, 1550-1559. http://hdl.handle.net/10125/70800

(CORE A-ranked and FIT quality conference)

Duan, Y., Yeh, C.-H., Dowe, D.L., 2018. Accounting results modelling with neural networks: The case of an international oil and gas company. *Proceedings of the 25th International Conference on Neural Information Processing* (ICONIP 2018), Part II, Siem Reap, Cambodia, LNCS 11302, 275-285. https://doi.org/10.1007/978-3-030-04179-3_24

(CORE A-ranked and FIT quality conference)

Duan, Y., Yeh, C.-H., 2018. An intelligent system based approach to accounting choices evaluation and selection. *Proceedings of the 22nd Pacific Asia Conference on Information Systems* (PACIS 2018), Yokohama, Japan, 165-172.

(CORE A-ranked and FIT quality conference)

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Chapter 1 Introduction

Selecting suitable accounting methods have been a long-standing challenge to companies, academic researchers and accounting partitioners. Accounting method selection is a decision problem where one or more accounting methods are to be selected from the applicable accounting method alternatives for their application in preparing accounting results. Accounting methods are a subset of accounting choice, which is defined as all accounting related decisions that are made purposefully to influence accounting information (de Almeida & Lemes, 2019; Fields et al., 2001; Lugovsky & Kuter, 2020). Accounting methods and accounting choices have significant impacts on the accounting result. Accounting results are the outcome of the accounting activities practised at a company, and they are used to communicate the economic performance of the company to its internal and external stakeholders, such as managers, investors and government agencies. Thus, through accounting method selection and a wide range of accounting choice, the perception and expectation of the company's past and future economic performance can be changed, such as adjusting the production level to increase/decrease fixed cost per unit to decrease/increase profit, selecting an accounting method in relation to how to record a transaction, and what and when to disclose certain information. In this chapter, first, the research background will be introduced to set the scene for this research. Second, the motivation for this research will be discussed. Third, the research objective and research questions will be articulated. Fourth, the impact and original contribution of this research will be briefly discussed. Fifth, to effectively address research questions and achieve the research objective, a research framework will be presented. Finally, the chapter summary of this thesis will be outlined.

1.1 Research background

Accounting is a systematic approach for measuring, processing and communicating business transactions or operations in the form of financial information (Bromwich & Scapens, 2016; Previts et al., 1990). Accounting results, also known as accounting information, financial reports or financials, are the outcome of accounting practices. Accounting results are commonly presented by the three statements, including the statement of the balance sheet, income statement and cash flow statement. Accounting results are kept in different accounting items, such as assets, liabilities, equity, revenue, expense, and cash from operating, investing and financing activities. Each statement keeps records of different accounting items but interconnected. The three statements together present a comprehensive picture of the company's operations. Companies periodically prepare and report their accounting results to the accounting information users, including managers, investors and government agencies, for supporting a wide range of decision making.

Accounting methods, also known as accounting policies, are the rules to be applied to record business transactions (Maalouf & El-Fadel, 2019; Reppenhagen, 2010). Different accounting method differs on how and when a business transaction should be measured and categorised to different accounting items. The application of a certain accounting method is referred to as treatment. To record different types of business transactions, different accounting method types are available for treatment. Clear definitions of the accounting methods are provided by accounting standards, such as the International Financial Reporting Standards (IFRS) or Generally Accepted Accounting Principles (GAAP).

A typical company will need to employ multiple accounting method types to correspond to its different types of operations. For instance, to record inventory related operations, one accounting method for inventory can be selected and applied among first-in-first-out (FIFO), last-in-first-out (LIFO) and weighted average (WA). Another example is to record cost associated with oil and gas exploration, the accounting method for exploration costing needs to be selected and applied from the full cost (FC) and successful effort (SE) methods. Normally, a number of other accounting method types would also be needed in preparing accounting results by a typical company, such as revenue recognition, cost recognition, research and development cost recognition (R&D), compensation recognition, depreciation and amortisation for evaluating financial instruments, intangible assists, property, plants and equipment. Each accounting method type has multiple accounting method alternatives, and only one accounting method from the accounting method alternatives of the required accounting method type by the company is selected. As an example, Figure 1-1 illustrates the relationship between three accounting method types and their associated accounting method alternatives. For example, accounting method type A has two accounting method alternatives, A1 and A2.

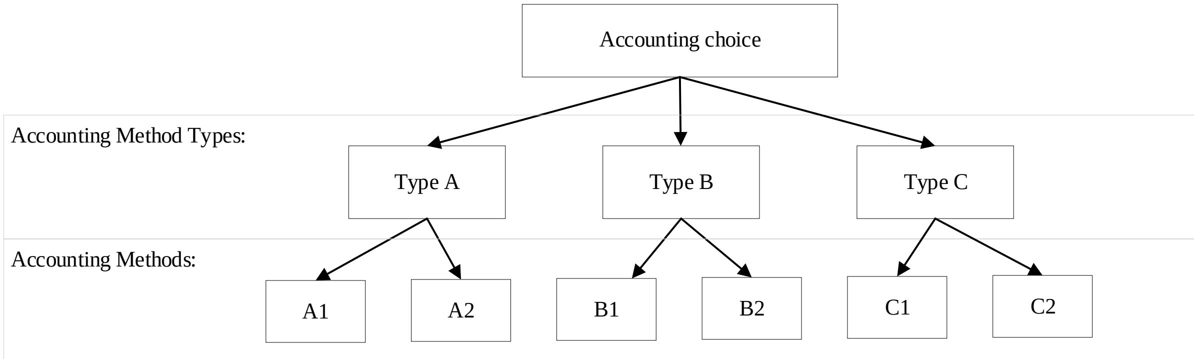

Figure 1-1. Relationship of accounting method types and accounting method alternatives

Accounting method selection is a crucial and complex decision problem. Applying a different accounting method will produce different accounting results given the same business operations. Accounting results are used as the basis for measuring and predicting the economic performance and financial health of a company by managers, investors and government agencies. Numerous managerial, financial and legal decisions are to be made based on accounting results, such as operation adjustments, tax obligation, debt raising, asset pricing, credit risk evaluation, bankruptcy prediction and contracting. Accounting method selection has significant impacts on accounting results and subsequently generates economic consequences (Dechow et al., 1996; Dichev & Li, 2013; Fields et al., 2001; Graham et al., 2005; Holthausen & Leftwich, 1983a; Jasinski et al., 2015).

Accounting method selection is a discretionary decision by senior management and accountants within the boundary of the companies' local laws and accounting standards. To assist companies in producing high-quality accounting results, companies are encouraged to choose the accounting methods that are most suited to the company's situation. In current practices, accounting methods are selected by executives and accountants who have a deep understating and knowledge of the company, the business and accounting standards. Accounting methods are often selected based on managements' expertise, mimicking similar companies, or following the best practice of the industry (Donatella & Tagesson, 2020; Fields et al., 2001; E. Lee et al., 2017; Reppenhagen, 2010).

1.2 Motivation of the research

To select an accounting method that is suitable for a company's circumstance, internal and external business factors are to be considered. For instance, internal business factors, such as CEO/CFO's preference, production settings, capital structure and the company's key performance indicator (KPI) targets, can determine what accounting method can help the company to reliably reflecting its operations and achieve its management incentives (Donatella & Tagesson, 2020; Lassini et al., 2016; Lourenço & Curto, 2010; W. Zhang, 2010). Externally business factors, such as industry characteristics, financial analyst benchmarks and economic performance, often have a great weight to whether accounting results are relevant for supporting decision making (Chalu, 2019; Hagerman & Zmijewski, 1979; Huang et al., 2015). It is believed that the complexity of the accounting method selection and expert-depended approach in practice makes the selected accounting methods often sub-optimal (de Almeida & Lemes, 2019; Donatella & Tagesson, 2020; Ge et al., 2011). Furthermore, while the internal and external business factors often change, the accounting methods in use are much less reviewed and changed to accommodate the changing conditions (Dichev & Li, 2013). This is due to the fact that no specific methodologies have been developed for evaluating and comparing the impacts of accounting method alternatives.

In accounting research, accounting methods are studied under a broader definition of the decisions relevant to accounting, namely accounting choice. The accounting choice research has investigated the determinants and economic consequences of accounting choice, including accounting method selection, from a positive approach for prescribing and predicting the accounting relevant decisions in a company. However, due to the limitation of the research design, ineffective research questions and inadequate modelling techniques, the accounting method related research often reach mixed conclusions. It is believed that accounting choice research has disconnected from the accounting choice practices and have not led to a better understanding of such decision problem since the 1980s (Fields et al., 2001; Francis, 2001). Hence, it is crucial to address this important gap in how to make a good accounting method selection in a rational and informed manner.

1.3 Research objectives and research questions

The objective of this research is to develop an intelligent system-based approach for evaluating and selecting accounting method alternatives in terms of their performance on a company's strategic goals.

With the current understanding of the determinants of the accounting method selection, accounting method selection is a company-specific decision problem. To achieve the research objective with a great extent of generalisability, two connecting modules comprising the intelligent system-based approach to accounting method selection are to be developed. To address the research questions for achieving the research objective in a company-specific setting, empirical studies with a case company from the oil and gas industry are to be conducted. Two accounting method alternatives (the full cost (FC) and successful effort (SE) methods) for the accounting method type of exploration costing and two accounting method alternatives (last-in-first-out (LIFO) and weighted average (WA)) for the accounting method type of inventory are to be evaluated individually and collectively. Figure 1-2 shows the relationship of accounting method types, namely exploration costing and inventory, with their accounting method alternatives.

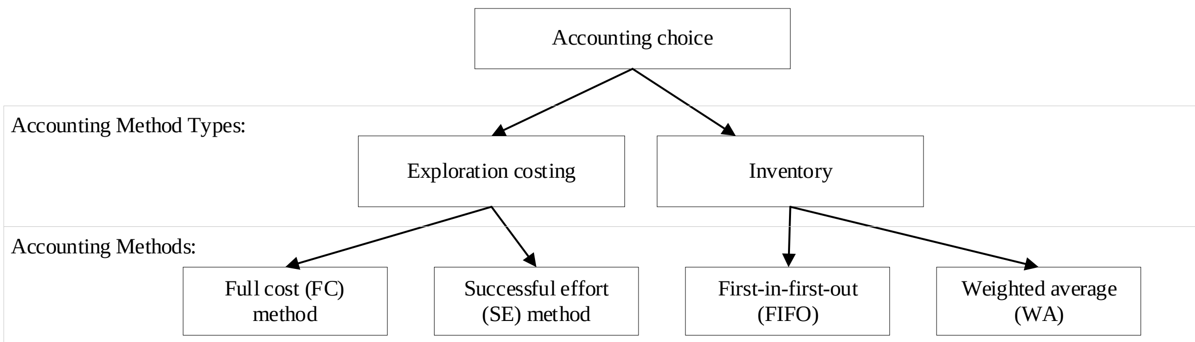

Figure 1-2. The relationship of exploration costing and inventory and accounting method alternatives for the empirical studies

Other accounting method types are excluded in this research, although they might be needed in the case company, such as revenue recognition methods, depreciation methods, research and development (R&D) costing. From a general point of view, three main reasons for focusing on two accounting method types of exploration costing and inventory are:

(a) The accounting method selection for exploration costing and inventory are the most studied and debated given their weights to the perceived business performance and impacts to the future growth (Bryant, 2003; Chalu, 2019; Hsu & Frankel, 2016; Jasinski et al., 2015; PwC, 2017; Spear & Leis, 1997). However, the debates have not reached a conclusion in the accounting choice research and industry practices. The selection of exploration costing has significant impacts on accounting results, especially on the statement of balance sheet and income statement. Tax obligations and share price can be substantially influenced (Atwood & Reynolds, 2008; Graham et al., 2005; Huang et al., 2015; Lara & Mora, 2004). Thus, a better understanding of how to select suitable accounting methods for exploration costing and for inventory is in the interests of the companies in the oil and gas industry, accounting professionals and government regulators.

(b) The relevant data for exploration costing and inventory is available. Oil and gas exploration and inventory are crucial business activities for an oil and gas company (Deloitte, 2016; PwC, 2017; Eni, 2018). Exploration is a core business operation for generating future economic benefits. Inventory, including finished and unfinished products, constitutes a large proportion of the assets held by a company. The relevant operational and accounting data are well kept and reported in the company's financial reports as required by government and trading regulatory authorities. By contrast, data relevant to other accounting method types may not be kept, not be disclosed, not acquirable or expensive to acquire.

(c) Accounting methods for exploration costing and inventory are the two accounting method types that are most common and highly relevant to accounting practices in the oil and gas industry. The study of these two accounting method types is of most importance to accounting practitioners and accounting standards setting institutions.

Therefore, to achieve the research objective, the following four research questions are to be addressed:

RQ1. How to model the relationship between business factors and accounting results that are relevant to the accounting method type under evaluation? In the empirical study conducted, the accounting method type under evaluation is the exploration costing, which has two accounting method alternatives, the full cost (FC) and successful efforts (SE) methods.

(a) What business activities do the accounting methods for exploration costing correspond to?

(b) What business factors are involved in the case company's relevant business activities?

(c) What accounting items in the accounting results are affected by the accounting method alternatives for exploration costing?

(d) How to model the relationships between identified relevant business factors and affected accounting results?

RQ2. How to obtain the accounting results under an unused accounting method alternative for a given accounting method type? In the empirical study conducted, the unused accounting method alterative for the evaluation period is the full cost (FC) method.

(a) How to predict the accounting results under an unused accounting method, FC, given the effect of the accounting method in use, successful effort (SE), on the accounting results for the evaluation period?

RQ3. How to evaluate applicable accounting method alternatives and identify the most suitable accounting method for a given accounting method type with respect to a company's strategic goals? In the empirical study conducted, the FC and SE methods are the applicable accounting method alternatives for exploration costing for evaluation.

(a) What are the evaluation criteria to be used to reflect a company's strategic goals?

(b) How to best weight the evaluation criteria to reflect a company's best possible operational condition for accounting method evaluation to achieve its strategic goals?

(c) How to obtain performance ratings for the accounting method alternatives, namely FC and SE, with respect to the identified evaluation criteria?

(d) How to aggregate criteria weights and performance ratings to obtain an overall performance value for each accounting method alternative?

RQ4. How to evaluate and select the most suitable accounting method combination for multiple accounting method types? In the empirical study conducted, two accounting method types (exploration costing and inventory) are considered.

(a) How to model the relationship between relevant business factors and affected accounting results for two accounting method types for predicting accounting results under the unused accounting method alternatives?

(b) How to evaluate accounting method alternative combinations of two accounting method types?

(c) What are the interacting effects between exploration costing and inventory in selecting the most suitable accounting methods?

1.4 Impact and original contribution to knowledge

This research makes an original contribution to knowledge conceptually, methodologically and empirically in addressing the evaluation and selection of accounting method alternatives as a complex decision problem. Conceptually, this research addresses the significant and long-standing accounting method selection problem from a novel decision support perspective.

Methodologically, the intelligent system-based approach represents a structured methodology for addressing the accounting method selection problem. Additionally, a new method for empirically examining the time delay effects of business transactions on accounting results is developed as a pioneering study in accounting research. Empirically, this research contributes to practical accounting method selection by (a) effectively supporting the accounting method selection and providing new insights into understanding the accounting method selection for the case company; (b) confirming the interacting effects of accounting methods on the accounting results and subsequently the strategic goals; and (c) empirically examining the time delay effects of business transactions on accounting results and providing useful insight into understating of the amount of the time delayed in the accounting results of the case company.

1.5 Research framework

To effectively address the four research questions and achieve the research objective, a research framework is developed to support research tasks in modelling, predicting and evaluating to be conducted in cohesion. Figure 1-3 shows the research framework of this research. The intelligent system-based approach sets the foundation for this research, as presented in Chapter 3. With the analysis of the case company in Chapter 4, the evaluation and selection of accounting method alternatives for a single accounting method type are carried out by applying the approach which addresses RQ1 to RQ3, as presented in Chapter 5. The evaluation of and selection of accounting method alternatives for two accounting method types are carried out in a similar fashion, which address RQ4, as presented in Chapter 6. The examination of the time delay effects of business transactions on accounting results, discussed in Chapter 7, is conducted based on the neural network (NN) module of the approach with a novel NN modelling method.

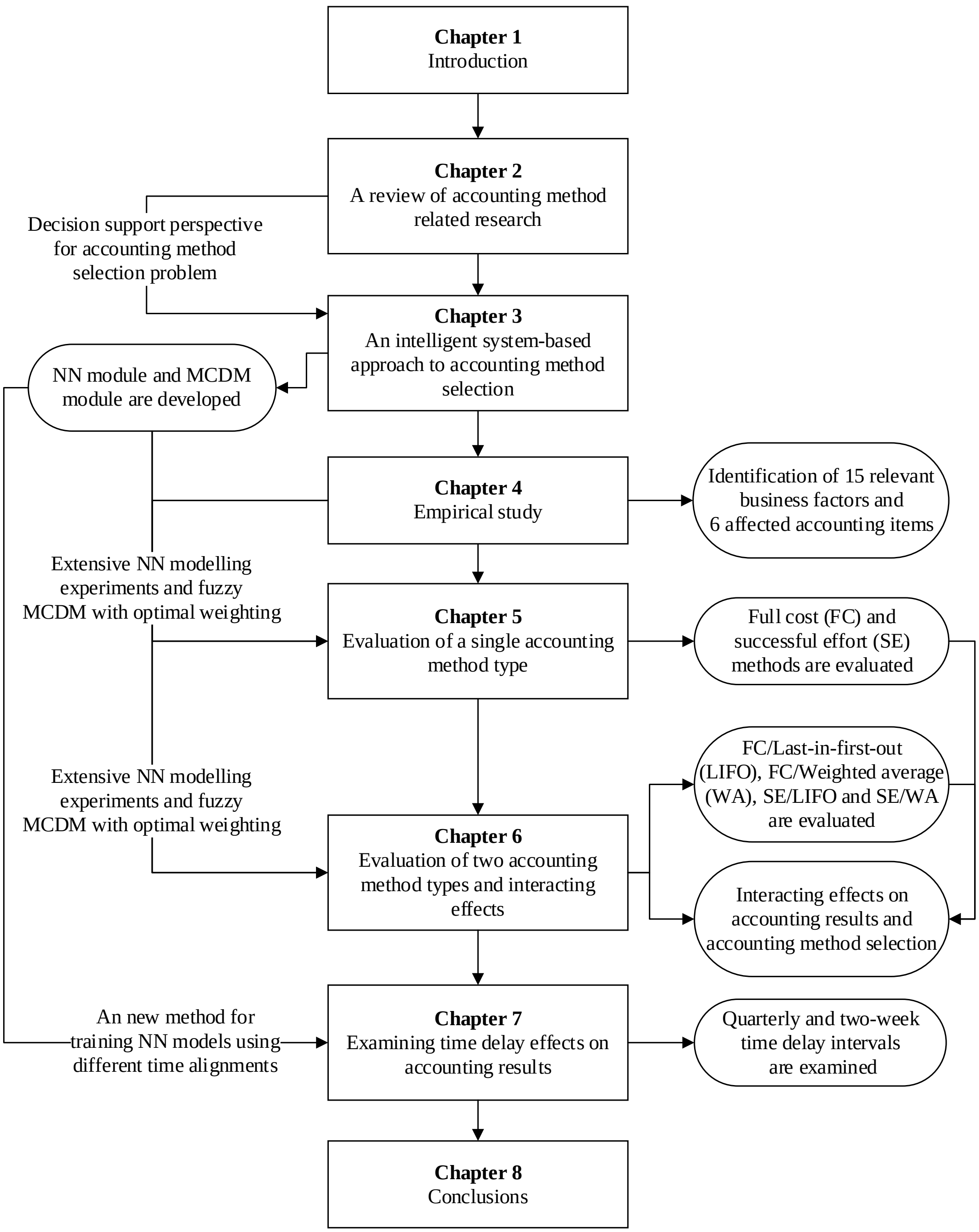

Figure 1-3. Research framework

1.6 Chapter summary

Chapter 1 sets the context of this research. The background and the motivation of this research are discussed. The research objective and research questions are identified and explained. The research framework for effectively addressing the research questions and achieving the research objectives is presented.

Chapter 2 reviews the research background and existing studies that are relevant to the accounting method selection problem. First, an introduction of accounting, accounting results and accounting choice is provided. Second, the main categorise of the accounting choice determinants are discussed to provide an overview of the current understanding of the accounting choice. Third, limited numbers of accounting choice research with a normative research approach are reviewed. Fourth, the research gaps in investigating accounting choice issues are reviewed. Lastly, a definition of accounting method selection is proposed to set the scope of this research.

Chapter 3 introduces the intelligence system-based approach to the accounting method selection problem. First, the structure of the approach is introduced. Second, neural networks (NNs) and multicriteria decision making (MCDM) are reviewed as suitable methods for the two modules of the approach and the benefits of the methods are discussed.

Chapter 4 gives an in-depth discussion of the case company for providing the context for the empirical study. The background of the case company and the significance of the two accounting method types, namely exploration costing and inventory, to be examined are discussed. The accounting method alternatives and their impacts on accounting results are explained, including the full cost (FC) and successful efforts (SE) methods for exploration costing, and last-in-first-out (LIFO), first-in-first-out (FIFO) and weighted average (WA) method for inventory. Under the context of the case company, the relevant business factors and affected accounting items are identified, respectively. The company's strategic goals and KPIs are identified and described as the objective and the evaluation criteria of the accounting method selection problem.

Chapter 5 demonstrates how the intelligent system-based approach works in a single accounting method type selection, exploration costing. The predication performance and advantages of NNs are compared with commonly used methods for time series forecasting. With the NN module, the best performing model for predicting accounting results is obtained by extensive experiments with four data scaling techniques, four NN architectures and four NN model training techniques. The accounting results under the unused FC accounting method alternative are obtained. With the MCDM module, four group criteria and 16 criteria derived from the strategic goals of the case company are identified. The performance ratings of the SE and FC methods on the evaluation criteria are obtained based on actual and predicted accounting results. The weights of the evaluation criteria are assigned by pairwise comparisons using fuzzy numbers. The overall performance value of the FC and SE methods are obtained by fuzzy MCDM with an optimal weighting model. The SE method is selected as the most suitable exploration costing method for the case company.

Chapter 6 demonstrates how the intelligent system-based approach works for selecting the accounting methods for two accounting method types, exploration costing and inventory. Four accounting method alternatives are evaluated, which are FC/LIFO, FC/WA, SE/LIFO and SE/WA. The SE/WA method achieves the highest overall performance value. To examine the interacting effects between the two accounting method types, exploration costing and inventory, the LIFO and WA methods are also evaluated in a single accounting method type selection setting. Significant interacting effects on the accounting results and subsequently the strategic goals are confirmed.

Chapter 7 develops a new method by training NN models using different time alignments between business factors and accounting results for examining the time delay effect of business transactions on accounting results. As a pioneering study in accounting research, the empirical result confirms the time delay effect and provides the case company with a useful insight into understanding the amount of time delayed in its accounting results.

Chapter 8 summarises the outcome and results of this research and outlines how the research questions are addressed. The conceptual, methodological and empirical contributions of this research are discussed. Future studies for applying and extending this research are suggested.

Chapter 2 A review of accounting method related research

This chapter presents a review of the accounting method related research. First, the general background of accounting and accounting choice research are introduced to provide a context for this research. Second, the determinants, implication and economic consequence of the accounting choice in existing accounting choice research are discussed. Third, research attempts to support accounting choice with deterministic models are described. Fourth, the research gaps in the existing accounting choice research are identified. Finally, the accounting method selection problem to be addressed in this research is defined.

2.1 Background of accounting and accounting choices

Accounting is a systematic and comprehensive approach for measuring, processing, recording and communicating companies' operations in financial information. Accounting is an essential part of a business that communicate business performance with stakeholders and fulfils legal obligations. The product of accounting is accounting results, also known as financial statements or financials, including the statement of the balance sheet, income statement and cash flow statement. Accounting research and practices have been generally categorised into five major fields, including managerial accounting, financial accounting, auditing, taxation and accounting information systems. Accounting results are often used as the basis for managerial, financial and legal decisions by internal and external information users, such as managers, investors, creditors and government agencies. As the crucial roles accounting plays, accounting practices are regulated by local laws and accounting standards. Multiple government agencies, professional authorities and large groups of practitioners have profound influences on accounting standards setting and the best practices of different industries.

To convey business performance in accounting result, business operations need to be measured and recorded accordingly. Accounting choice, decisions in relation to how to measure and record operational data in financial information, are needed. Therefore, accounting choice has significant impacts on accounting results. The concept of accounting choice is defined as any decision that purposefully influences the output of the accounting system (Fields et al., 2001). Under this definition, the accounting related decisions include a wide range of decisions, such as increasing production to reduce fixed cost, reducing R&D expenditures to increase earnings, choosing an accounting method (e.g. LIFO vs. FIFO), structuring a contact so that the contract related activities can be recorded in accordance with their accounting system, deciding on the level of financial information disclosure, and choosing the timing of new standards adoption (Cazavan-Jeny et al., 2011; Fields et al., 2001; E. Lee et al., 2017; Stent et al., 2017). The essence of this accounting choice definition is managerial intent.

Since the propose of the positive accounting theory by Watts and Zimmerman (1978), the accounting choice research has been dominated by the positive research approach. Under the assumption that empirical accounting choice decisions are efficient, the determinants and implications of the accounting choice in practice have been studied aiming at prescript and predict a company's accounting choice since the 1970s (Fields et al., 2001; Watts & Zimmerman, 1978, 1990). To provide a better understanding of accounting choice determinates, explaining why managers and accountants would choose a particular accounting choice became the focus of the accounting choice research (Bromwich & Scapens, 2016).

2.2 Accounting choice determinates

Developed upon the existing definition of accounting choice and accounting positive theory, the accounting choice research has examined numerous factors that could drive a particular accounting choice to be made and implications to different aspects of a business from the perspectives of agency cost, information asymmetries, and externalities affecting non-contracting parties. Relevant accounting choice studies are categorised based on four major incentives that show insights into driving accounting choice for the purpose of this research: (a) principle-agent hypothesis, (b) true reflection hypothesis, (c) income management hypothesis, and (d) comprehensive framework of the accounting choice determinates.

2.2.1 Principle-agent hypothesis

The principle-agent hypothesis is related to the agency cost of accounting to overall business performance. Chief Executive Officers (CEOs) or senior management, as decision makers of the accounting choice with discretion, are considered as agents to a principle, the company of employment. The personal motivation and influences of CEOs and senior managers have been examined. Personal economic benefits, reputation and tenure are linked to the decision incentives for accounting choice. Bonuses are often used to incentivise CEOs for better performance that measured by earnings or losses. The timing and the amount of earning and losses recognition are utilised to maximise CEO's bonus (Francis et al., 1996; Guidry et al., 1999). Voluntary disclosure of a company's performance is used to maximising the perceived CEO reputation, which might not be legally required and are to be used for comparing with benchmarks (Lewellen et al., 1996). Additionally, a more recent study finds that CEOs will be less aggressive in choosing accounting choices if more tenure certainty is given, while more aggressive accounting choices to inflate earnings would be used by new CEOs to establish the reputation or CEOs in the final year of tenure to assist in seeking next employer (W. Zhang, 2010). Despite contracting is used to align the interests of the shareholders and CEOs, accounting choice is evidently associated with maximising agents' personal benefits (Lobo et al., 2018; Tahir et al., 2019).

2.2.2 True reflection hypothesis

On the other hand, numbers of studies hypothesising CEOs and senior managers made particular accounting choices to merely reflect the true performance, financial situation and future projection of the company (DeAngelo et al., 1994; Wyatt, 2005). Using an initial public offering (IPO) event as a significant incentive, a study has analysed the accounting choices made before and after IPOs and find no substantial evidence indicating manipulation of financial reports by CEOs (Aharony et al., 1993). The study believes that the accounting choice changes made prior to IPOs are made to reflect the rapid growth of the companies' assets and prospective profit. Furthermore, another study has conducted an analysis of R&D accounting choice in French. After controlling the industry differences, the study finds that companies with (a) smaller size, (b) financially more leveraged and (c) more uncertainty in the return of R&D effort would significantly increase the tendency of a company to capitalise the R&D expenditures. Capitalising R&D expenditures is a more aggressive accounting choice than expending the R&D expenditures as the recorded assets are associated with a higher level of uncertainty of the R&D projects. However, the proportion of expended R&D expenditures is strongly negatively correlated with future performance projection, which indicates the essence of the expected economic performance of the R&D projects is reflected in the accounting results. The applied R&D accounting choice is simply used to reflect the judgement on the R&D projects' expected performance (Cazavan-Jeny et al., 2011). Another study finds income-deceasing accounting choice is made to be informative rather than to be opportunistic during the negotiation with trade unions regarding labours concessions (García Osma et al., 2015). Lastly, a survey analysis of 260,000 observations over 50 years finds that there is no strong evidence suggesting aggressive accounting choices are used to intentionally increase reported income (Dichev & Li, 2013).

2.2.3 Income management hypothesis

The concerns over accounting choice are used to inflate a company's income have further developed the income management hypothesis. This hypothesis examines whether a wide range of accounting choice is used as a mean for managing a company comprehensive income, including minimising tax, influencing stock price, influencing contracting and maximising CEOs' personal benefits. The impacts of accounting choice are widely recognised among government and standard-setting authorities, industries participants and accounting professionals. Studies conducted by regulatory agencies and academics hypothesise that several accounting choices are applied to increase reported income. As a result, the U.S. Securities and Exchange Commission (SEC) Chairman confirms that earning-decreasing accounting choices are made to reverse the increased income after the release of signs for increasing compliance monitoring (Levitt, 1998). IFRS has prohibited the use of LIFO since 2003 to prevent it is being used for managing income. In the financial market, Friedlan (1994) finds the IPO issuers do make income increasing accounting choices by accruing more income before the IPO. This conclusion is opposite to the finding by Aharony et al. (1993). Moreover, numbers of accounting choice research have suggested that the accounting choices would be influenced by the pressure for meeting or beating the benchmark and financial analyst expectation (Fields et al., 2001; Gietzmann & Ireland, 2005; Huang et al., 2015; Moyer, 1990). Earing-decreasing accounting choices are also used for cheaper management buyouts (Perry & Williams, 1994). Hence, using accounting choices for income management is easily suspected since investors also have a limited understanding of the role accounting choice played in the overvalued balance sheet (Hirshleifer et al., 2004).

2.2.4 Comprehensive frameworks of the accounting choice determinates

To obtain a better understanding of the accounting choice determinates, recent studies have examined the accounting choice determinants in alignment with real-world practice by including various accounting choice and management incentives. The complex decision environment of accounting choice involving endogenous and exogenous factors are studied, such as political factors, economic factors, financial factors, people factors, industrial factors and company internal factors (Cohen, 2003; Groot, 2015; Pierk, 2014). By interviewing managers and accountant, Groot (2015) has proposed a comprehensive framework of structured process representing how accounting choices are made. The framework involves four reviewing steps with different objective and constraints. The accounting choice alternatives are reviewed in an iterative process until an accounting choice alternative satisfies the objectives of all four steps:

(a) Financial review. This review considers the influences of accounting outcome on the financial structure, the capability of raising funds and repay debts. It also ensures the financial accounting procedures comply with the accounting rules and the accounting recordings represent the business activities incurred.

(b) Operational review. This review assesses the quality of operation data used as a basis for accounting recordings. The result of the assessment should decide whether to rely on the operation data or to make the best estimates of the operation data is inaccurate or incomplete.

(c) Valuation review. This review evaluates and decides an appropriate monetary value for the recorded item. The evaluation determines whether the value of the items is from standard transactions or need to be adjusted to better reflect the current value of the item.

(d) Overall review. This step reviews and analyses the differences between the current accounting outcome and the expected outcome. It evaluates the potential effect of the current accounting outcome on investors, debtors, customers, or government agencies, and determine whether an alternative accounting choice should be made.

This framework describes the practical accounting choice decision making process. As a result, keeping using the current accounting choice or making a change can be decided. The exercise of the iterative reviews ensures the accounting process can record, measure, monitor and communicate its financial information in the way best suited to the situation of the company.

2.3 Decision support to accounting choice

Accounting choice can significantly influence the outcome of accounting and expectantly affects other aspects of the business and business performance through managerial and financial decisions. With a deep understanding of the business and accounting standards, accounting choices are made by CEOs, senior management and accountants under the influences of the best practice and personal experiences.

Based on the current understanding of the principles of accounting standards, companies with different business models should adopt different accounting methods to best suit their circumstances. As an example, two leading technology companies with different business models, Microsoft Corp. and Apple Inc. have chosen different inventory accounting methods. The inventory methods applied are stated in their 10-K filings to the U.S. Securities and Exchange Commission (SEC):

> In Microsoft Corp, "Inventories are stated at average cost, subject to the lower of cost or market. Cost includes materials, labour, and manufacturing overhead related to the purchase and production of inventories. We regularly review inventory quantities on hand, future purchase commitments with our suppliers, and the estimated utility of our inventory. If our review indicates a reduction in utility below carrying value, we reduce our inventory to a new cost basis throughout a charge to cost of revenue" (Microsoft Corp. 10-K Form, 2016).
>
> Whereas,

> In Apple Inc, "Inventories are stated at the lower of cost, computed using the first-in, first-out method and net realisable value. Any adjustments to reduce the cost of inventories to their net realisable value are recognised in earnings in the current period. As of September 24, 2016, and September 26, 2015, the Company's inventories consist primarily of finished goods" (Apple Inc. 10-K Form, 2016).

On the contrary, with a sample size of 103 European public traded companies, the empirical evidence shows no significant differences in accounting choice made among the companies with the significant different business models (Lassini et al., 2016). To support accounting choice decision making, few accounting choice research has taken the normative approach. A limited number of early studies proposed mathematical models for making the optimal inventory accounting method decision between LIFO and FIFO to influence the value of the asset and the cost of produced goods to reduce tax (Morse & Richardson, 1983; Sunder, 1976). Further development has broadened the scope to consider tax-saving and investor reaction simultaneously, which maximises the total economic benefits to the company (Hughes & Schwartz, 1988). From the perspective of supporting inventory accounting method decision making, the proposed models can help to choose the optimal inventory accounting method with single or multiple objectives. However, decision support for accounting choice has not been extended to other accounting method types.

2.4 Research gaps

The positive accounting theory has dominated the accounting choice research since the late 1970s. The accounting choice research design the studies with hypothesis testing techniques (Kaya, 2017). However, the positive research approach in accounting choice research attracts continuous criticism. One of the most significant drawbacks is that the positive research approach does not provide an effective approach for improving accounting choice decisions (Fields et al., 2001). The research findings under the positive approach have been strongly criticised due to three reasons. First, the fundamental assumption of self-interest is flawy. Second, the fundamental assumption of the efficient market is questionable by the 2008 global financial crises. Third, the applicability and significance of the conclusions to other cases are questionable (Boland & Gordon, 1992; Milne, 2002).

Despite the understanding of accounting choice has been enhanced, how to make a good accounting choice decision has not been addressed. Fields et al. (2001) reviewed accounting choice research since the 1990s and concludes that the past two decades has not made a better understanding of how should accounting choices been made. This is due to, in real-world practices, numerous means are available for companies to achieve their goals, and the accounting research has not evolved with the increasing complexity and volatility of the business environment (Fields et al., 2001; Holthausen & Leftwich, 1983; Lugovsky & Kuter, 2020; Watts & Zimmerman, 1990). It is believed that the following drawbacks have limited the accounting choice research (Fields et al., 2001):

(a) Multiple types of accounting choice increase the difficulty in research designs. Numerous types of accounting choice can be used by companies to achieve the same goal. By contrast, researchers often design the studies to examine the determinants of a single type of accounting choice for achieving a particular objective which can be achieved through other accounting choices.

(b) Multiple and conflicting objectives are not considered. Accounting choice research hypothesises and tests the link between an accounting choice and a single management incentive as its decision objective. Multiple objectives are commonly observed and recognised in research, but they are often ignored in the assumption. In addition, the interaction effects and trade-offs of accounting choice alternatives to multiple objectives have left unexamined.

(c) Research questions are not effective for making better accounting choice decisions. Influenced by the paradigm of positive accounting theory, accounting choice research addresses the research problem by investigating what factors are correlated with the accounting choices under investigation in practice. The findings are able to explain and might be able to predict the accounting choice decision making. Instead, it seems to be more effective to examine whether the accounting choices are made in consistence with the decision objectives.

(d) Traditional techniques are not sufficient. Hypothesis testing and linear regression are used in most accounting choice research. The role of accounting choice plays in producing accounting results and achieving management incentives is complex and non-linear. The techniques used in existing accounting choice research are insufficient for supporting accounting choice decision making.

In addition to the fast-changing economy and increasingly complex business environment, the current practice for accounting choice decision making became less effective. Exiting accounting choice research provides a limited understanding and further disconnected from the practice. It is difficult to make good accounting choice decisions. Accounting choice needs to be better supported (DeAngelo et al., 1994; Dichev & Li, 2013; Gietzmann & Ireland, 2005; Napier, 2006).

2.5 A definition of accounting method selection problem

To support accounting choice decisions and to address how to make better accounting choices that are aligned with business objectives, a new definition of accounting method selection is required. The broad definition of an accounting choice is any accounting related decision that is primarily made to influence accounting results (Fields et al., 2001). This definition includes common and uncommon accounting related decisions. The common accounting related decisions are encountered by all companies and required to be disclosed to the users of the accoutring results. The uncommon accounting related decision problems only occur in particular settings to some companies and might not be required to report. To support accounting choice decisions, common and uncommon accounting related decision problems need to be distinguished.

Within the broad accounting choice definition, a subset of accounting choice decisions is to select one or more accounting method from the applicable alternatives, also referred to as accounting method choice. Accounting methods are sets of well-defined rules for how to measure and classify business transactions into accounting results. Accounting method selection is a commonly encountered decision problem by companies in different industries. The selected accounting methods are used in preparing accounting results and required to be disclosed in their financial statements. A distinguishable character of the accounting method selection from uncommon accounting related decisions or general accounting choices is whether the decision is visible. General accounting choices are mostly unique decisions to the company, uncommon and invisible. Distinguishing accounting method selection from general accounting choices helps to define the scope of this research. Hence, the definition of accounting method selection is given as follows:

> Accounting method selection is a decision that selects one or more accounting methods from applicable accounting method alternatives which explicitly defines the rules for how to measure and record business transactions in accounting information.

As the rules applied in preparing accounting results, accounting methods can significantly affect accounting results (Christie, 1990; Fields et al., 2001; Lugovsky & Kuter, 2020; Watts & Zimmerman, 1990). Different accounting method types impact on different items of the accounting results that correspond to different types of business transactions. For instance, inventory accounting methods set rules for how financial information that is relevant to the change of inventory should be recorded, regardless of the physical inventory operation. It sets the rules for recording the change in quantity and value during a time period for a number of inventory items, such as produced goods, raw material, parts, components, feedstock. The accounting value recorded for the inventories is assets. Change in the accounting value of the inventory affects multiple accounting items, including assets, cost of goods sold (COGS), profit, earnings or the cost of revenues.

To support accounting method selection, Chapter 3 will present an intelligent system-based approach to accounting method selection. As accounting method selection is a company-specific problem, Chapter 4 will introduce a case company for an extended empirical study. The elements of the approach in the context of the empirical case will be specified, including the accounting method types for evaluation, applicable accounting method alternatives, relevant business factors, affected accounting results and evaluation objectives. With a single accounting method type selection setting, Chapter 5 will address research questions RQ1 to RQ3. With a selection setting of multiple accounting method types, Chapter 6 will address research question RQ4.

Chapter 3 An intelligent system-based approach to accounting method selection

Accounting results are crucial information for communicating the outcome of a companies' operations to stakeholders for supporting a wide range of decisions. This information is the translation of business operations according to the accounting methods applied. In addition, accounting results convey information other than the results of operations the company attempts to communicate, such as productivity rates, R&D project risks and expected growth (Cazavan-Jeny et al., 2011; Dichev & Li, 2013; Hann et al., 2019). An important element of this information is the company's strategic objectives and its performance on the objectives (Fujiyama & KUROKI, 2020; García Osma et al., 2015). To select the most suitable accounting method from the perspective of the performance of the company's strategic goals, an intelligent system-based approach that involves accounting methods, relevant business factors, accounting results and strategic goals is developed. In this chapter, first, the approach will be presented together with its two modules that enable the evaluation of accounting method alternatives. Second, feasible modelling techniques and evaluation methods for the two modules will be discussed to support the accounting method alternative evaluation and selection. Lastly, concluding remarks will be presented.

3.1 An intelligent system-based approach to accounting method selection

Based on the current understanding, accounting methods have immediate impacts on the accounting results. The performance of a company's strategic goal often involves the performance of its financial aspects, namely, accounting results (Busch & Hoffmann, 2011). Hence, to establish the links between accounting methods, accounting results and strategic goals are crucial. Additionally, in practice, companies must select multiple accounting method types for accounting results preparation. To ensure the applicability of the approach to the selection of different accounting method types, the accounting method types are regarded as one component of the approach. This avoids the need to develop different approaches in dealing with the selection of different accounting method types. Figure 3-1 illustrates the intelligent system-based approach to accounting method selection.

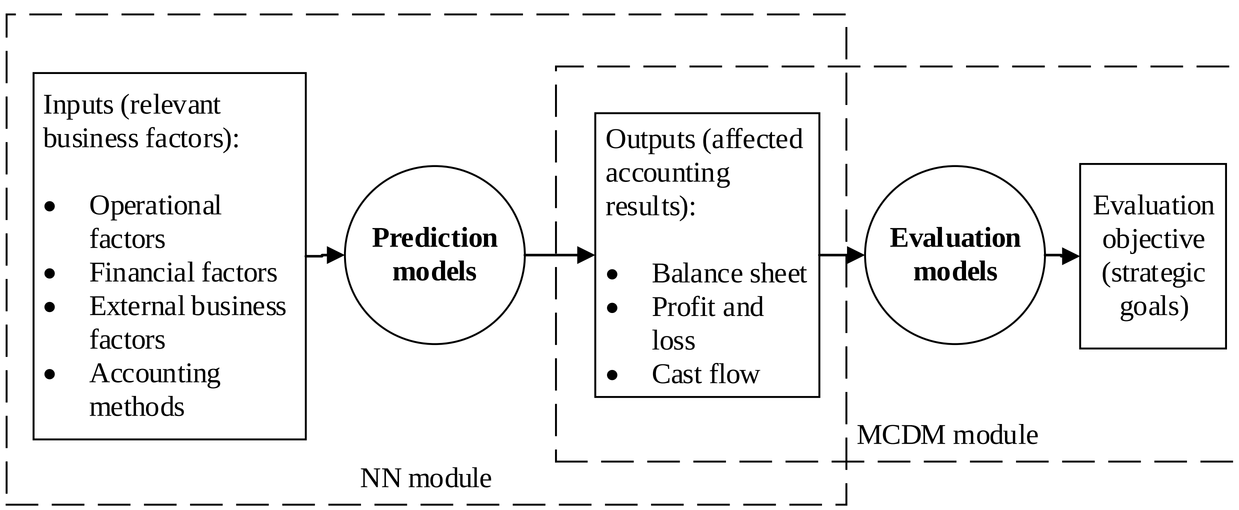

Figure 3-1. An intelligent system-based approach to accounting methods selection

The approach consists of two modules, a neural network (NN) module and a multicriteria decision making (MCDM) module. The performances of the accounting method alternatives are to be rated and ranked, and the best performing alternative can be identified. Having accounting results as an intermediate, the two modules work jointly to enable the evaluation and selection of accounting method alternatives.

The NN module is developed for predicting the accounting results under unused accounting method alternatives. Reflecting the mechanism of accounting information flow, NN models are used to model the relationships between business factors, accounting method and accounting results. Relevant business factors and the applied accounting methods are the model inputs, and affected accounting results are the outputs. The relevant business factors include a company's endogenous and exogenous factors of its operating condition. Endogenous factors are mainly the results of the operation. Exogenous factors are external business factors that can substantially affect the company's operating results, such as financial, economic and market factors. Model outputs are the accounting items affected by the selected inputs and the accounting method alternatives under evaluation. The accounting results prediction can be obtained by the best performing model from all prediction models built by this module. With the approach, the inputs, outputs and prediction models are to be identified and built for an accounting method selection problem in a company-specific setting.

The MCDM module is used to evaluate and select the most suitable accounting method alternatives with respect to the evaluation objective, namely the company's strategic goals. Evaluation criteria, criteria weights and alternative performance ratings are to be obtained in this module. The evaluation criteria are derived from the strategic goals of the company in need. The alterative performance ratings are measured using key performance indicators (KPIs) which are associated with the strategic goals. Using actual and predicted accounting results from the NN module, the performance ratings for used and unused accounting method alternatives are to be obtained. Criteria weights can be assigned by decision makers or by an optimal weighting model. By aggregating criteria weights and performance ratings, the overall performance value of the accounting method alternatives can be obtained. The most preferable accounting method can be identified.

This approach addresses the challenge of obtaining accounting results under unused accounting method alternatives, which has been unfeasible. Additionally, the accounting method alternatives are evaluated on multiple criteria and with respect to company strategic goals are new in supporting accounting method selection. The approach is a distinctive novelty of this research.

3.2 Modelling techniques

The intelligent system-based approach requires effective techniques for achieving accurate prediction and consistent evaluation. Various techniques can meet these requirements. In the context of accounting results prediction and accounting method alternatives evaluation, this section reviews neural networks (NNs) and multicriteria decision making (MCDM) as suitable modelling techniques for developing the approach and for addressing the four research questions identified.

3.2.1 Neural networks (NNs)

Accounting results are the outcome of business operation recordings by following the rules of different accounting method types. The accounting results under unused accounting method would not be recorded and kept. Given the complexity of business operations, obtaining accounting results under unused accounting method alternatives are either costly or infeasible. Accounting method alternatives could categorise the same business transaction to different accounting items, account for different value for the same event occurred, or recognise the same business transaction at different times. This effect brought by accounting methods is complex. The relationships between operation data and accounting results are none-linear. Only one exception is that accounting results under LIFO and FIFO can be converted with a formula. No transforming method is available for other accounting method types. No exiting research has investigated the underlying relationships between operation data and accounting results, given the influence of accounting methods.

A neural network (NN) is a structured network of simplified mathematical model of neurons. Inspired by the neural system of the human brain, it uses the weighted connections between input signals and output signals to represent synapses (Aladag et al., 2009; Gardner & Dorling, 1998). With different neuron activation functions and different network architectures, NNs can mimic the learning process of the human brain. An NN is essentially a large amount of parallel distributed data processing network. Comparing to traditional statistical models, it has appealing features that made wide adoption in industry and academic (Gardner & Dorling, 1998; Jang et al., 2019; Kubat, 1999; Levine et al., 2017; Widrow et al., 1994).

A basic NN consists of three layers, including an input layer, hidden layer(s) and an output layer. The commonly seen activation functions in NN modelling include ReLu, sigmoid, softmax and tanh. Activation functions can be further modified to build more customised and advanced NNs. The widely used NN architectures include feedforward network, recurrent networks, adaptive resonance theory maps and competitive networks (Russell & Norvig, 2010). Depending on the characteristics of the problem, NN applications may use different architectures. The most suited NN architectures for modelling business factors and accounting results include the following:

(a) Feedforward network: it flows signal from input units to output units with signal directions. It can have multiple layers of processing neurons. Both single hidden layer and multiple hidden layer feedforward networks have been widely applied for forecasting problems as they have a higher prediction accuracy and are simple to use (Gardner & Dorling, 1998; Russell & Norvig, 2010).

(b) Recurrent network: it has feedback connections through bi-directional data flow between needed neurons. It is better fitted for the problems with the time-series feature (Aladag et al., 2009; Russell & Norvig, 2010; G. P. Zhang, 2001).

The application of NN models significantly increases the prediction accuracy while remaining easy to implement in numerous scenarios. Examples of NN models include predicting share pricing in Initial Public Offering (IPO), predicting account balance, predicting sales, detecting fraud in auditing and accounting, predicting bankruptcy, credit rating and customer segmentation (Koskivaara, 2000; Omar et al., 2017; Salehinejad & Rahnamayan, 2016; Sharda, 1994; Teles et al., 2020; Thomassey & Happiette, 2007; Tkáč & Verner, 2016).

The learning capability of NN models is achieved through adjusting the weights among the whole network by data training. There are three types of learning, including supervised, unsupervised and reinforcement learning. The key factors for successful NN modelling are (a) to obtain sufficient data for the selected model, (b) to determine the NN inputs based on problem and theory, (c) to select the appropriate NN architecture that matches the problem, and (d) to limit the data fitting problems with data pre-processing, algorithm tuning, and ensembles different models (Kalogirou, 2001; Rumelhart et al., 1994). Furthermore, as the complexity of the problem increases, less theoretical understanding can be provided from the existing research (Gardner & Dorling, 1998). NN's learning capability can provide benefits in modelling complex problems in specialised domains, which includes the following:

(a) NN modelling requires few assumptions about the underlying model form.

(b) NN is nonlinear, which can be applied to complex problems.

(c) NN is a universal functional approximator. It can be used in a wide range of problems with good prediction accuracy. Provided with a large enough network and sufficient training data, it can outperform traditional models (Zhang, 2001).

3.2.2 Multicriteria decision making (MCDM)

Accounting method selection is a decision problem with multiple criteria to be met (Fields et al., 2001; Groot, 2015). To effectively support accounting method selection, accounting method alternatives should be evaluated with respect to the multiple criteria that are a specification of the company's strategic goals. Multicriteria decision making (MCDM) is suitable for accounting method alternative evaluation.

MCDM is a commonly used method that can effectively evaluate and prioritise decision alternatives with respect to multiple evaluation criteria (Al-Hamadi, 1995; Henig & Buchanan, 1996; Lee & Chang, 2018; Xu et al., 2020; Yeh, 2003; Yoon & Hwang, 1995a; Zhang et al., 2020). Various MCDM techniques have been developed for addressing decision making problems in economic analysis, strategic planning, portfolio management, supply chain management and medical diagnosis (Dimova et al., 2006; Parkash & Kumar, 2017; Sánchez-Lozano et al., 2015; Yue, 2011).

Decision problems are often presented with the issue of rationality, consistency and complexity (Kelemenis et al., 2011; Swenson & McCahon, 1991; Yeh, 2003). The benefit of MCDM techniques in supporting decision making is to ensure consistency of making good or optimal decisions as the complexity of the problem increases (Timmermans & Vlek, 1992; Tversky & Kahneman, 1981; Tzeng & Huang, 2011).

The common elements of an MCDM problem include (Korhonen et al., 1992; Tzeng & Huang, 2011; Yoon & Hwang, 1995a):

(a) The decision maker of the decision problem: the decision maker or stakeholder determines how to identify alternatives, what the evaluation criteria are, how to weight criteria and how to rate performances of the alternatives. Accounting method selection problems often have CEO and/or senior management as decision makers.

(b) Decision alternatives: decision alternatives are a finite number of candidates that are to be evaluated and selected for the decision. One or more decision alternatives can be selected. In the case of accounting method selection problem, only one accounting method within each accounting method type can be selected. The accounting method selection problem can consider one or more accounting method types in the selection problem.

(c) Evaluation criteria: evaluation criterion are the measurements used for comparing the competitiveness of the decision alternatives. Evaluation criterion often reflects the objectives of the decision making, and they are usually independent and collectively exhaustive. A criterion can be combined if less important. Accounting method selection is proposed to be made in algin with the company's strategic goals which are commonly measured by KPIs.

(d) Performance rating: performance ratings are the value of the alternative's competitiveness with respect to the identified evaluation criteria. Performance ratings of the accounting method alternatives are usually financial ratios and accounting items that are used for KPIs.

(e) Criteria weights: criteria weights are the relative importance of the decision criterion. Criteria weights can be assigned by decision makers or obtained by weighting methods. Different weighting methods will lead to different decision outcome. On the other hand, a dominating criterion will result in the same decision outcome using different performance value aggregation methods.

(f) Decision matrix: A decision matrix consists of a set of evaluation criteria in columns and decision alternatives in rows, where decision alternatives are rated against the criterion. Accounting method selection problems can be concisely expressed in the form of a decision matrix.

The decision matrix shows the performance ratings of decision alternatives with respect to evaluation criteria. The decision matrix is aggregated with the criteria weights to obtain the overall performance value. The ranking of the decision alternatives can be obtained by the overall performance value. Simple additive weighting (SAW) and the analytic hierarchy process (AHP) are often used in MCDM score aggregation for their simplicity (Greco et al., 2008; Tzeng & Huang, 2011; Yoon & Hwang, 1995b).

3.3 Concluding remarks

This chapter has presented the intelligent system-based approach to accounting method selection. The two modules of the approach and suitable techniques for fulfilling the requirements of the modules have been discussed. Neural networks (NNs) and multicriteria decision making (MCDM) are considered suitable methods to be adopted by the approach for predicting accounting results under unused accounting methods and for evaluating accounting method alternatives with respect to multiple criteria derived from company strategic goals. From a novel decision support perspective, this approach provides a structured methodology for evaluating accounting method alternatives in terms of their performance on a company's strategic goals. The accounting method selection can be carried out in a rational and informed manner. The feasibility and effectiveness of this approach will be demonstrated with an empirical case company to be introduced in Chapter 4 for the selection problem of a single accounting method type in Chapter 5 and for the selection problem of multiple accounting method types in Chapter 6.

Chapter 4 A case company for empirical studies

This chapter introduces a case company for conducting empirical studies to illustrate how the research questions are addressed. With the background information of the case company, two accounting method types of significance are chosen for investigation, namely exploration costing and inventory. Business factors and accounting items that are relevant to the two accounting method types are subsequently identified and discussed. Then, the business strategic goals and KPIs, as evaluation criteria and measurements for the performance rating of accounting method alternatives, are identified and discussed. Relevant empirical data are made possible by the regulatory requirements of the countries where the case company is based. At last, the structure of the intelligent system for accounting method selection of the case company, empirical data and the data source used in the empirical studies are discussed. This chapter addresses research questions RQ1(a) to RQ1(c) and RQ3(a).

4.1 Background of the empirical studies

The case company, Eni S. p. A., is a leading multinational integrated oil and gas company with 50 billion euros (approximately 60 billion US dollars) of market capitalisation as in December

2018. Eni has a complex capital structure and sources operation finding through debts, company shares, profits of the company investment and collaborative project funding with partners. Its operation expands to oil and natural gas exploration, field development and production, as well as in the supplying, trading and shipping of natural gas, liquid natural gas (LNG), electricity, fuels and chemical products. The Eni headquarter is located in Italy, and its shares are publicly traded at the New York Stock Exchange (NYSE) and the FTSE MIB of the Milan Stock Exchange. Eni's operations can be divided into two main categories, upstream activities and mid-downstream activities. Upstream activities include oil and gas resource exploration, onshore and offshore production, developing oil and gas fields. The reserves found in exploration activity are the most important asset as they are the source of generating future economic benefits for the company. The reserves that can be recovered with a reasonable level of certainty are proved reserves. However, the reserves may or may not be recovered economically. Thus, commercially viable exploration is most desired. Mid-downstream activities include production and sales of gas, electricity, LNG oil products, and financial trading activities for a cost-efficient supply of oil and gas.

As Eni operates on an international scale, external business factors, including macroeconomic, oil commodity price, currency exchange rates and interest rate, can significantly influence the outcome of its operation. Those factors are the risks to the company performance and cause fluctuations in its accounting results. For instance, the crude oil sale price is largely affected by the oil futures price due to the mechanism of the oil market, despite the fact that the futures market is purely a market of financial instrument. Thus, crude oil as the raw material for production, revenue from the sales of energy products can be impacted by oil futures. Companies in the oil and gas industry normally hold oil futures for offsetting the risks of fluctuating crude oil price.

Additionally, the currency exchange rate and interest rates can also impact revenue, expense and cost of funding due to its international operation and the use of foreign currencies.

Eni's goal is to engage long-term value creation for shareholders, stated in the annual report 2018. To navigate the complex business environment and manage the company's progress towards its goal, the executives establish business strategic goals and business models. Eni uses KPIs, drawn from a number of measurements from operational data and financial data, to monitor and communicate the company's performance with stakeholders. Between 2015 to 2018, Eni uses KPIs from six aspects of the business models in which three aspects can be impacted by accounting results.

4.2 Accounting method types to be investigated

This empirical study is conducted to examine and help the selection of two accounting method types, exploration costing accounting method and inventory accounting method. The exploration costing accounting method, referred to as exploration costing methods, includes the full cost (FC) and successful efforts (SE) methods. The inventory accounting method, referred to as inventory method, includes methods of LIFO and weighted average (WA) in the context of this empirical study. These accounting methods are well defined by accounting standards and commonly used in accounting practice. Companies are required to disclose the accounting methods that have been applied to producing the accounting results presented in their financial statement. In addition to the reasons discussed in Section 1.3, specifically to this empirical study, two reasons for examining the exploration costing method and the inventory method:

(a) The exploration costing method and the inventory method are significant accounting method types to Eni. Their oil and gas exploration activities constitute a large proportion of the operation carried out. The inventory also accounts for a substantial part of assets excluding property, plant and equipment. The impact of the exploration costing method and the inventory method on Eni is significant enough to cause Eni to make changes in 2016 and 2006, respectively.

(b) The relevant operational data for the exploration costing method and the inventory method are acquirable from Eni's financial statements.

In the subsequent Sections 4.3 to 4.6, to examine the interaction effects between the two accounting method types (i.e. research question RQ4(c)), the business factors, accounting items and KPIs that are relevant to both accounting method types are identified and selected without being over-specific and exclusive to each other.

4.3 Business factors for exploration costing accounting method

Exploration costing is the first accounting method type under examination in the empirical study. The exploration costing method has two accounting method alternatives, which are the full cost (FC) and successful efforts (SE) methods. It sets the rules for how to measure and record expenditures in searching for, acquiring and developing the reserves. The two accounting methods are described as follows (Wright, 2017a):

(a) Full cost (FC) method: All cost that is related to searching for, acquiring and developing the reserves in the geographic cost centre, which normally is a country, are recorded as assets. Then, the parts that are not assets will be depleted on the production within the cost centre. Unless the exploration is unsuccessful for the whole cost centre, the costs will be recorded as expense.

(b) Successful effort (SE) method: All cost that is related to searching for, acquiring and developing reserves are determined on a field-by-field basis. Expenditures are first recognised as expense as incurred. To record expenditures as assets, the field needs to satisfy the company's commercial viability. Otherwise, the expenditures will remain as expense.

A crucial characteristic of the business in the oil and gas industry is that it requires substantial capital investment in operations and has long-lead-time from the initial investment to the earliest time of sales can be made. The most influential accounting standards, namely IFRS and US GAAP, allow companies to choose between FC and SE based on their companies' situation. As reserves are the source of the company's future economic benefits, the selection of exploration costing method can significantly impact the accounting results on assets, cost of product sold, net income and profit.

For the short-term accounting results, FC defers more exploration and development expenses to be charged in the future, while SE provides more conservative and reliable accounting information. In comparison to FC, SE is not able to reflect the operation cycle in full due to the long-lead-time characteristic of the oil and gas business (Bryant, 2003). Although the accounting result would be the same in the long term, assuming the identical operation result, the FC would report more net income in the early stage of exploration and development than SE. However, in the later stage, if no success in finding new reserves, FC would report less net income (Wright, 2017a). Eni raises funding from both the debt and share markets, and the debtors and the investors pay great attention to its financial statements. The exploration costing method selection can significantly impact its fundraising ability for its future operation through the accounting results. With the majority of the companies in the oil and gas industry switched from FC to SE, Eni has changed its exploration costing method in 2016 to improve the understandability and comparability of Eni's accounting results to other competitors.

Therefore, given the essence of FC and SE, to examine the impact of the exploration costing method on the accounting results, relevant business factors are identified. In accordance with the intelligent system-based approach, as shown in Figure 3-1, the business factors include operational factors (B_1 and B_2), organisational factor (B_3), financial factors (B_4), external factors (B_5 to B_7) and accounting method (B_8). Preliminary NN modelling experiments have been carried out. The results suggest that combing originally collected data into combined business factors are beneficial for the prediction accuracy of NN modelling. Hence, business factors are organised as follows:

B_1 *Oil and natural gas reserve*

This factor refers to the total volume of the proved reserves that can be estimated with reasonable certainty to be economically extracted by the analysis of geoscience and engineering data. This is the results of the exploration activities, which is the source for generating future economic benefits (Wright, 2017b). Relevant accounting items are recorded base on this factor. Three types of proved reserves are recorded and reported, including proved reserves of liquids (mmbbl, million barrels), natural gas (bcf, billion cubic feet) and hydrocarbons (mmboe, million barrels of oil equivalent). To reduce the total number of inputs of the NN model, a combined input of the three is used as an NN input.

B_2 *Oil and natural gas production*

This factor refers to the total volume of production. This is the results of the production actives that sets the basis for recording inventory, sales and profit. Exploration costing method impacts accounting results though how the exploration expenditures are allocated to the cost of goods sold (COGS). To reduce the total number of inputs of the NN model, a combined value of production is used, including liquids (mmbbl, million barrels), natural gas (bcf, billion cubic feet) and hydrocarbons (mmboe, million barrels of oil equivalent).

B_3 *Oil and natural gas products actualising price*

This factor refers to the price of sold products, including liquids, natural gas and hydrocarbons. This is the price agreed for supplying and trading the oil-based and natural gas products, such as fuels, natural gas and petrochemicals to industrial and domestic wholesalers/distributors. At what price the crude oil and oil-based refinery products have directly affect revenue and profits given the production level. To reduce the total number of inputs of the NN model, a combined value of actualising price for liquids (USD), natural gas (USD) and hydrocarbons (USD) is used.

B_4 *Company share effect*

This factor is the product of the three-month averaged share price and the total traded volume over the three-month period. The share price is the price sellers and buyers agreed upon transaction for a unit of the company's share. The volume is the number of shares that have been traded over a given time period. The performance of the companies' shares is used as one of the key measures for the performance of the CEO and senior management, which is believed as a significant determinant of accounting method selection. Company share performance is often regarded as the company's capability in making profits for its shareholders. Furthermore, as a publicly traded company, Eni's company share is one of the major funding sources.

B_5 *Interest rate effect*

This factor is the average of a three-month averaged USD and EUR central bank benchmark interest rates. The central bank benchmark interest rates are the basis for and lower than the loan interest rates by the commercial banks. Eni is based in the Eurozone, and Eni's international operation and commodity trading determine the use of USD. Both USD and EUR interest rates impact the cost of financing. The interest rates are identified as one of the financial risk factors by Eni, and the interest rates are also generally regarded as an important factor for capital-intensive industries. The fluctuation of the interest rates can bring considerable changes to the market value of Eni's finical assets and liabilities, the profitability and the ability of financing. Eni does not hedge the interest rate risk and manages risk exposure by its central financial department. Accounting results (to be described in Section 4.5) that are affected by the exploration costing method are also affected by this factor.

B_6 *Exchange rate effect*

This factor is the exchange rate for USD/EUR. While the global oil and gas market trades in USD, Eni uses EUR as the base currency. In addition, Eni's shares are listed in both the New York Stock Exchange (NYSE) and the FTSE MIB of the Milan Stock Exchange. Eni's global operations made the exchange conversions occur at different times, which cause substantial impacts on revenues and expenses, consequently, impact on profit by operation and overall profit. The exchange rate is also identified as a market risk factor to Eni's overall performance. Eni does hedge the exchange rate risk by holding exchange rate related financial instruments, such as currency swaps, forward and options, at Eni's central financial department. The holdings of the financial instruments affect total assets, comprehensive income and profit.

B_7 *Oil commodity effect*

This factor is the average of three-month averaged oil futures price and traded volume over three months in the Light Sweet Crude Oil in the ICE West Texas Intermediate futures market and the Brent futures market. The oil future price and the volume of oil futures demand determine the crude oil spot price, which is the sale price of crude oil in the physical commodity trade market. Consequently, revenue, cost of goods sold (COGS) and operating profit are to be affected through the realisable sale prices of oil and gas products in the market. A decrease in oil and gas prices negatively impact Eni's results of operations and accounting results. The achievement of financial related goals and future plans can be undermined. It is a strategically significant risk factor, recognised by Eni's CEO and senior management. Hence, Eni engages crude oil futures trading to mitigate the risks of crude oil supply in quantity and price fluctuation in order to stabilise its economic results by a trading and shipping unit at Eni. The holdings of the financial instruments also affect total assets, comprehensive income and profit.

B_8 *Exploration costing method*

This factor is the accounting method type to be modelled and evaluated. The full cost (FC) and successful efforts (SE) methods are the two accounting method alternatives that have been used prior to 2016, and FC is in use currently. In NN modelling, FC and SE will be represented by a numerical value of 0 and 1, respectively.

4.4 Business factors for inventory accounting method

The second accounting method type under examination is the accounting methods for inventory. The inventory accounting method measures and records the value of the goods that are in raw materials during the stages of processing and ready for sale. Depending on accounting standards adopted in different countries, in general, their inventory methods and their variations are permitted, including first-in-first-out (FIFO), last-in-first-out (LIFO) and weighted average (WA). Accounting practices in the US follow GAAP and allow FIFO, LIFO and WA. In contrast, accounting practice within the European Union follows IFRS, which only allows FIFO and WA. The three accounting methods are described as follows:

(a) First-in-first-out (FIFO). It requires the value of the oldest inventory items to be accounted for the item sold or used.

(b) Last-in-first-out (LIFO). It requires the value of the newest inventory items to be accounted for the item sold or used.

(c) Weighted average (WA). It accounts the weighted average using the number of items and its corresponding value, then divided by all items available for sale or use during the accounting period.

The impacts of the inventory accounting method alternatives occur when the cost associated with inventory changes. More specifically, when the prices of the cost associated with inventory rise, LIFO reports lower net income, lower profit and lower assets. Conversely, FIFO reports higher net income, lower profit and lower assets. WA takes the quantity averaged value of inventory for the given product as the cost of goods sold (COGS), which averages the influence of the inventory material price changes. When prices of the cost associated with inventory decline, the effects reverse.

Specifically, to the application of LIFO by Eni prior to 2006, changes in oil and refined products prices did not impact the values of inventories, which was affected only by declines in volumes. With the adoption of the weighted average (WA), changes in oil and refined products prices have a direct effect on the recognition of profit or loss. In comparison, the accounting results under LIFO provide better aligned income with the COGS as the accounted value of the COGS and revenues have less time gap than accounting results under FIFO or WA. Consequently, tax obligation is reduced for the reporting period.

Inventories are assets to a company. Similar to the exploration costing method, the impacts of the inventory method are pronounced given identical physical inventory operations. Companies with different operation settings and in different situations may be impacted differently by the inventory accounting method. To examine the impact of the inventory accounting method at Eni, business factors that relevant to the physical inventories and the accounted market value of the physical inventories should be considered. The relevant business factors identified for exploration costing, as discussed in Section 4.3 can be used, which includes Oil and natural gas reserve (B_1), Oil and natural gas production (B_2), Organisation size (B_3), Company share effect (B_4), Interest rate effect (B_5), Exchange rate effect (B_6) and Oil commodity effect (B_7). To represent the inventory method in modelling, the business factor for the inventory method is:

B_9 *Inventory accounting method*

This factor is the applicable inventory method to be modelled and evaluated. Last-in-first-out (LIFO) and weighted average (WA) are the two accounting method alternatives that have been used prior to 2006, and WA is in use. In NN modelling, LIFO and WA will be represented by a numerical value of 0 and 1, respectively.

4.5 Affected accounting items

Accounting items are the listed items or categories used for distinguishing and organising associated financial value of the business transactions in the statement of the balance sheet, income statement and cash flow statement. The list is known as the chart of accounts, and the categories or the items also been referred to as accounts. The name of the accounting item identifies the categories of financial value and segregates one from the other from the perspectives of recording and communicating a company’s business operating results. Given the numbers of accounting items in the accounting results, fewer accounting items are relevant to and can be used for examining the exploration costing method and the inventory method and approximating KPIs are chosen in this empirical study. In addition, fewer accounting items reduce the complexity of the underlying relationships that NN modelling aims at capturing while achieving satisfactory prediction accuracy. To offer sufficient accounting items for rating the performance of the accounting method alternatives on Eni’s strategic goals by MCDM, the affected accounting items form Eni’s quarterly accounting reports are:

A_1 Total asset

Total asset is the total value of the resources owned or controlled by an economic entity that is able to provide future economic benefits. Total asset is an item that appears on a company's balances sheet.

A_2 Total liability

Total liability is the total value of the financial obligations owed by an economic entity to external entities. Total liability is an item that appears on a company's balances sheet.

A_3 Total equity

Total equity is the total value of resources brought by the ownership of an economic entity. It is also referred to as the total value of the economic entity after its liabilities. Total equity is an item that appears on a company's balances sheet.

A_4 Revenue

Revenue is the total amount of money earned from selling goods and services after returns, damaging, missing and discounts from its normal operation. Revenue is an item that appears on a company's income statement, also known as profit and loss (P&L) statement.

A_5 Gross profit

Gross profit is the profit made after deducting the costs associated with production or providing services and sales. Gross profit is an item that appears on a company's income statement.

A_6 Operating income

Operating income is the profit made through the business normal and repeating operations after operating expenses, including wage, depreciation and cost of goods sold (COGS). Operating income is an item that appears on a company's income statement.

4.6 Strategic goals and KPIs of the case company

Strategic goals consist of the key information about the direction of the company's future plans, and KPIs measure and monitor the progress towards the goals. Accounting choice research find that compared to the current normative research approach, accounting choice research could gain more insights by investigating how to make accounting methods decision that best achieves the business goals (Fields et al., 2001). As a significant element for recording, measuring and communicating business operation with stakeholders, the accounting method used should be well suited to reflect the economic performance of the company, the situation the company is in and the outlook for future performance. The most suitable accounting method needs to be best aligned with the business strategic goals. As to Eni, the changes made to the inventory accounting method from LIFO to WA in 2006 in conjunction with the adoption of IFRS and to the exploration costing accounting method from FC to SE in 2016 aimed at increasing comparability with competitors. To this end, it is crucial to examine whether the switched accounting methods help to better achieve Eni's strategic goals.

To understand the elements of Eni's strategic goals, this empirical study has reviewed Eni's integrated annual reports between 2014 and 2018 and the business literature to obtain preliminary views. Eni's business strategy is to engage in long-term value creation activates for both the company and stakeholders. Eni aims at achieving competitiveness in the industry by transferring its business into a responsible company to shareholders, the community and the environment. As the transfer from traditional fossil fuel into new renewable energy with concerns for global warming, as well as the pollution created during the traditional energy production, Eni plans to increase the proportion of sustainable energy, the development of new technology, creating values for the economy, environment and society. To achieve these goals, Eni's has defined a comprehensive structure and KPIs for measuring the performance in terms of the strategic goals which are presented on its annual reports. The four fundamental pillars that support Eni to engage long term value creation activities are:

C_1 Achieve the goals in relation to profitability and growth

C_2 Achieve the goals in relation to operational excellence

C_3 Achieve the goals in relation to preventing of business risks

C_4 Achieve the goals in relation to social and environmental sustainability

The four major aspects are to be adopted as group criteria in the accounting method selection. Further, employing Eni's reported KPIs, 16 criteria from the aforementioned four aspects have been chosen for measuring the performance of accounting method alternatives in terms of Eni's strategic goals, which are described in Table 4-1.

Table 4-1. Accounting method selection group criteria, criteria and description

Group criteria (C_i)	**Criteria (c_{ij})**	**Description**
Profitability and growth (C_1)	Operating profit (c_{11})	An accounting measurement of the profit earned from a company's ongoing core business operations. It does not include interest, taxes, profit earned from the non-core business operation. It is one of the most important indications of the company ability in generating future profit from its core business. The shortcoming is that operating profit does not include the effects of financial cost and taxes.
	R&D expenditure (c_{12})	Expense associated with the research and development activities that relevant to the regular business of the company's goods or service.
	Exploration CAPX (c_{13})	Capital expenditure in exploration. It is the funds used for reserve exploration activities.
	Margin (c_{14})	Margin is a ratio reflecting the company's ability in generating profit from each dollar of sale to service its other cost. The higher the margin is, the more efficient the company can generate profit. It is an important indicator for managers and investors in monitoring the operation efficiency financially. Operation profit/Net sale from the operation.
	Return on Assets (ROA) (c_{15})	Return on asset is a ratio indicating how profitable a company is relative to its total asset. This study uses operating profit divided by total assets, which is a slight modification of the ROA that reflect the core business profitability relative to its total asset. ROA offers information on the profits generated through resources from both investors and debtors.
	Return on Equity (ROE) (c_{16})	Return on equity is a ratio indicating how profitable a company is relative to its total equity. This study uses operating profit divided by total equity, which is a slight modification of the ROE that reflects the core business profitability relative to its total equity. ROE provides information on generating profits with its investors' resource.

Table 4-1. Accounting method selection group criteria, criteria and description (continued)

Group criteria (C_i)	**Criteria (c_{ij})**	**Description**
Profitability and growth (C_1)	Asset turnover (c_{17})	Asset turnover is a commonly used financial ratio measures the sales relative to the value of a company's asset. It is calculated as revenues / total asset.
Operational Excellence (C_2)	Total production (c_{21})	It is the number of the combined volume of liquids, natural gas and hydrocarbons in production. It is the product of value in the form of good to be sold.
	Proved reserve (c_{22})	It is the number of combined volumes of proved reserves of liquids, natural gas and hydrocarbons. It is the source for value creation that has been considered one of the
Business risk (C_3)	Future price impact (c_{31})	It is the product of averaged oil future price and traded volume of the Light Sweet Crude Oil in the ICE West Texas Intermediate futures market and the Brent futures market. It has a substantial impact on the sale price of crude oil and the performance of the oil and gas company.
	Interest rates impact (c_{32})	It is the average of averaged past three-month exchange rate for USD and EUR. It is one of the financial risks that have significant impacts on the cost of debts. The interest rate is not only being identified as a risk by Eni as a specific company. The fluctuation of the interests can bring significate changes to its profitability and funding.
Social and environmental sustainability (C_4)	Employment (c_{41})	It is the total number of employees. It reflects the level of Eni in contributing to social sustainability.
	Emissions (c_{42})	It is the volume of GHG emissions that includes CO_2, CH_4 and N_2O. It reflects the level of commitment and performance in environmental sustainability.
	Book-to-market ratio (c_{43})	It is a financial ratio by contracting company's accounting value to its total market value know as market capitalisation. The ratio value can be used in approximating the company's financial sustainability.

Table 4-1. Accounting method selection group criteria, criteria and description (continued)

Group criteria (C_i)	**Criteria (c_{ij})**	**Description**
Sustainability (C_4)	Sharp ratio (c_{44})	It is a widely used financial ration that measures how much excess return received for the extra unit of uncertainty. The modified calculation in this paper uses (operation profit – the return of interest rate)/standard deviation of operating profit. The value of Sharpe ratio indicates the attractiveness of the company to a certain level of risk preference investors in the share markets that Eni’s share is traded in.
	Debt ratio (Leveraging ratio) (c_{45})	It is one of several financial ratios that measure the proportion of debt in total capital, which reflects the level of financial obligation one company is bearing. It is calculated by Total liability / total asset. The value of the debt ratio is used as an indicator for the level of flexibility of the company’s financing structure.

4.7 Structure of the intelligent system for accounting method selection for Eni and data collection

By addressing the three research questions RQ1(a) to RQ1(c), the relevant business factors affected accounting items and KPIs for measuring the performance with respect to the strategic goals are identified. The intelligent system-based approach can be applied to the exploration costing method and inventory method selection for the case company with empirical data. The structure of the intelligent system is shown in Figure 4-1.

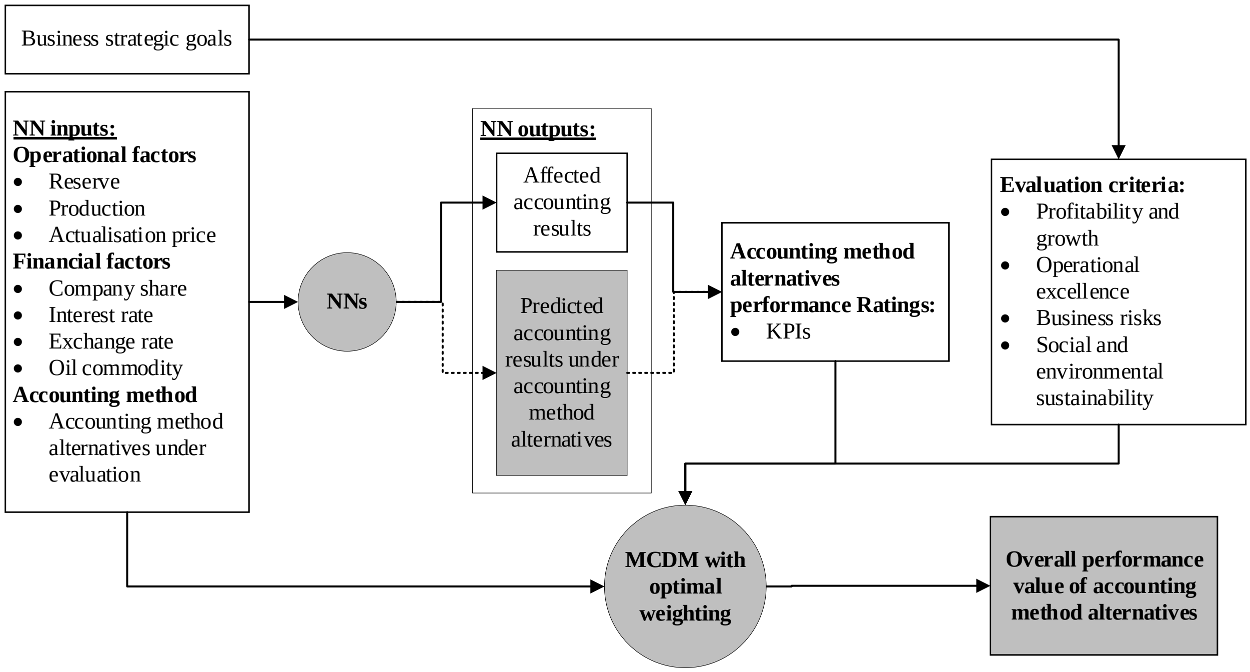

Figure 4-1. Intelligent system-based approach to accounting method selection

Empirical data are collected from publicly available documents and databases. For accounting results and endogenous business factors, namely operational factors, Eni's annual reports, Eni's Factbook and U.S. Securities and Exchange Commission (SEC) 20-F filings are used, shown in Table A-4, Table A-1 and Table A-2 in Appendix A, respectively. For exogenous business factors, namely financial factors, Yahoo finance and the economic research data repository of Federal Reserve Bank of St. Louis (FRED) are used, shown in Table A-3 in Appendix A. As a result of the availability and data quality, 55 sets of 25 quarterly data points between the second quarter of 2005 to the fourth quarter of 2018 are collected to be used for NN modelling.

Chapter 5 Evaluation of a single accounting method type – accounting methods for exploration costing

5.1 Introduction

This chapter introduces the first application of the proposed intelligent system-based approach to accounting method selection in the selection of the exploration costing method at Eni, as presented in Chapter 4. The objective of this application is to evaluate the performance of the full cost (FC) and successful efforts (SE) methods with respect to identified Eni's strategic goals, as discussed in Section 4.6, leading to the most suitable exploration costing method specifically to Eni's situation being identified. The performance evaluation consists of two main steps using the two modules of the approach, namely NN module and MCDM module. The NN module is used to predict the accounting results under the unused accounting method for 2018, namely FC, with the identified relative business factors and the affected accounting items, as discussed in Sections 4.3 and 4.5, respectively. The NN modelling is designed to examine four data scaling techniques, four NN architectures and four model training techniques for achieving the best prediction accuracy. The best performing NN model is to be identified. The predicted accounting results under the unused accounting method alternative can be subsequently obtained. This NN module and task carried out address research questions RQ1(d) and RQ2. Then, the MCDM module is used to construct a hierarchical structure for evaluating the performance of FC and SE. With the identified strategic goals as evaluation criteria, the performance ratings of FC and SE can be obtained with the actual and predicted accounting results. For obtaining the criteria weights, fuzzy numbers represented five linguistic value are used in a pairwise comparison process. An optimal weighting model is developed to determine the criteria weights to meet the best operational settings of the case company. Then, the overall performance of FC and SE on the strategic goals of the case company can be obtained, and the most suitable exploration costing method can be identified. This MCDM module addresses the three research questions RQ3(b) to RQ3(d).

5.2 Neural network modelling

5.2.1 Performance comparison with ARIMA and Persistence Algorithm

To understand whether NN models can perform well, it is necessary to establish a baseline performance with the commonly used prediction methods in the context of accounting. To this end, the nature of data and commonly used modelling techniques are to be identified. As described in Section 4.5, all the affected accounting items are observations arranged in chronological orders. It is a typical characteristic of the time series. Common modelling techniques used in economy and finance research and for the time series data prediction that can be used for the prediction performance baseline include autoregressive integrated moving average (ARIMA) and the persistence algorithm (the “naïve” forecast) (Tkáč & Verner, 2016).

The ARIMA technique is widely used in problems of complex data modelling and forecasting as its accuracy and flexibility. The ARMIA (p, d, q) model describes the autocorrelations in the modelling data, where p is the order of the autoregressive part, d is the degree of first differencing involved, and q is the order of the moving average part. The general equation for ARMIA forecasting is given as

$$\hat{y}_t = c + \phi_1 y_{t-1} + \ldots + \phi_p\, y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \tag{5-1}$$

The persistence algorithm, in this case, is an easy technique to implement and not a problem-specific time series prediction model. It uses the value of Y_{t-1} at time t-1 as the predictor for predicting the value of $\hat{Y}_t$ at time t while minimising the prediction error for the length of the dataset number of times. The prediction error is measured by the mean squared error (MSE), as given in Eq. (5-2).

$$MSE = \frac{1}{n} \sum_{n=1}^{t} \left(Y_t - \hat{Y}_t\right)^2 \tag{5-2}$$

By using the affected accounting items individually in ARIMA and persistence algorithm modelling, the first two rows of Table 5-1 show the MSE for each accounting items and the averaged MSE in the first six columns and the last column, respectively. To compare the performance of NN modelling with these two techniques, a widely used recurrent NN in time series prediction, long short-term memory (LSTM) is used. Excluding the accounting method in the NN inputs, the performance of a two-layer LSTM is shown in the last row of Table 5-1.

Table 5-1. Performance of ARIMA, the persistence algorithm and LSTM

	Accounting item						Averaged MSE
Modelling methods	A_1	A_2	A_3	A_4	A_5	A_6	
ARIMA	17.660	11.917	0.676	0.245	6.368	4.060	6.821
Persistence algorithm	0.6	0.333	0.2	0.067	4.8	3	1.5
NN (LSTM)							0.844

As shown in Table 5-1, LSTM achieves significantly a better averaged MSE. In terms of the modelling capability, LSTM can model all accounting items as a whole in one model. In comparison with ARIMA and the persistence algorithm, the relative relationships between different accounting items can be learnt with LSTM, which can benefit a higher accuracy for obtaining financial ratios to be used in assessing the performance ratings of accounting method alternatives.

5.2.2 Data preparation

To obtain the best performing NN model among many available NN models, the original data needs to be prepared based on the features presented by the training dataset, NN architectures and model training techniques applied. By adding, deleting or transforming the dataset for model training, the collected original data are to be pre-processed. The collected original data, as described in Section 4.7, is complete for the time period between the second quarter of 2005 and the fourth quarter of 2018. Hence, additions or deletions are not required. However, the business factors that are to be used as NN inputs have different measurement units, and the scales of the different business factors and accounting items are quite distanced. Thus, four commonly used scaling techniques in NN modelling are to be tested, including (1) no scaling, (2) minimax scaling, (3) normaliser scaling and (4) ratio scaling. No scaling does not apply any scaling on the original dataset. Minimax scaling transforms the original data into the range between zero and one by subtracting the original minimum in the dataset and divided by the difference between the original maximum and the original minimum. Normaliser scaling uses original data in the dataset, subtracting the mean and divided by the standard deviation of the original dataset. Lastly, ratio scaling transforms the original dataset into a dataset with a maximum number of data points ranging between zero and ten. Mathematical formulas are given respectively as:

$$X' = X \tag{5-3}$$

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{5-4}$$

$$X' = \frac{X - \mu}{\sigma} \tag{5-5}$$

$$X' = \frac{X}{10^i} \tag{5-6}$$

where X' is the processed value, X is the original value. μ and σ are the mean and standard deviation of a data series; X_{max} and X_{min} are the maximum and minimum of a data series; i in 10^i is the i^{th} to the 10th power that can make the maximum number of X' to a single digit of a data series.

5.2.3 NN architectures and model training techniques

In the context of business factors and accounting results modelling, as supervised learning for regression problems, several NN architectures can be used. In addition to the NN architecture that is commonly used and able to achieve high accuracy, including single layer perceptrons (SLPs), multilayer perceptrons (MLPs) and recurrent neural networks (RNNs), long short-term memory (LSTM) will also be applied in NN modelling. LSTM is an extended architecture of RNNs. LSTM is proposed to model long-term dependencies and optimal time delay for time series problems (Hochreiter & Schmidhuber, 1997; Ma et al., 2015). A basic unit of LSTM is a block that includes a cell, an input gate, an output gate and a forget gate. The cell is to remember values over arbitrary time intervals, and the three gates regulate the flow of information into and out of the cell. This architecture helps to solve the vanishing gradient problem. LSTM is able to model complex relationships without being limited by the level of effectiveness in model training and is adopted in problems such as time series classification and predictions (Gers et al., 1999; Malhotra et al., 2015). The robustness and features of LSTM are desirable for business and accounting data modelling (Längkvist et al., 2014).

NN models can be training with a single output and multiple outputs. The benefits of including multiple outputs outweigh a single output as the relative relationship between different accounting items are important for obtaining financial ratios. Hence, a representative graph of the business factors and accounting result model is shown in Figure 5-1. The first layer of the NN model is an input layer that contains combined and pre-processed data. The second layer is the hidden layer that can be structured differently for implementing different NN architectures. The third layer is the output layer which contains the accounting results.

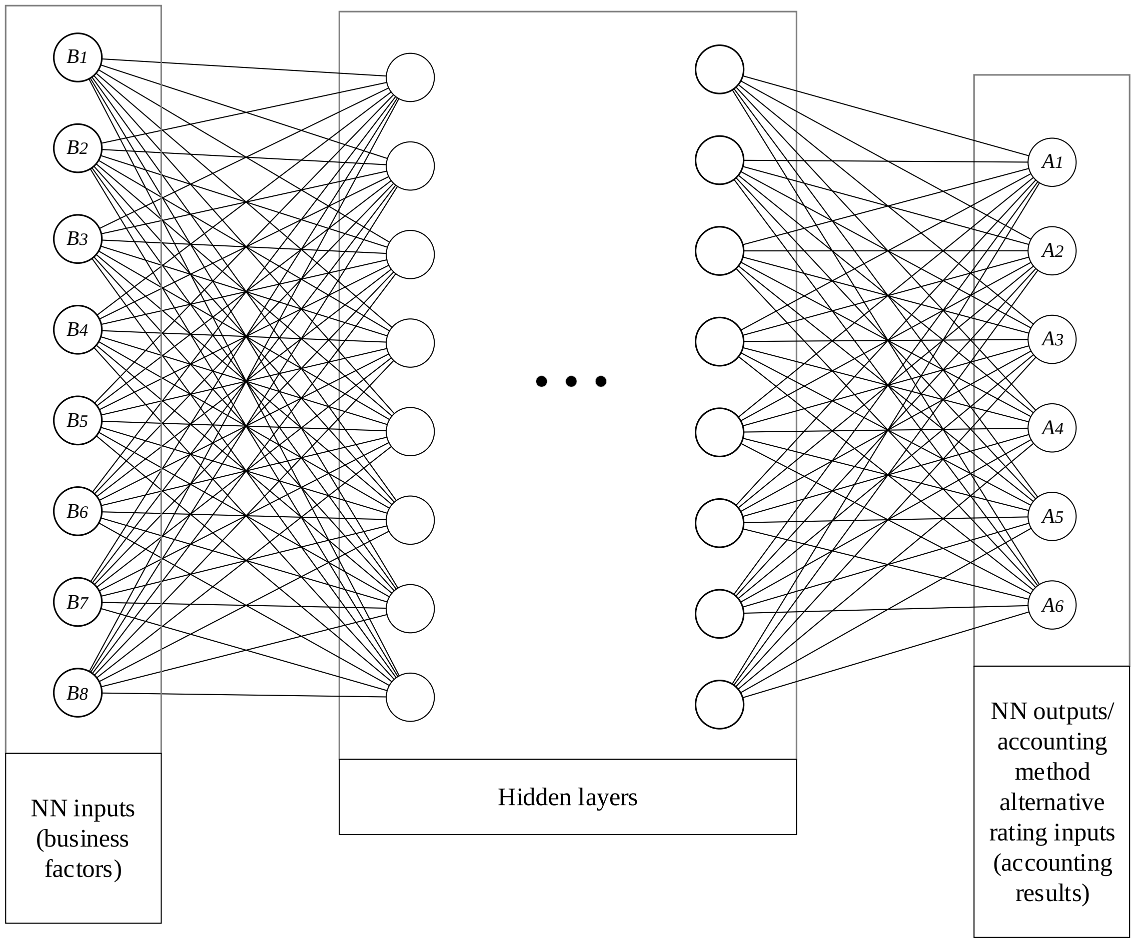

Figure 5-1. The structure of the NN model for modelling business factors and accounting results

Further, to improve the prediction accuracy of the NN models to be trained, four different model training techniques are to be tested. First, a 20% randomly selected data is implemented for model validation as the basic model training, denoted as N. To avoid overfitting in NN models and to improve the generalisation error, dropout layers are added. A 20% neural dropout layer is the second model training technique for testing, denoted as D. Third, due to the fact that having more accurate prediction of more recent accounting results is more important for this application, using 2017 data for model validation in model training is another model training technique to be implemented for testing, denoted as V. Lastly, the model performance is tested by training with dropout layer and specified validation dataset at the same time, denoted as D&V. Table 5-2 shows the setting of the model training techniques to be tested and their corresponding symbol.

Table 5-2. NN model training technique setting and symbol

Model training technique	**Symbol**
20% randomly selected data for validation	N
20% neural dropout layer	D
Specified validation data set using more recent data	V
Both dropout layer and specified validation data set	D & V

5.2.4 Model training and results

In NN model training, the original data for 2018 are reserved as test data. Then, the rest of the data are used as training data. NN models are trained using four data scaling techniques in data pre-processing, four NN architectures and four model training techniques, as presented in Sections 5.2.2 and 5.2.3. As the NN models are initialised randomly, to avoid achieving good results by probability, 30 randomly initialised models are trained in each model training setting. The performance of the NN models are measured using the averaged mean absolute percentage error (MAPE) and the averaged mean absolute error (MAE) of the 30 NN models trained in each model training setting. MAPE is a measurement of prediction accuracy commonly used in machine learning research involving economic data forecasting, which is given as (Widrow et al., 1994)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \bar{Y}_i}{Y_i}\right| \tag{5-7}$$

MAPE has two disadvantages. First, MAPE is inapplicable if the data series has a value of zero. Second, when data is a positive number, MAPE has a heavier penalty on negative errors. Hence, a second measurement, MAE, is used as a reference for validating the results given by MAPE within each model training setting. MAE is given as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \bar{Y}_i| \tag{5-8}$$

Figure 5-2 illustrates the NN model training process for obtaining the best performing NN model.

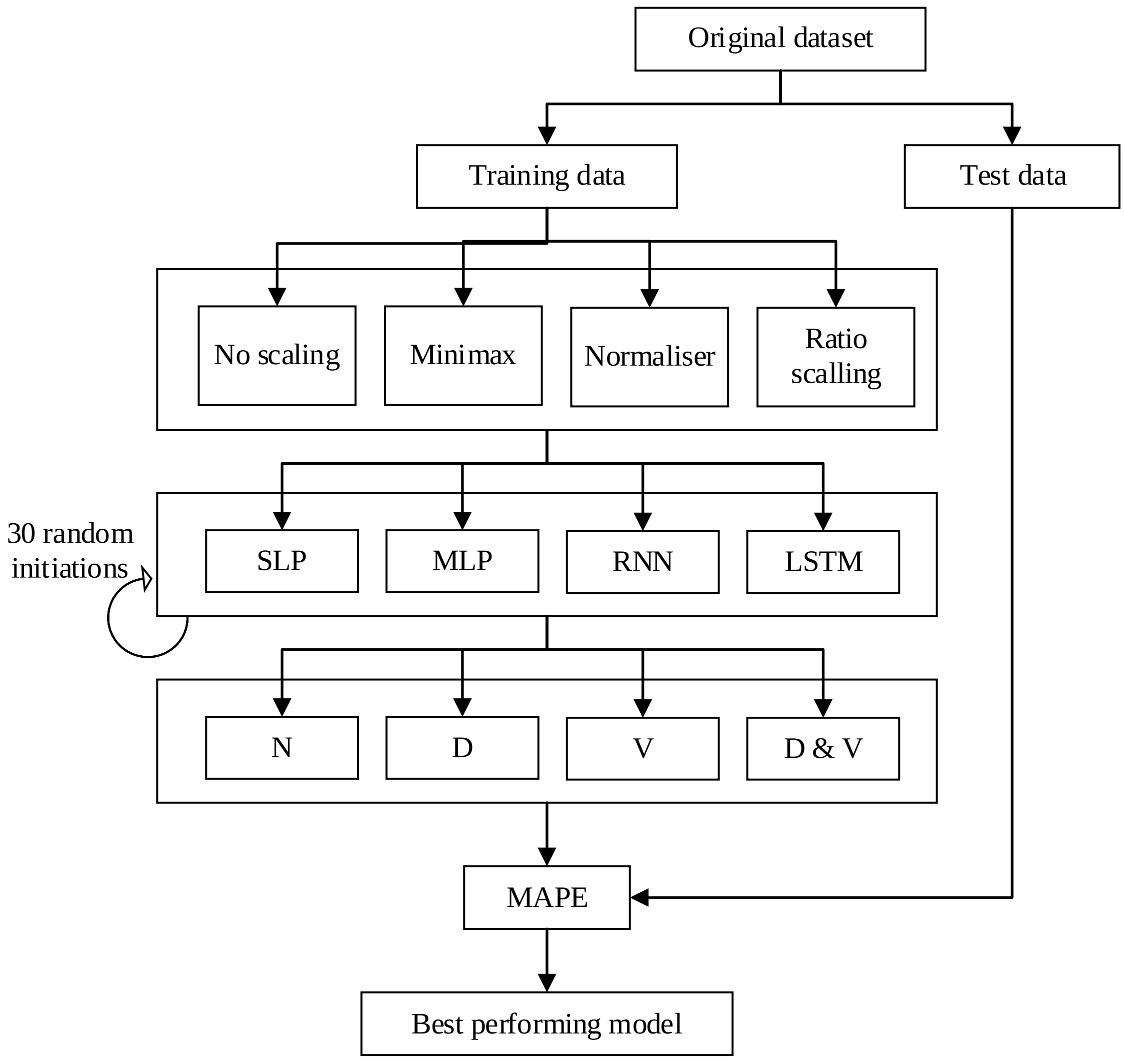

Figure 5-2. The NN model training process for obtaining the best performing NN model

A total number of 1,920 NN models are trained with the model training process. Table 5-3 shows the model prediction performances in 64 different model training settings.

Table 5-3. NN model prediction performance by model training settings

Model training setting No.	Accounting method type	Data scaling	NN architecture	Model training technique	MAPE	MAE
M1	Exploration costing	Original data	SLP	N	23.26%	13,123.30
M2				D	10.09%	3,839.55
M3				V	9.86%	4,405.18
M4				D&V	13.91%	5,152.63
M5			MLP	N	25.11%	13,579.01
M6				D	27.93%	13,676.72
M7				V	19.54%	6,847.25
M8				D&V	12.36%	3,880.43
M9			RNN	N	10.74%	9,723.47
M10				D	15.19%	9,819.90
M11				V	9.18%	3,825.29
M12				D&V	16.97%	11,258.34
M13			LSTM	N	12.64%	10,325.61
M14				D	13.10%	10,543.17
M15				V	9.53%	3,973.88
M16				D&V	9.53%	3,974.51
M17		Minimax scaling	SLP	N	33.41%	24,744.41
M18				D	35.25%	21,062.57
M19				V	16.90%	6,468.63
M20				D&V	12.60%	3,487.17
M21			MLP	N	35.20%	27,295.89
M22				D	31.91%	23,807.18
M23				V	20.10%	7,474.85
M24				D&V	15.11%	6,793.37
M25			RNN	N	10.64%	9,693.52
M26				D	10.71%	9,714.91
M27				V	9.17%	3,822.39

Table 5-3. NN model prediction performance by model training settings (continued)

Model training setting No.	Accounting method type	Data scaling	NN architecture	Model training technique	MAPE	MAE
M28	Exploration costing	Minimax scaling	RNN	D&V	9.95%	4,124.62
M29			LSTM	N	13.24%	10,601.13
M30				D	13.22%	10,595.09
M31				V	9.44%	3,934.64
M32				D&V	9.51%	3,969.91
M33		Normaliser scaling	SLP	N	35.17%	18,117.41
M34				D	31.85%	20,413.48
M35				V	13.34%	4,991.34
M36				D&V	14.91%	4,174.48
M37			MLP	N	32.86%	19,883.48
M38				D	30.28%	16,271.37
M39				V	20.89%	8,268.43
M40				D&V	13.04%	4,799.22
M41			RNN	N	14.21%	11,242.49
M42				D	10.97%	9,817.39
M43				V	9.08%	3,793.00
M44				D&V	9.38%	3,898.00
M45			LSTM	N	13.24%	10,602.14
M46				D	12.83%	10,434.92
M47				V	9.30%	3,873.31
M48				D&V	9.54%	3,979.94
M49		Ratio scaling	SLP	N	6.08%	0.5973
M50				D	8.44%	0.6316
M51				V	6.05%	0.4743
M52				D&V	8.02%	0.6528

Table 5-3. NN model prediction performance by model training settings (continued)

Model training setting No.	Accounting method type	Data scaling	NN architecture	Model training technique	MAPE	MAE
M53	Exploration costing	Ratio scaling	MLP	N	12.49%	0.9634
M54				D	4.07%	0.4152
M55				V	4.47%	0.4183
M56				D&V	10.15%	0.6127
M57			RNN	N	26.32%	5.0199
M58				D	12.78%	0.6054
M59				V	38.16%	1.6250
M60				D&V	16.12%	0.8172
M61			LSTM	N	30.89%	1.6816
M62				D	14.14%	0.6861
M63				V	28.14%	1.4516
M64				D&V	24.20%	1.4351

As shown in Table 5-3, MPL with ratio scaled data and D NN model training technique overperforms other model training settings by achieving the best MAPE performance of 4.07%. Hence, for predicting accounting results for examining the impact of the exploration costing method, MPL with ratio scaled data and D technique is best suited.

5.2.5 Predicting accounting results

To predict the accounting results under the accounting method alternative for 2018, FC (0) is replaced with SE (1) for the accounting method factor (B_8). Using the best performing model from the 30 MPL models with ratio scaled data and the D model training technique, Table 5-4 shows the predicted accounting results under FC. For comparison, Table 5-5 shows the actual accounting results under SE.

Table 5-4. Predicted accounting results considering exploration costing method for 2018

Accounting method alternative for exploration costing	Quarter	Accounting results (USD in millions)					
		A_1	A_2	A_3	A_4	A_5	A_6
FC	1	152,737.5	89,764.5	62,464.7	17,460.1	1,924.3	1,223.5
	2	158,016.6	92,167.3	64,666.7	20,242.6	2,930.6	1,833.6
	3	154,556.1	89,915.5	63,443.9	20,524.8	3,360.2	1,920.5
	4	150,676.2	88,086.3	61,780.2	18,556.7	2,642.3	1,598.7

Table 5-5. Actual accounting results considering exploration costing method for 2018

Accounting method alternative for exploration costing	Quarter	Accounting results (USD in millions)					
		A_1	A_2	A_3	A_4	A_5	A_6
SE	1	140,527.0	81,240.3	59,286.8	22,208.0	6,434.9	2,948.9
	2	141,112.0	80,920.3	60,191.7	22,471.0	6,232.5	3,147.3
	3	143,231.0	84,086.5	59,144.2	23,147.0	7,046.0	4,010.2
	4	139,798.0	79,481.3	60,317.2	23,037.8	5,460.9	1,683.7

By comparing accounting results under FC and SE, FC reports higher total asset (A_1) and equity (A_3), but significantly less gross profit (A_5) and operating income (A_6). Additionally, FC produces slightly more total liability (A_2) and slightly less revenue (A_4). Assuming the same operational results, the differences in total asset, liability and equity are consistent with the current understanding of the impact of the exploration costing method alternatives to accounting results. Further, the significant difference on gross profit (A_5) is consistent with the reported effects of its dual exploration model at the operation level and reserve the replace rate by Eni. Given operating income (A_6) can be affected by wage, depreciation, cost of goods sold (COGS) and other operating expenses, consequently, the difference in operating income (A_6) is considerably smaller as compared to revenue (A_4).

The prediction results suggest that the best performing NN model captures the essential characteristics and impacts of different accounting method alternatives of exploration costing on the accounting results and produce satisfactory predictions. The relative relationships among different accounting items are learnt by the best performing NN model.

5.3 MCDM-based performance evaluation for exploration costing accounting method

The MCDM module is the second module of the intelligence system-based approach for accounting method selection. This module is used to evaluate the performance of accounting method alternatives using multicriteria decision making (MCDM). The MCDM evaluation problem involves, as discussed in Section 3.2.2, decision makers, decision alternatives, evaluation criteria, criteria weights, performance ratings of the decision alternatives on evaluation criteria represented as a decision matrix.

5.3.1 Problem formulation for evaluating exploration costing methods

To address the research questions (RQ3(b) to RQ3(d)) of how to identify the most suitable exploration costing method, the MCDM evaluation problem involves two decision alternatives, namely the full cost (FC) and successful efforts (SE) methods. The objective of the evaluation problem is to rank FC and SE by their relative performance value for achieving the company’s strategic goals. The most suitable exploration costing method achieves a higher overall performance value. The company's strategic goals and KPIs, as identified in Section 4.6, are the evaluation criteria c_{ij} (i = 1, 2, …, 4 and j = 1, 2, …, 7) in measuring the performance ratings x_{ij} (i = 1, 2, …, 4 and j = 1, 2, …, 7) of each alternative. The performance ratings x_{ij} can be objectively obtained by KPIs measured using the actual and predicted accounting results A_i (i = 1, 2, …, 6) which are directly affected by the application of different accounting method alternatives, FC or SE. The performance value is to be obtained by multiplying the performance ratings x_{ij} and criteria weights w_{ij} (i = 1, 2, …, 4 and j = 1, 2, …, 7). The criteria weights w_{ij} are to be obtained through pairwise comparisons using linguistic terms represented by fuzzy numbers to deal with the subjectiveness in assessing criteria weights. An optimal weighting model is used to determine the optimal criteria weights that best reflect the best operational settings of the company. Finally, the overall performance value of accounting method alternatives are obtained and the most suitable exploration costing accounting method is identified.

Hence, to evaluate the two decision alternatives FC and SE in terms of their relative performance for 2018 with respect to the evaluation criteria C_1 to C_4, the evaluation problem with a hierarchical structure is formulated, as shown in Figure 5-3. C_1 to C_4 are the group criteria for exploration costing method selection, which are the four aspects that support the strategic goals. Each group criterion Ci consists of multiple criteria c_{ij}. The accounting method alternatives (B_8) are to be evaluated based on the accounting results (A_1 to A_6) and endogenous business factors (B_1 to B_4). The value of accounting results is the resultant of the endogenous business factors (B_1 to B_4) and exogenous business factors (B_5 to B_7).

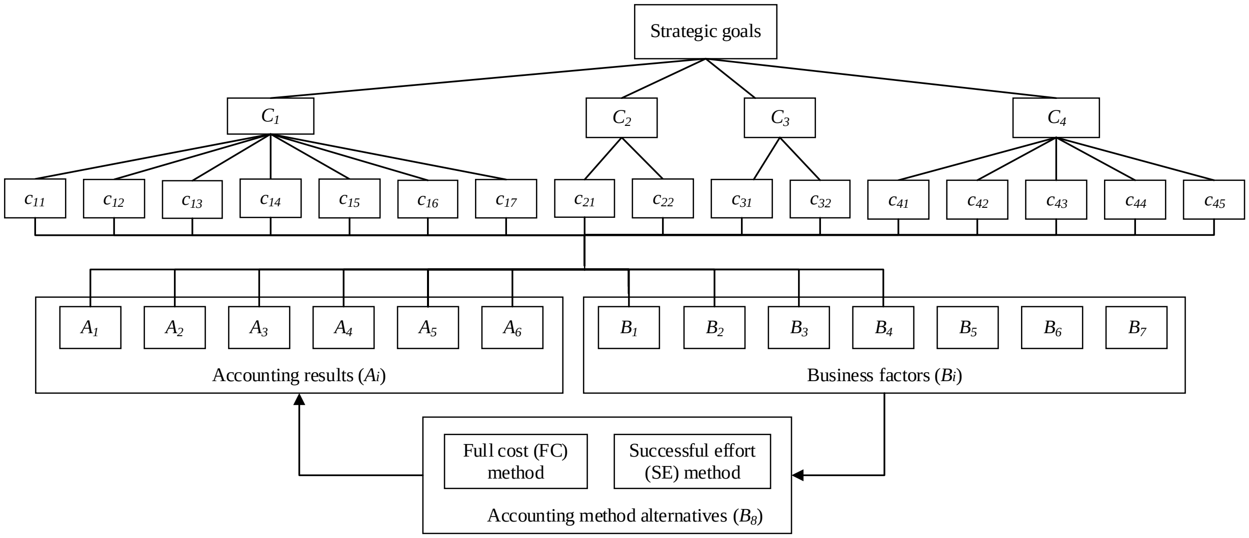

Figure 5-3. The structure of the MCDM evaluation for exploration costing's methods

5.3.2 Criteria weighting

To reflect the company's strategic goals in evaluating FC and SE, a proper weighting of the elevation criteria is better than using equal or arbitrary weights. To weight the criteria, fuzzy numbers are used to represent the linguistic term that defines the relative importance of the group criteria and criteria in pairwise comparisons. The fuzzy number is used to deal with the subjectiveness and impreciseness of human assessment and linguistic terms for inherent imprecision, vagueness, and uncertainty (Deng, 1999). The fuzzy number has been widely used in assisting decision problems since its application is simple and effective not requiring knowledge of fuzzy number by the decision makers in practical applications (Emrouznejad et al., 2014; Klir & Yuan, 1995).

A triangular number set M is defined by a membership function $f_M(x)$, $x \epsilon X$, which maps each element x in X to a real number in the interval [0,1], where $f_M(x)$ is used to represent the grade of membership of x in M (Dubois & Prade, 1978). A number can be fuzzified into a triangular fuzzy number set using the membership function $f_M: \mathrm{R} \rightarrow [0, 1]$, shown as follows:

$$f_M(x) = \begin{cases} \dfrac{x - c}{a - c}, & c \leq x \leq a, \\[2ex] \dfrac{x - b}{a - b}, & a \leq x \leq b, \\[2ex] 0, & otherwise \end{cases} \tag{5-9}$$

where $-\infty < c \leq a \leq b < \infty$. The triangular fuzzy number can be denoted by (c, a, b), where a is the most possible value of a linguistic term, and c and b are the lower and upper bounds of the fuzziness for weighting.

Two fuzzy set $M_1 = (c_1, a_1, b_1)$ and $M_2 = (c_2, a_2, b_2)$ can apply algebraic operations, also known as fuzzy arithmetic operations, as follows (Zadeh, 1965):

1) Fuzzy addition:

$$M_1 + M_2 = (c_1 + c_2, a_1 + a_2, b_1 + b_2) \tag{5-10}$$

2) Fuzzy subtraction:

$$M_1 - M_2 = (c_1 - b_2, a_1 - a_2, b_1 - c_2) \tag{5-11}$$

3) Fuzzy multiplication:

$$M_1 * M_2 = (c_1 * c_2, a_1 * a_2, b_1 * b_2) \tag{5-12}$$

$$k * M_2 = (k * c_2, k * a_2, k * b_2) \tag{5-13}$$

4) Fuzzy division:

$$M_1 / M_2 = (c_1 / b_2, a_1 / a_2, b_1 / c_2) \tag{5-14}$$

$$1 / M_2 = (1 / b_2, 1 / a_2, 1 / c_2) \tag{5-15}$$

A 1-9 scale is used in corresponding to a set of linguistic terms and provides nine possible fuzzy numbers for the five terms (Chang et al., 2007). The scale method has been proved effective in measuring qualitative information and offering approximation (Vreeker et al., 2002). Figure 5-4 and Table 5-6 show the membership function and value fuzzification used for weighting the criteria using pairwise comparisons. For instance, if a strongly more important is given in a pairwise comparison, then the fuzzy representation of the weighting is (3, 5, 7).

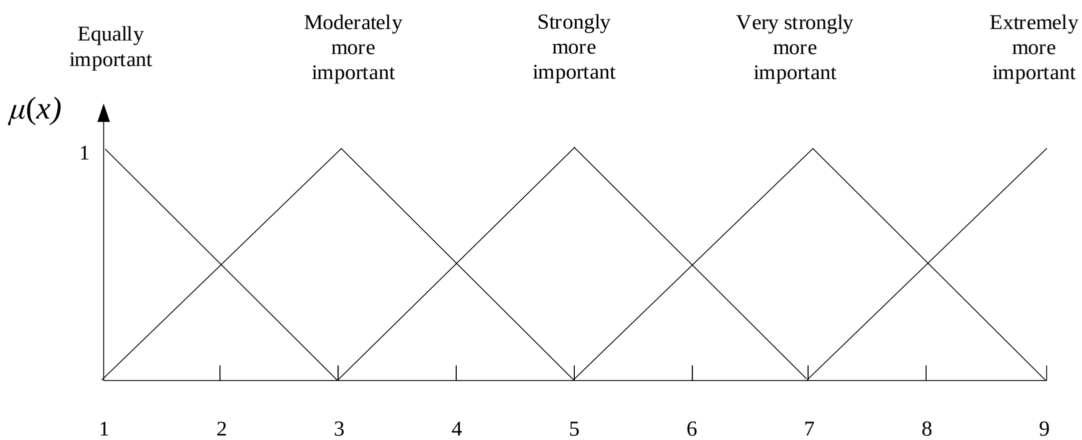

Figure 5-4. Membership functions of linguistic terms for assessing the relative importance of the criteria

Table 5-6. Value fuzzification for importance pairwise comparisons of the criteria

Equally important	Moderately more important		Strongly more important		Very strongly more important		Extremely more important	
1	2	3	4	5	6	7	8	9
		b		*a*		*c*		

The fuzzy pairwise comparison assessments for the weights of the evaluation criteria c_{ij} for each group criteria of C_i generate *i* positive $J_i \times J_i$ fuzzy positive reciprocal matrix M = $[\widetilde{a_{ij}}]$ that the elements $\widetilde{a_{ij}} = \frac{1}{\widetilde{a_{ji}}}$. The geometric mean for each criterion is computed as

$$\widetilde{g_{ij}} = \left(\prod_{j=1}^{J_i} \widetilde{a_{ij}}\right)^{\frac{1}{J_i}} \tag{5-16}$$

The relative fuzzy weights $\widetilde{w_{ij}}$ for group criteria J_i are then computed as

$$\widetilde{w_{ij}} = \frac{\widetilde{g_{ij}}}{\sum_{j=1}^{J_i} \widetilde{g_{ij}}} \tag{5-17}$$

Fuzzy arithmetic operations are used on fuzzy triangular fuzzy numbers (Kauffman & Gupta, 1991).

$$\widetilde{w_{ij}} = \left(w_{ijl},\, w_{ijm},\, w_{iju}\right) \tag{5-18}$$

Based on the interpretation of Eni's strategic goal description, pairwise comparisons are carried out for assigning weights for *Ci* and c_{ij} within *Ci*, respectively. Tables 5-7 and 5-8 show the results.

Table 5-7. Criteria weights by pairwise comparison

	C_1	C_2	C_3	C_4
C_1	(1, 1, 1)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)
C_2	(1, 0.33, 0.2)	(1, 1, 1)	(0.33, 0.2, 0.14)	(1, 0.33, 0.2)
C_3	(0.33, 0.2, 0.14)	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)
C_4	(0.2, 0.14, 0.11)	(1, 3, 5)	(1, 0.33, 0.2)	(1, 1, 1)

Table 5-8. Criteria pairwise comparison

		c_{11}	c_{12}	c_{13}	c_{14}	c_{15}	c_{16}	c_{17}
C_1	c_{11}	(1, 1, 1)	(3, 5, 7)	(1, 3, 5)	(1, 1, 1)	(3, 5, 7)	(5, 7, 9)	(1, 1, 1)
	c_{12}	(0.33, 0.2, 0.14)	(1, 1, 1)	(0.33, 0.2, 0.14)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
	c_{13}	(1, 0.33, 0.2)	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
	c_{14}	(1, 1, 1)	(1, 0.33, 0.2)	(1, 0.33, 0.2)	(1, 1, 1)	(0.2, 0.14, 0.11)	(0.2, 0.14, 0.11)	(3, 5, 7)
	c_{15}	(0.33, 0.2, 0.14)	(1, 0.33, 0.2)	(1, 0.33, 0.2)	(5, 7, 9)	(1, 1, 1)	(3, 5, 7)	(0.33, 0.2, 0.14)
	c_{16}	(0.2, 0.14, 0.11)	(1, 0.33, 0.2)	(1, 0.33, 0.2)	(5, 7, 9)	(0.33, 0.2, 0.14)	(1, 1, 1)	(1, 0.33, 0.2)
	c_{17}	(1, 1, 1)	(1, 0.33, 0.2)	(1, 0.33, 0.2)	(0.33, 0.2, 0.14)	(3, 5, 7)	(1, 3, 5)	(1, 1, 1)

		c_{21}	c_{22}
C_2	c_{21}	(1, 1, 1)	(1, 0.33, 0.2)
	c_{22}	(1, 3, 5)	(1, 1, 1)

		c_{31}	c_{32}
C_3	c_{31}	(1, 1, 1)	(5, 7, 9)
	c_{32}	(0.2, 0.14, 0.11)	(1, 1, 1)

		c_{41}	c_{42}	c_{43}	c_{44}	c_{45}
C_4	c_{41}	(1, 1, 1)	(3, 5, 7)	(0.2, 0.14, 0.11)	(0.2, 0.14, 0.11)	(0.2, 0.14, 0.11)
	c_{42}	(0.33, 0, 0.14)	(1, 1, 1)	(0.33, 0.2, 0.14)	(0.33, 0.2, 0.14)	(0.2, 0.14, 0.11)
	c_{43}	(5, 7, 9)	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)	(1, 3, 5)
	c_{44}	(5, 7, 9)	(3, 5, 7)	(1, 0.33, 0.2)	(1, 1, 1)	(1, 0.33, 0.2)
	c_{45}	(5, 7, 9)	(5, 7, 9)	(1, 0.33, 0.2)	(1, 3, 5)	(1, 1, 1)

Then, fuzzy weight $\widetilde{w_{ij}}$ of each criterion to the overall evaluation objective is obtained, shown in Table 5-9.

Table 5-9. Triangular fuzzy number set for criteria

Group criteria	**Criteria**	**Fuzzy criteria weight ($\widetilde{w_{ij}}$)**
C_1	c_{11}	(0.0615, 0.0639, 0.0718)
	c_{12}	(0.0357, 0.0405, 0.0402)
	c_{13}	(0.037, 0.0495, 0.0604)
	c_{14}	(0.0335, 0.0221, 0.0192)
	c_{15}	(0.0409, 0.0346, 0.0343)
	c_{16}	(0.0358, 0.0261, 0.024)
	c_{17}	(0.0469, 0.0395, 0.0395)
C_2	c_{21}	(0.0503, 0.0536, 0.0603)
	c_{22}	(0.0894, 0.1744, 0.2709)
C_3	c_{31}	(0.0924, 0.1781, 0.2752)
	c_{32}	(0.0302, 0.0416, 0.0507)
C_4	c_{41}	(0.0336, 0.0533, 0.0704)
	c_{42}	(0.0455, 0.0609, 0.0643)
	c_{43}	(0.0574, 0.0578, 0.0636)
	c_{44}	(0.0469, 0.0423, 0.0437)
	c_{45}	(0.0574, 0.0619, 0.0703)

5.3.3 Performance ratings of accounting method alternative

The performance ratings of an accounting method alternatives on evaluation criteria represent the degree to which the accounting method alternative satisfy each criterion. The performance ratings of FC and SE are assessed based on the predicted and actual accounting results for 2018. Especially to this empirical study, the exploration costing method impacts a limited number of the group criteria and criteria that have been identified in Section 4.6, which include c_{11}, c_{14}, c_{15}, c_{16}, c_{17} and c_{45}. The excluded criteria are independent of the impacts of exploration costing method selection. Using all group criteria and criteria in criteria weighting is necessary to obtain appropriate company-wide relative weights. The excluded criteria in exploration costing method selection might be required in applications of the proposed approach for other accounting method types. Hence, the relevant criteria and the measurements of the criteria to be used for obtaining accounting method alternatives' performance ratings are shown in Table 5-10.

Table 5-10. Group criteria, criteria and measurements for evaluation

Group criteria		**Criteria**		**Measurement**
C_1	Profitability and growth	c_{11}	Gross profit	O_5
		c_{12}	R&D expenditure	Not applicable
		c_{13}	Exploration CAPX	Not applicable
		c_{14}	Margin	O_6/O_5
		c_{15}	Return on Assets (ROA)	O_5/O_1
		c_{16}	Return on Equity (ROE)	O_5/O_3
		c_{17}	Asset turnover	O_4/O_1
C_2	Operational excellence	c_{21}	Total production	Not applicable
		c_{22}	Proved reserve	Not applicable
C_3	Sustainability	c_{31}	Employment	Not applicable
		c_{32}	Emissions	Not applicable
C_4	Business risk	c_{41}	Future price impact	Not applicable
		c_{42}	Interest rates impact	Not applicable
		c_{43}	Book-to-market ratio	Not applicable
		c_{44}	Sharp ratio	Not applicable
		c_{45}	Debt ratio (Leveraging ratio)	O_2/O_1

Therefore, using the actual accounting results for SE and the predicted accounting results for FC, the alternative performance ratings of SE and FC are shown in Table 5-11.

Table 5-11. Performance ratings for SE and FC for 2018

Accounting method alternative	**Applicable evaluation criteria**					
	c_{11}	c_{14}	c_{15}	c_{16}	c_{17}	c_{45}
SE	25,174.2	0.4683	0.0446	0.1054	0.1609	0.5768
FC	10,857.4872	0.1414	0.0176	0.043	0.1247	0.5843

The obtained performance ratings are in different scales and units of measurements. To aggerate the performance ratings with criteria weights for the overall performance value, the performance ratings of accounting method alternatives need to be normalised to make them comparable for their aggregation with criteria weights. Table 5-12 shows the normalised performance ratings of two accounting method alternatives.

Table 5-12. Normalised performance ratings for SE and FC for 2018

Accounting method alternative	**Applicable evaluation criteria**					
	c_{11}	c_{14}	c_{15}	c_{16}	c_{17}	c_{45}
SE	0.6987	0.7681	0.7167	0.71	0.5635	0.4968
FC	0.3013	0.2319	0.2833	0.29	0.4365	0.5032

5.3.4 Optimal weighting and overall performance value aggregation

The fuzzy criteria weights shown in Table 5-9 represent the case company's preferences in weighting the criteria. To aggregate the criteria weights and performance ratings, c_{11}, c_{14}, c_{15}, c_{16}, c_{17} and c_{45} will be used as other criteria will hold constant. The criteria weights for the included criteria may not necessarily reflect its best possible operational setting. To reflect the case company's best possible operational setting for evaluating the two accounting method alternatives, FC and SE, an optimal weighting model is developed for obtaining the optimal weights for the six included criteria. The optimal weighting model maximizes the overall performance of FC and SE as a whole. As such, the optimal weights enable FC and SE to be evaluated under the best possible operational setting.

To be in line with the case company's criteria weighting preferences for ensuring its acceptance, the optimal weighting model considers the fuzzy criteria weights as its constraints. To achieve this, the concept of α-cut is used to derive the lower and upper bounds of the case company's preferred criteria weights. The lower and upper bounds are given as,

$$w_{ijl}^{\alpha} = \left(w_{ijm} - w_{ijl}\right)\alpha + w_{ijl} \tag{5-19}$$

$$w_{iju}^{\alpha} = w_{iju} - \left(w_{iju} - w_{ijm}\right)\alpha \tag{5-20}$$

where $0 \leq \alpha \leq 1$

To reflect that the case company has no particular confidence degree on the fuzzy criteria weights, the mean value of all α-cuts (i.e. the average of value intervals of all α-cuts on the fuzzy number) is used (Yeh & Kuo, 2003). Columns 1 and 2 of Table 5-13 show the notation (g_i) used for criteria weights for optimal weighting model and the applicable evaluation criteria being represented, respectively. Columns 4 and 5 of Table 5-13 show the crisp lower bounds (l_i) and upper bounds (u_i) of the six criteria, respectively.

Table 5-13. Fuzzy weights of the six criteria using pairwise comparisons

Notation for evaluation criteria	**Evaluation criteria**	**Fuzzy weight**	l_i	u_i
g_1	c_{11}	(0.224, 0.367, 0.575)	0.2955	0.471
g_2	c_{14}	(0.048, 0.084, 0.162)	0.066	0.123
g_3	c_{15}	(0.09, 0.186, 0.361)	0.138	0.2735
g_4	c_{16}	(0.066, 0.122, 0.254)	0.094	0.188
g_5	c_{17}	(0.068, 0.135, 0.25)	0.1015	0.1925
g_6	c_{45}	(0.05, 0.106, 0.23)	0.078	0.168

The optimal weights for the six criteria when considering the two accounting method alternatives can be obtained by the following optimal weighting model:

Objective

$$Maximize\ P = \sum_{j}^{2} \sum_{i}^{6} w_i x_{ij} \tag{5-21}$$

Subject to:

$$l_i \le w_i \le u_i \tag{5-22}$$

$$\sum_{i}^{6} w_i = 1 \tag{5-23}$$

Where

Decision variable:

w_i = optimal weights for criteria g_i

Parameters:

x_{ij} = the performance rating for accounting method alternative j for criteria g_i

l_i = the lower bound of the criteria weights for criteria g_i

u_i = the upper bound of the criteria weights for criteria g_i

The objective function (5-21) is to maximize the overall performance value of the two accounting method alternatives. Constraints (5-22) impose that the optimal criteria weights generated must lie within the criteria weight ranges specified by the case company using fuzzy pairwise comparisons. Constraint (5-23) states that the optimal weights generated are to be normalized to sum to 1. By solving the optimal weighting model ((5-21) to (5-23)), Column 4 of Table 5-14 shows the optimal weights of the six criteria. The last row of Table 5-14 shows the overall performance value of FC and SE.

Table 5-14. SE and FC performance ratings and optimal weights for 2018

Evaluation criteria (g_i)	**SE performance rating (x_{i1})**	**FC performance rating (x_{i2})**	**Optimal weight (w_i)**
g_1	0.699	0.301	0.4710
g_2	0.768	0.232	0.1175
g_3	0.717	0.283	0.1380
g_4	0.710	0.290	0.0940
g_5	0.563	0.437	0.1015
g_6	0.497	0.503	0.0780
Overall performance value	0.6809	0.3191	

The result in Table 5-14 suggests that SE achieves a much higher overall performance value. As such, the SE (successful effort) method should be selected for the accosting method type of exploration costing, which can help Eni to better achieve its strategic goals. The evaluation of FC and SE conducted in this empirical study provides a piece of new and justifiable evidence to support Eni's change from FC to SE in 2016.

5.4 Concluding remarks

The selection of the full cost (FC) and successful efforts (SE) methods for exploration costing is one of the most debated accounting method selection problem. The exploration costing selection has significant impacts on accounting results which should ideally be in line with a company's strategic goals. In the case of the case company, the company had changed from FC to SE in 2016 to increase the comparability of their accounting results to the competitors. In this chapter, the FC and SE methods have been evaluated by applying the intelligent system-based approach, based on their impact on accounting results in 2018 and their performance on the company's strategic goals. As demonstrated, neural networks (NNs) have been proven adequate for accounting results modelling. The modelling process is effective in finding the best performing model for accounting results prediction. Given the formulated problem, the best performing NN model produces satisfactory accounting results predictions. With an optimal criteria weighting model, the MCDM module effectively addresses the accounting method selection problem. The outcome of this empirical study offers supporting evidence to the exploration costing's method switch from the perspective of the company's strategic goals. It addresses two research questions (RQ1(d) and RQ2) by the NN module and three research questions (RQ3(b) to RQ3(d)) by the MCDM module.

Chapter 6 Evaluation of two accounting method types and interacting effects – accounting methods for exploration costing and inventory

6.1 Introduction

This chapter examines the selection problem of two accounting method types using the intelligence system-based approach. The selection of accounting methods for exploration costing and for inventory in the context of the case company is to be examined. Not being able to address the determinants and interacting effects of multiple accounting method types by existing accounting choice research is one of the recognised research gaps (Fields et al., 2001). The selection of accounting methods for multiple accounting method types is more desirable as it occurs more often in practice.

In addition to the full cost (FC) and successful efforts (SE) methods for exploration costing, the applicable accounting methods for inventory in this empirical study includes last-in-first-out (LIFO) and weighted average (WA). Given the identified strategic goals in Section 4.6, four combinations of two accounting method types (i.e. FC/LIFO, FC/WA, SE/LIFO and SE/WA) are to be evaluated. This chapter addresses one research question RQ4.

6.2 NN modelling and accounting results prediction for exploration costing and inventory accounting methods

Given the identified relevant business factors and affected accounting results, as discussed in Sections 4.4 and 4.5, the NN module is used for obtaining the accounting results under unused accounting method alternatives. In this empirical study, three unused accounting method alternatives are FC/LIFO, FC/WA and SE/LIFO.

In the exploration costing method selection problem presented in Chapter 5, the accounting method factor is represented by a single input of 0 and 1 for representing FC and SE, respectively. In this selection problem, NN models can be structured with (a) a single input or (b) two inputs for representing the accounting method factor. One advantage of using a single input for two accounting method types is that it does not increase the number of NN inputs which may reduce the prediction accuracy of the NN models. However, using a single input is not a viable approach. Using a single input format, the accounting method NN input would form four values representing the four accounting method alternatives. Only SE/LIFO has not been used at any time. Using numerical values for categorical variables, the NN model is not able to learn the relationships that have not been presented in the training data. On the other hand, using two inputs is easy to implement and not constrained by the availability of the empirical data. With two NN inputs for exploration costing and for inventory separately, the NN model would be able to model the relationships required for predicting the accounting results under all unused accounting methods for 2018 given the empirical data collected. The drawbacks of a possibly decreased prediction accuracy by the increased number of inputs can be limited by the modelling process of the NN module, which performs NN modelling on four data scaling, four NN architecture and four NN model training techniques. Hence, two inputs are used. It also benefits the applicability of the approach to the accounting method selection problem involving more than two accounting method types.

Relevant business factors and affected accounting items, as discussed in Sections 4.4 and 4.5, are used as NN inputs and NN outputs for NN models. Similar to the NN model for the accounting method selection of exploration costing, the inventory accounting method (B_9), which has a value of 0 and 1 for representing LIFO and WA, respectively, is added to the NN inputs. Figure 6-1 illustrates the structure of the NN model.

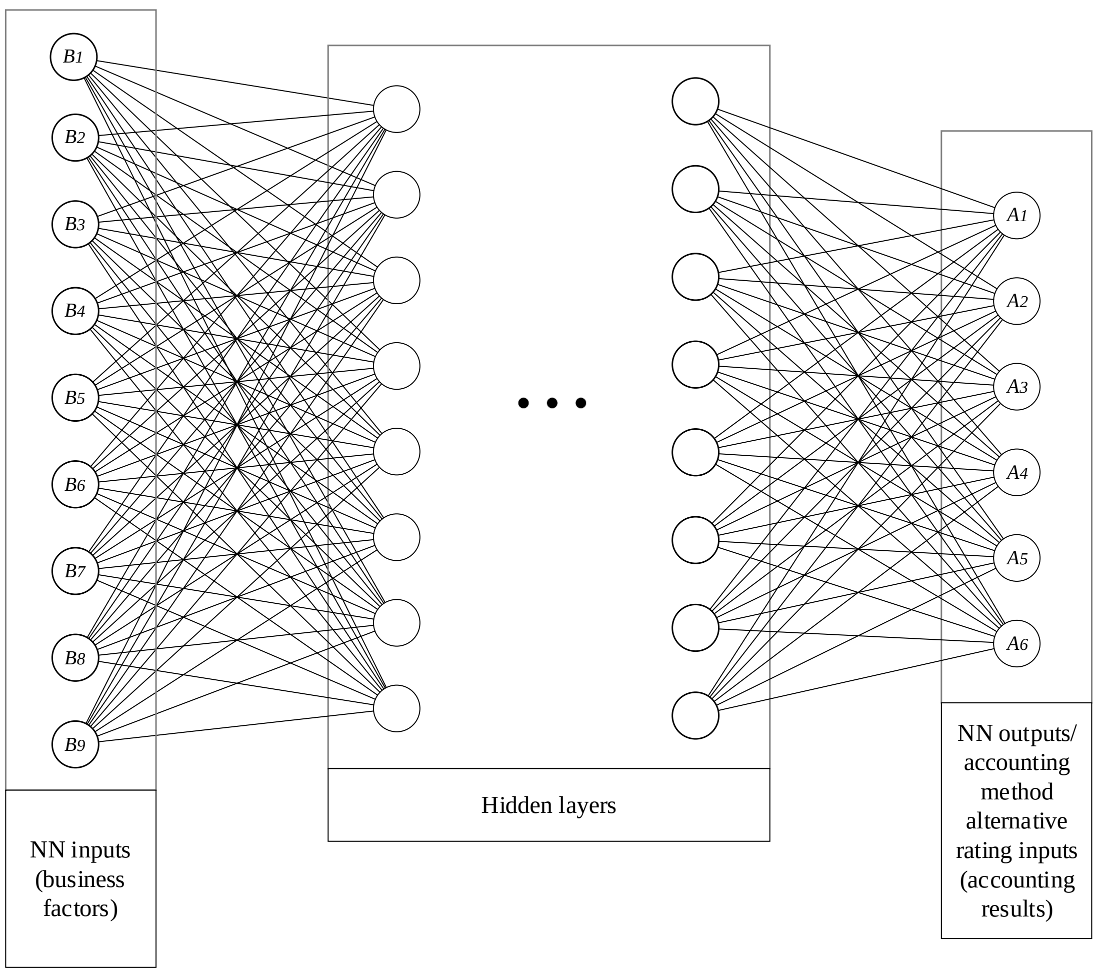

Figure 6-1. The structure of the NN model for business factors and accounting results

As shown in Figure 5-2, to identify the best performing model, 30 randomly initialised NN models are trained using four data scaling techniques, four NN architectures and four model training techniques. As previously discussed in Section 5.2, the model prediction accuracy is measured by MAPE and MAE. The best performing NN model with the highest prediction accuracy is obtained and will be used for accounting result prediction. Table 6-1 shows the model prediction performances.

Table 6-1. NN model prediction performance by model training settings for exploration costing and inventory method selection

Model training setting No.	**Accounting method type**	**Data scaling**	**NN architecture**	**Model training technique**	**MAPE**	**MAE**
M1	Exploration costing & Inventory	Original data	SLP	N	10.10%	4,336.74
M2				D	8.01%	2,151.23
M3				V	14.17%	5,815.72
M4				D&V	5.62%	1,841.22
M5			MLP	N	17.31%	6,783.50
M6				D	10.72%	3,750.50
M7				V	16.06%	4,687.53
M8				D&V	11.62%	3,609.21
M9			RNN	N	10.96%	9,300.59
M10				D	25.78%	7,218.95
M11				V	11.33%	3,791.04
M12				D&V	9.12%	3,718.67
M13			LSTM	N	10.85%	9,057.47
M14				D	10.69%	8,967.20
M15				V	10.85%	3,603.99
M16				D&V	10.65%	3,519.01

Table 6-1. NN model prediction performance by model training settings for exploration costing and inventory method selection (continued)

Model training setting No.	Accounting method type	Data scaling	NN architecture	Model training technique	MAPE	MAE
M17	Exploration costing & Inventory	Minimax scaling	SLP	N	38.02%	19,638.53
M18				D	32.20%	17,626.79
M19				V	17.96%	5,710.41
M20				D&V	14.57%	3,349.59
M21			MLP	N	20.92%	7,160.55
M22				D	33.59%	18,492.57
M23				V	15.54%	4,805.88
M24				D&V	11.67%	3,944.48
M25			RNN	N	10.81%	9,612.09
M26				D	8.79%	8,202.60
M27				V	10.23%	3,398.42
M28				D&V	11.19%	3,713.59
M29			LSTM	N	11.01%	9,193.33
M30				D	10.06%	8,729.32
M31				V	10.86%	3,611.29
M32				D&V	10.86%	3,611.67
M33		Normaliser scaling	SLP	N	33.37%	15,879.14
M34				D	29.86%	17,360.93
M35				V	18.27%	6,388.14
M36				D&V	16.32%	3,764.99
M37			MLP	N	36.84%	16,641.20
M38				D	29.20%	15,433.65
M39				V	17.53%	6,178.97
M40				D&V	15.59%	5,489.90

Table 6-1. NN model prediction performance by model training settings for exploration costing and inventory method selection (continued)

Model training setting No.	**Accounting method type**	**Data scaling**	**NN architecture**	**Model training technique**	**MAPE**	**MAE**
M41	Exploration costing & Inventory	Normaliser scaling	RNN	N	10.98%	9,693.32
M42				D	10.97%	9,480.07
M43				V	11.39%	3,823.53
M44				D&V	10.98%	3,622.32
M45			LSTM	N	11.00%	9,184.34
M46				D	10.95%	9,144.38
M47				V	10.94%	3,641.48
M48				D&V	10.87%	3,611.40
M49		Ratio scaling	SLP	N	10.19%	0.7065
M50				D	8.71%	0.5975
M51				V	10.21%	0.7511
M52				D&V	5.24%	0.4516
M53			MLP	N	10.95%	0.6790
M54				D	10.94%	0.8054
M55				V	14.62%	0.9683
M56				D&V	4.91%	0.4034
M57			RNN	N	12.71%	0.7577
M58				D	18.60%	0.9998
M59				V	11.12%	0.9109
M60				D&V	27.38%	1.5340
M61			LSTM	N	7.45%	0.6413
M62				D	11.77%	0.6883
M63				V	24.72%	3.0587
M64				D&V	34.47%	1.7693

As Table 6-1 shows, MPL with ratio scaled data and the D&V model training technique achieves the best performance with MAPE of 4.91%. It is noteworthy that for NN modelling of two accounting method types, the best prediction accuracy with a similar MAPE is achieved by a different model training setting, compared to a single accounting method type of exploration costing only. This indicates that the NN module is robust for achieving satisfactory accuracy for predicting accounting results under different scenarios.

With the best performing model obtained from a total number of 1,920 trained NN models, the accounting results under unused accounting method alternatives FC/WA, SE/LIFO and FC/LIFO for 2018 can be predicted. The predicted accounting results and actual accounting results, shown in Table 6-2, are to be used to obtain the performance ratings of accounting method alternatives for the MCDM module to evaluate the performance of the four accounting method alternatives in terms of strategic goals of the case company.

Table 6-2. Predicted and actual accounting results considering accounting methods for exploration costing and inventory for 2018

Accounting method alternatives for exploration costing and inventory	**Quarter**	**Accounting results (USD in millions)**					
		A_1	A_2	A_3	A_4	A_5	A_6
FC/WA	1	141,275.0	81,268.0	60,093.8	25,189.7	6,853.9	1,964.8
	2	151,421.7	87,669.3	64,882.7	25,728.6	6,903.3	1,985.0
	3	143,728.9	82,554.8	60,771.2	27,526.7	7,272.3	1,988.9
	4	141,256.6	81,412.5	60,385.9	24,044.4	6,628.9	1,969.4
SE/LIFO	1	141,215.5	81,231.4	60,067.5	25,174.3	6,851.4	1,964.5
	2	151,365.2	87,634.1	64,857.4	25,715.0	6,901.0	1,984.7
	3	143,669.4	82,518.2	60,745.0	27,511.2	7,269.8	1,988.6
	4	141,200.1	81,377.2	60,360.5	24,030.7	6,626.6	1,969.1
FC/LIFO	1	141,248.3	81,252.0	60,082.3	25,184.2	6,853.0	1,964.8
	2	151,396.2	87,653.8	64,871.6	25,723.8	6,902.5	1,984.9
	3	143,702.3	82,538.8	60,759.8	27,521.1	7,271.5	1,988.8
	4	141,231.1	81,397.0	60,374.8	24,039.5	6,628.1	1,969.3
SE/WA (Actual)	1	140,527.0	81,240.3	59,286.8	22,208.0	6,434.9	2,948.9
	2	141,112.0	80,920.3	60,191.7	22,471.0	6,232.5	3,147.3
	3	143,231.0	84,086.5	59,144.2	23,147.0	7,046.0	4,010.2
	4	139,798.0	79,481.3	60,317.2	23,037.8	5,460.9	1,683.7

6.3 MCDM evaluation for exploration costing and inventory accounting methods

The four accounting method alternatives are to be evaluated in terms of the identified strategic goals using the MCDM module. As shown in Figure 6-2, the four accounting method alternatives are FC/LIFO, FC/WA, SE/LIFO and SE/WA, and the rest of the MCDM structure remains the same with the MCDM structure for the exploration costing method selection.

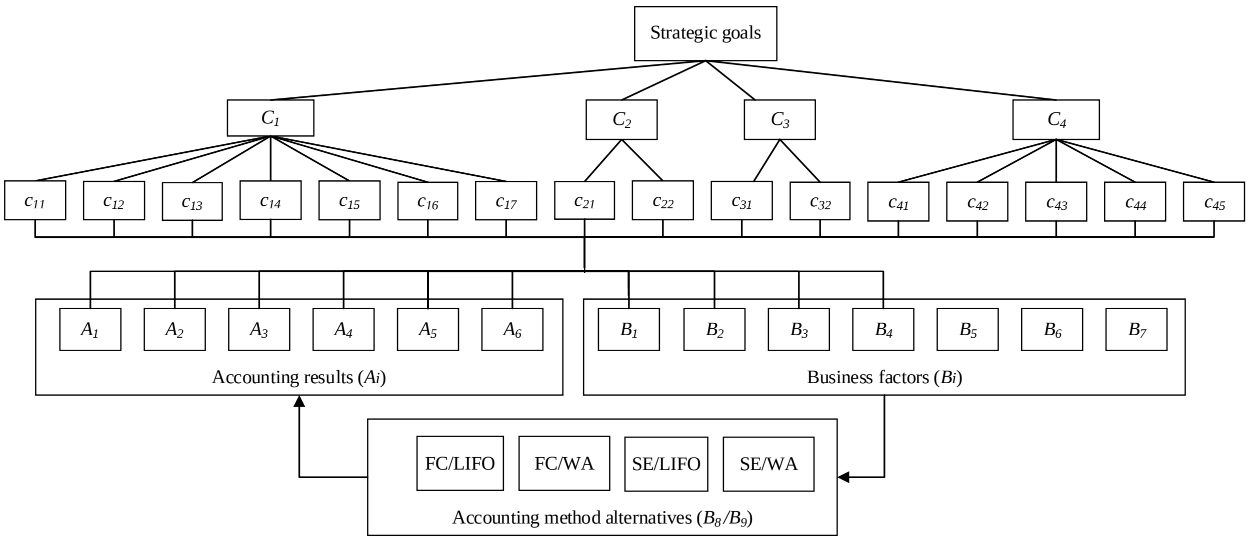

Figure 6-2. MCDM evaluation structure for exploration costing and inventory method

As the decision objectives remain the same, the fuzzy criteria weights obtained by the pairwise comparison process in Section 5.2.2 can be applied in this evaluation. To meet the best possible acceptance of the criteria weights and to reflect no particular confidence degree on the fuzzy criteria weights, the mean value of all α-cuts is applied to obtain the lower and upper bounds of the criteria weights, which are to be used as the constrains for optimal weighting model. Columns 1 and 2 of Table 6-3 show the notation (g_i) used for criteria weights for optimal weighting model and the applicable evaluation criteria being represented, respectively. Columns 4 and 5 of Table 6-3 show the crisp lower bounds (l_i) and upper bounds (u_i) of the six criteria, respectively.

Table 6-3. Fuzzy weights of the six criteria using pairwise comparisons

Notation for evaluation criteria	**Evaluation criteria**	**Fuzzy weight**	l_i	u_i
g_1	c_{11}	(0.224, 0.367, 0.575)	0.2955	0.471
g_2	c_{14}	(0.048, 0.084, 0.162)	0.066	0.123
g_3	c_{15}	(0.09, 0.186, 0.361)	0.138	0.2735
g_4	c_{16}	(0.066, 0.122, 0.254)	0.094	0.188
g_5	c_{17}	(0.068, 0.135, 0.25)	0.1015	0.1925
g_6	c_{45}	(0.05, 0.106, 0.23)	0.078	0.168

The optimal weighting model is applied to obtain the optimal weights for the six criteria when considering the four decision alternatives, given as

Objective

$$Maximize\ P = \sum_{j}^{4} \sum_{i}^{6} w_i x_{ij} \tag{6-1}$$

Subject to:

$$l_i \leq w_i \leq u_i \tag{6-2}$$

$$\sum_{i}^{6} w_i = 1 \tag{6-3}$$

where

Decision variable:

w_i = optimal weights for criteria g_i

Parameters:

x_{ij} = the performance rating for accounting method alternative j for criteria g_i

l_i = the lower bound of the criteria weights for criteria g_i

u_i = the upper bound of the criteria weights for criteria g_i

Similar to the optimal criteria weighting model in Chapter 5, the objective function (6-1) is to maximize the overall performance value of the four accounting method alternatives. Constraints (6-2) impose that the optimal criteria weights generated must lie within the criteria weight ranges specified by the case company using fuzzy pairwise comparisons. Constraint (6-3) states that the optimal weights generated are to be normalized to sum to 1.

Columns 2 to 5 of Table 6-4 show the performance value of the four alternatives (SE/WA, FC/WA, SE/LIFO FC/LIFO and SE/LIFO) with respect to the six criteria. By solving the optimal weighting model ((6-1) to (6-3)), Column 6 of Table 6-4 shows the optimal weights of the six criteria. The last row of Table 6-4 shows the overall performance value of the four alternatives.

Table 6-4. Relative performance value of accounting method alternatives for two accounting method types

Evaluation criteria (g_i)	SE/WA performance rating (x_{i1})	FC/WA performance rating (x_{i2})	SE/LIFO performance rating (x_{i3})	FC/LIFO performance rating (x_{i4})	Optimal weight (w_i)
g_1	0.249	0.243	0.259	0.249	0.4710
g_2	0.412	0.193	0.180	0.215	0.1175
g_3	0.253	0.235	0.269	0.243	0.1380
g_4	0.248	0.238	0.273	0.242	0.0940
g_5	0.243	0.255	0.240	0.262	0.1015
g_6	0.253	0.249	0.246	0.252	0.0780
Overall performance value	0.2682	0.2373	0.2493	0.2452	

The evaluation results in Table 6-4 suggest that SE/WA achieves the highest overall performance value, relative to the other three alternatives. This result supports the current selection of the exploration costing and inventory accounting methods in use at the case company Eni. The overall performance value of the exploration costing and inventory accounting method alternatives on the company's strategic goals provide new supporting evidence for using the accounting methods for exploration costing and for inventory in 2018.

6.4 Interacting effects of multiple accounting method types

Accounting methods are the intermediate process between operational results and accounting results. Each accounting item is set for recording a category of transactions from an accounting perspective; the resultant accumulated value of an accounting item can be the records of different kind of business operations. For example, the operation results of exploration activities and inventory activities can both add value to the accounting items, total asset. In comparison, an expense account could be used for recording the same operation results of the exploration activities if a different accounting method is applied for treatment. On the other side, the recognised value added to the total asset can be affected by both the production level and accounting method alternatives for exploration costing. Switching the exploration costing method would have interacting effects on the contribution of inventory to a company's KPIs that involves total asset. Thereafter, the performances of the accounting method alternatives for inventory to the company strategic goals would be affected differently, given a different accounting method for exploration costing. In practice, the complexity of the interacting effects increases as the business complexity increases. The accounting method selection for multiple accounting method types is more commonly observed and recognised by accounting choice research. It is believed that the interacting effects are overlooked, and the interacting accounting method types need to work coherently for achieving the management incentive (Fields et al., 2001).

In order to examine the interacting effects of the accounting methods for exploration costing and for inventory, the relative performance values of the accounting method alternatives of each type are needed in the context of both a single and multiple accounting method types selections. The full cost (FC) and successful efforts (SE) methods have been examined in the accounting method type selection of exploration costing in Chapter 5. The combination of accounting methods for exploration costing and for inventory have also been examined in a dual accounting method types selection in Sections 6.1 and 6.2. As a result, the last-in-first-out (LIFO) and weighted average (WA) methods are to be evaluated in a single accounting method type selection setting.

With the NN module, the best performing NN model for predicting accounting results under the unused accounting method for inventory, namely LFIO, and the overall performance value of LIFO and WA are obtained. Using the two best performing data scaling techniques, the prediction performance of NN models are shown in Table B-1 in Appendix B. Having the best performing NN model, the predicted accounting results under LIFO and actual accounting results under WA for 2018 are shown in Table 6-5.

Table 6-5. Predicted and actual accounting results under accounting methods for inventory for 2018

Accounting method for inventory	**Quarter**	**Accounting results (USD in millions)**					
		A_1	A_2	A_3	A_4	A_5	A_6
LIFO	1	135,189.8	79,426.8	56,206.1	18,666.2	4,395.2	1,705.1
	2	139,984.8	81,910.4	57,812.4	20,693.0	5,078.8	2,105.7
	3	140,466.3	82,025.7	58,413.8	22,393.4	5,422.8	2,021.6
	4	132,894.4	78,415.8	54,923.1	18,655.6	4,646.7	1,857.5
WA (Actual)	1	140,527.0	81,240.3	59,286.8	22,208.0	6,434.9	2,948.9
	2	141,112.0	80,920.3	60,191.7	22,471.0	6,232.5	3,147.3
	3	143,231.0	84,086.5	59,144.2	23,147.0	7,046.0	4,010.2
	4	139,798.0	79,481.3	60,317.2	23,037.8	5,460.9	1,683.7

Then, with the MCDM module, the optimal weights and the overall performance value of LFIO and WA are shown in the last row and the last column of Table 6-6.

Table 6-6. Performance ratings, optimal weights and overall performance value for inventory's methods

Evaluation criteria (g_i)	**WA performance rating (x_{i1})**	**LIFO performance rating (x_{i2})**	**Optimal weights (w_i)**
g_1	0.563	0.437	0.4710
g_2	0.543	0.457	0.1175
g_3	0.556	0.444	0.1380
g_4	0.551	0.449	0.0940
g_5	0.523	0.477	0.1015
g_6	0.496	0.504	0.0780
Overall performance value	0.5493	0.4507	

The relative overall performance value in Table 6-6 shows that WA is the most suitable accounting method for inventory, given SE for exploration costing.

Using the overall performance value in the multiple accounting method types selection, shown in Table 6-4, the performance value can be consolidated and re-arranged as shown in Table 6-7. For comparison, the overall performance values of accounting method alternatives for exploration costing and for inventory in a single accounting method type selection are shown in Table 6-8.

Table 6-7. Overall performance value of accounting method alternatives for exploration costing and for inventory in multiple accounting method types selection

Accounting method as condition	**Relative overall performance of the accounting method alternatives for comparison**	
	Exploration costing	
Inventory	SE	FC
WA	0.5306	0.4694
LIFO	0.5041	0.4959
	Inventory	
Exploration costing	WA	LIFO
SE	0.5182	0.4818
FC	0.4918	0.5082

Table 6-8. Overall performance value of accounting method alternatives for exploration costing and for inventory in single accounting method type selection

Accounting method as condition	**Relative overall performance of the accounting method alternatives for comparison**	
	Exploration costing	
Inventory	SE	FC
WA	0.6809	0.3191
	Inventory	
Exploration costing	WA	LIFO
SE	0.5493	0.4507

For exploration costing, SE is consistently identified as the most suitable accounting method over FC given different inventory methods as conditions. However, for inventory, WA only outperforms LIFO given SE for exploration costing. If FC is given, LIFO performs the best in terms of the strategic goals of the case company. Additionally, changing from WA to LIFO as a condition, the difference between the relative performances of SE and FC is narrowed. The comparison result confirms the notion that different accounting method types have interacting effects and companies can use multiple means in achieving the same objectives as commonly observed. Additionally, the comparison result suggests that different accounting method types have different impacts on the relative performance of the accounting method alternatives. Particularly to the case company, the accounting method selection for exploration costing is not dependent on the accounting method selected for inventory, and not vice versa. This provides more insights into understanding the accounting method selection problem for the case company.

6.5 Concluding remarks

Accounting method selection for multiple accounting method types is more commonly occurred and recognised by existing research. Despite its significance for companies and practitioners, this selection problem is left unaddressed. To gain a better understanding of the multiple accounting method types selection and their interacting effects, this chapter has first evaluated four accounting method alternatives for exploration costing and for inventory collectively, including full cost (FC)/last-in-first-out (LIFO), FC/weighted average (WA), successful effort (SE)/LIFO and SE/WA. With the NN module and the MCDM module of the intelligent system-based approach, SE has been effectively identified as the most suitable accounting method alternative. The NN modelling has been proven capable of predicting satisfactory accounting results. The MCDM module has been effective in evaluating accounting method alternatives of multiple types based on multiple evaluation criteria in line with the strategic goals of the case company. This result has facilitated further analysis of the interacting effects of different accounting method types, which has been identified as a research gap in accounting choice research. The outcome of this empirical study provides supporting evidence for the case company to use SE for exploration costing and WA for inventory, as these two accounting methods combined best achieve the company's strategic goals. The examination on interacting effects between different accounting method types has confirmed that significant interacting effects exist. The examination result is in line with the notion in accounting choice research that there are multiple means available for companies to achieve their goals through the accounting method selection, which is purposefully made for influencing accounting results. In addition, the consistent selection results produced by the intelligent system-based approach for the selection problems of a single accounting method type and of two accounting method types have demonstrated its effectiveness for accounting method selection.

Chapter 7 Examining time delay effects on accounting results

7.1 Introduction

The time delay is ubiquitous in reporting accounting results. The time delay of business transactions on accounting results refers to the delay between business transactions occurred and the transaction has been recorded and reflected in the accounting results that are to be used for decision making. The most adopted accounting standard, International Financial Reporting Standard (IFRS), qualifies a short time delay as a crucial characteristic of high-quality accounting information, also known as timeliness. As the role of accounting results plays in making managerial and financial decisions, it is desirable and beneficial for managers and investors to have the most up-to-date accounting information. As a pioneering study in accounting research, this chapter develops a new method by training neural network (NN) models using different time alignments between the business factors and accounting results, described in Chapter 4, to empirically examine the time delay effect of business transactions on accounting results in a company-specific setting.

The time delay in accounting and financial data is commonly observed yet not fully understood in research (Callen et al., 2013; Herkenhoff & Ohanian, 2012). In the context of accounting research, the concept of timeliness of accounting information has been formulated as information asymmetry. The asymmetric information of the business performance and the reported performance through accounting information, in terms of timeliness, has been largely used in investigating the level of conservatism of the company's accounting practice, the effectiveness of the accounting practice governance, and the issues in financial asset pricing (Badertscher & Burks, 2011; Bushman et al., 2000, 2004; Chen et al., 2014; Dietrich et al., 2007; Ettredge et al., 2012). To better understand the time delay in accounting results, the research attempted to gain insights into the time delay effects from auditing related factors, such as auditing fees, audit committee personnel and types of audit reports (Abernathy et al., 2014; Hackenbrack et al., 2014; Soltani, 2002). The amount of the time delayed between business operations and accounting results has not been directly addressed.

In general practice, the released financial statements at the reporting period end are required to comply with the accounting standards. Especially to the case company, Eni adopts one of the most recognised and widely adopted accounting standard, International Financial Reporting Standard (IFRS). Eni's financial calendar coincides with the calendar year approved by the Board of Directors. As Eni releases quarterly financial reports, also known as the interim financial report, the financial reports are the products of a full accounting cycle at the reporting period end. Eni's accounting practice sets a quarter time to complete an accounting cycle, which generally includes the following steps:

(a) Collect and analyse data. The company begins an accounting cycle by identifying, collecting and analysing business transactions that comprise an accounting record. This event can be a sale, a purchase of goods or services, a payment to a supplier or a refund to a customer.

(b) Journalise business transactions. The accounting professionals record the business transactions using journal entries which are based on supporting documents and data of the business transactions, such as recognition of sales, purchase, fund transfer or other economic events. Each business transactions will generate two entries that record the source and destination of resources involved in the business transaction, also known as double entries.

(c) Post to the general ledger. After the business transaction is recorded as a journal entry, the journal entries will be recorded under an accounting item, also known as accounting in the general ledger. Examples of accounting items are asset, liability, and equity.

(d) Prepare an unadjusted trial balance. The trial balance is a step for accounting information quality assurance by ensuring total debits equal the total credits in accounting results.

(e) Adjust journal entries. At the end of a reporting period, adjustment journal entries are recorded for ensuring correct accounting results while the passage of time. For instance, interests of debt or cash in the bank are generated on the passage of time without a specific transactional event.

(f) Prepare an adjusted trial balance and create a financial statement. With adjected entries recorded in the general ledger and accounting result are ensured correct, the formalised financial statement is to be produced.

(g) Close the books. Closing journal entries of revenues, expenses, etc. at the end of the reporting period are recorded to signify the finish of an accounting cycle. The remaining value is transferred to the general ledger to the next accounting cycle.

Accounting results can only be used to complete an accounting cycle. High-quality accounting information is reliable and relevant in a timely manner (Barth et al., 2008; Soderstrom & Sun, 2007).

7.2 Examining quarterly time delay using four NN and results

The process of recording business transactions and producing accounting results indicates the complexity of accounting practice. With increasing complex business operations, it is more difficult for accounting results to be able to reflect all the business transactions occurred. Having neural network (NN) models that can achieve high accuracy in modelling the relationship between business factors and accounting items, the time delay effects between the two can be estimated by changing the time alignment between the data of business factors and accounting results.

Given the empirical data are quarterly data, A_T and B_T are used to denote the accounting results and business factors, respectively, at time T with a quarter interval. The time delay effect on a quarterly basis is first examined. The time delay effect is tested by aligning the business factor data B_T with the accounting data A_T, A_{T+1}, A_{T+2}, A_{T+3} and A_{T+4} for no delay, one quarter delay, two quarters delay, three quarters delay and four quarters delay, respectively. Figure 7-1 illustrates how the business factors and accounting results are aligned for examining quarterly time delay experiments.

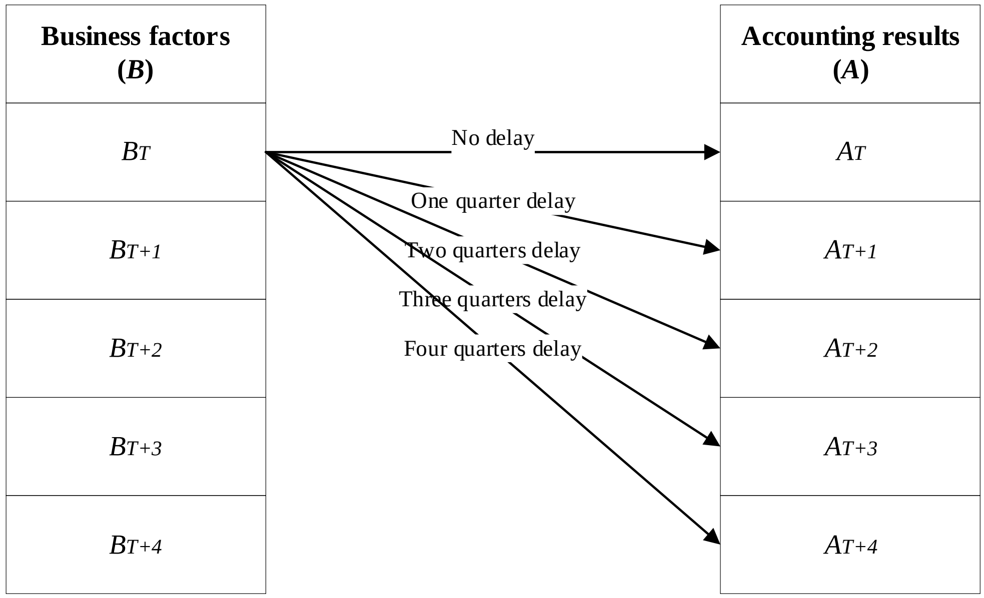

Figure 7-1. Data alignment illustration for quarter time delay interval experiments

As the accounting method is one of the most contributing variables in modelling the relationships between business factors and accounting results, exploration costing and inventory are included in the NN modelling for examining the time delay effects of business transactions (Duan & Yeh, 2018). Using the NN inputs and outputs for the evaluation of two accounting method types, as discussed in Chapter 6, the performance of the trained NN models is measured using the mean absolute percentage error (MAPE). The ratio scaling technique is used for data pre-processing as it has been proven to achieve the best prediction accuracy, as shown in Chapters 5 and 6. A single layer perceptron (SLP) has also been proven to be effective for modelling the relationship, with the benefits of a lower computing resource cost. To ensure the model performance are not achieved by random initialised NNs, 30 NN models are trained, and the averaged MAPE is reported. Table 7-1 shows the performance of the NN models by a quarter delay interval.

Table 7-1. NN performance by quarter delay interval with two accounting method types

NN architecture	**Data set**	**Model performance by a quarter delay interval**				
		0	**1**	**2**	**3**	**4**
SLP	Training	11.84	12.60	12.15	14.10	14.99
	Validation	30.50	41.49	36.82	35.95	35.15

The first column in Table 7-1 shows the NN architecture used for modelling. The second column indicates the data set, namely training and validation, on which the model performance is measured by MAPE. The results show the models perform the best when there is no quarterly delay and the worst for four quarterly delays which are equivalent to a year delay. This result indicates no time delay in a quarter interval because the model performance declines as the delay interval increases. This result is consistent with the accounting practice at the case company Eni since it discloses its accounting results on a quarterly basis.

7.3 Examining two-week interval time delay using four NN architectures and results

To estimate the time delay interval of a smaller scale, the best alignment of the quarterly data will be further examined in a two-week delay interval. Data point using quarterly time scale (T) is divided into six data points with two-week intervals (i.e. t, $t+1$, ..., $t+5$). To estimate the data required for the business factors and accounting results at the two-week interval, two methods are applied. For the business factors and accounting results that have an accumulated value (such as

B_1, B_4 to B_7, and A_1 to A_3), the value difference between time T and time $T+1$ is obtained by using the straight-line method. The method divides the difference into six data points and assigns the divided difference according to the new data in time order. The formula of the method is given as

$$A'_{t+\Delta t} = A_T + \frac{\Delta t(A_{T+1} - A_T)}{6} \qquad \Delta t = 0, 1, \ldots, 5 \tag{7-1}$$

For the business factors and accounting results that have a non-accumulative value (such as B_2, A_4 *to* A_6), the value difference between time T and time $T+1$ is simply one sixth of the value at $T+1$. The formula of the method is given as

$$A'_{t+\Delta t} = \frac{A_T}{6} \qquad \Delta t = 0, 1, \ldots, 5 \tag{7-2}$$

For the business factors that have a measurement of an averaged value, such as oil and natural gas products average actualisation price (B_3), the value at time T is the same as the value at time t. The formula is given,

$$A'_{t+\Delta t} = A_T \qquad \Delta t = 0, 1, \ldots, 5 \tag{7-3}$$

Figure 7-2 illustrates how the business factors and accounting results are upscaled and aligned to examine two-week delay (Δt) intervals using experiments.

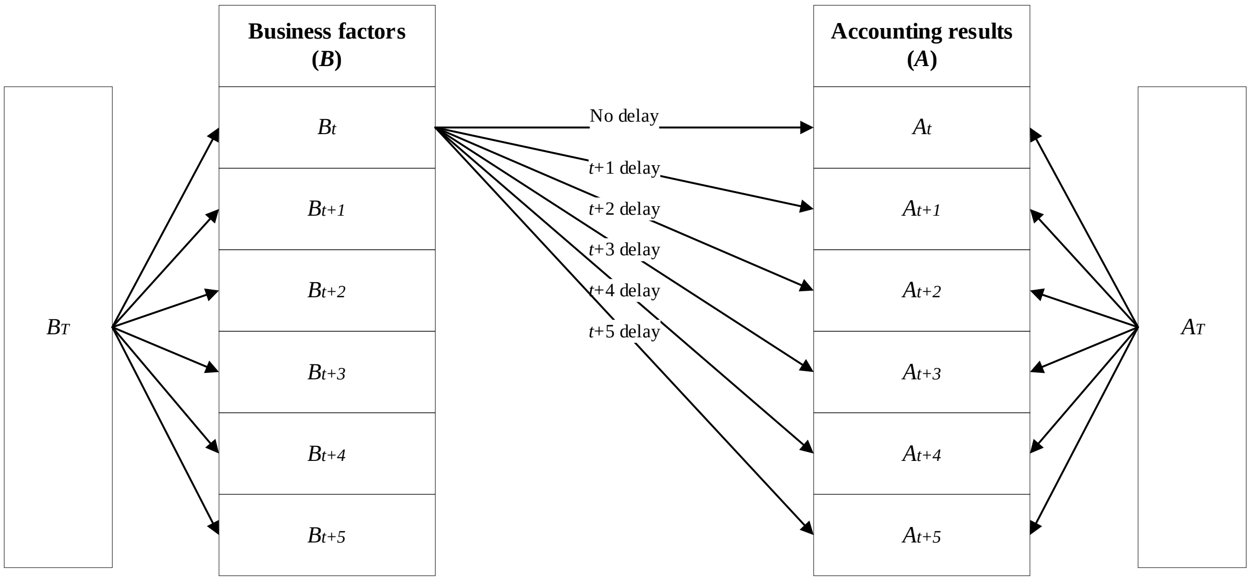

Figure 7-2. Data alignment illustration for two-week time delay interval experiments

Similar to NN modelling with a quarter time delay interval, the performance of the trained NN models is measured by MAPE. The ratio scaling technique is used for data pre-processing. To achieve conclusive results for the time delay effects of business transactions on accounting results, NN models with a single accounting method type and with two accounting method types using four NN architectures are tested. Each NN architecture has 30 randomly initialised models for training. Tables 7-2 to 7-4 show the performance of the NN models using four NN architectures (i.e. single-layer perceptrons (SLPs), multilayer perceptrons (MLPs) and recurrent neural networks (RNNs), long short-term memory (LSTM)) for a two-week delay interval.

Table 7-2. Performances of NN models by delay period with exploration costing's method

NN architecture	Data set	Model performance by a two-week delay interval						
		0	**1**	**2**	**3**	**4**	**5**	**6**
SLP	Training	28.28	57.22	37.86	22	50.48	26.48	35.7
	Validation	36.44	61.05	45.98	31.92	54.65	33.05	41.18
MLP	Training	30.8	59.56	37.26	30.62	35.15	24.54	30.2
	Validation	39.3	66.34	46.65	40.16	52.95	33.55	41.19
RNN	Training	14.44	11.26	9.29	8.6	8.96	10.62	13.45
	Validation	24.19	17.17	13.01	11.69	13.34	17.84	25.18
LSTM	Training	13.82	10.67	8.76	8	8.47	10.14	13.01
	Validation	24.11	17.12	12.94	11.69	13.3	17.8	25.18

Table 7-3. Performances of NN models by delay period with inventory's method

NN architecture	Data set	Model performance by a two-week delay interval						
		0	**1**	**2**	**3**	**4**	**5**	**6**
SLP	Training	23.77	54.93	39.81	20.2	41.67	22.63	27.24
	Validation	31.41	57.36	42.51	28.44	48.53	25.73	34.13
MLP	Training	28.92	58.14	33.19	26.7	28.78	23.96	31.14
	Validation	35.63	63.5	40.83	34.63	44.98	31.51	36.23
RNN	Training	14.16	11.25	9.46	8.63	9.11	10.56	13.07
	Validation	21.26	15.2	11.66	10.54	11.81	15.64	21.86
LSTM	Training	13.22	10.43	8.7	8.01	8.37	9.78	12.22
	Validation	21.16	15.14	11.55	10.43	11.79	15.59	21.91

Table 7-4. Performances of NN models by delay period with exploration costing and inventory

NN architecture	**Data set**	**Model performance by a two-week delay interval**						
		0	**1**	**2**	**3**	**4**	**5**	**6**
SLP	Training	27.03	54.7	39.92	20.37	42.18	22.62	30.08
	Validation	33.52	56.97	42.7	29.04	48.82	27.35	35.27
MLP	Training	30.74	55.91	32.67	24.29	27.12	25.87	31.74
	Validation	34.41	63.05	40.2	32.38	44.08	32.26	35.4
RNN	Training	13.9	11.17	9.57	8.61	9.09	10.28	12.8
	Validation	21.34	15.21	11.61	10.48	11.81	15.69	21.91
LSTM	Training	13.24	10.44	8.72	8.02	8.39	9.79	12.22
	Validation	21.17	15.12	11.51	10.4	11.75	15.55	21.89

As the results in Tables 7-2 to 7-4 show, NN models for a six two-weeks delay which is equivalent to a quarter delay perform no better than NN models for no delay. Three two-weeks delays generally perform the best under the three settings with the accounting method using SLPs, RNNs and LSTM. The NN models for a three two-weeks delay perform the second best using MLPs. This result indicates that it is highly likely that the accounting results of the case company Eni have a six weeks' time delay in responding to the reported operational data. This suggests that the accounting results of the current period most likely is a reflection of the business operations carried out six weeks earlier.

7.4 Concluding remarks

The timeliness of accounting results is a crucial factor of quality accounting information. The time delay effects of business transactions on accounting results are commonly observed but not well understood. Instead of estimating the timeliness of the accounting results from their correlations to the factors of auditing, this chapter has developed a new NN modelling method for examining the time delay effects of business transactions on accounting results using different time alignments between business factors and accounting results. This NN modelling method is a pioneering study in accounting research. The time delay effect has been confirmed by the empirical study, whose result provides the case company with a useful insight into understanding the amount of time delayed in its accounting results.

Chapter 8 Conclusions

8.1 Summary of research developments

This research has developed an intelligent system-based approach for addressing accounting method selection problems from a decision support perspective. The research framework presented in Chapter 1 outlines how the intelligent system-based approach is developed and applied in accounting method selection problems. With the development of a neural networks (NNs) module and a multicriteria decision making (MCDM) module using optimal weighting, the approach presented in Chapter 3 is a distinctive novelty of this research. The approach represents a novel structured methodology for addressing accounting method selection problems in a rational and informed manner. To demonstrate the feasibility and effectiveness of the approach, specific accounting method selection problems of a case company from the oil and gas industry have been analysed and discussed in Chapter 4 for the empirical studies.

In the two empirical studies conducted the context of the case company in Chapters 5 and 6, the approach has been used to evaluate and select accounting method alternatives in two settings respectively: (a) a single accounting method type (i.e. exploration costing) and (b) two accounting method types (i.e. exploration costing and inventory). The most suitable accounting method alternatives with the highest relative overall performance scores in both studies have been identified. Subsequently, by comparing the results of the two studies, the interacting effects of different accounting method types on accounting results and on the accounting method selection have been confirmed. Illustrated with two empirical studies, the intelligent system-based approach to accounting method selection has been proven to be feasible and effective. More specifically, the NN module is adequate for predicting the accounting results under unused accounting method alternatives. With experiments on 16 different model training settings, the NN modelling process implemented has been effective in finding the best performing NN model for predicting accounting results. The best performing NN model predicts satisfactory accounting results to be used in the MCDM module. The MCDM module with optimal weighting is able to effectively address multiple evaluation criteria and criteria weighting issues involved in the accounting method selection problem.

This research has also developed a new method for training NN models using different time alignments between business factors and accounting results in an attempt to examine time delay effects of business transactions. This is a pioneering study in accounting research to empirically examine the time delay effects of business transactions on accounting results. The empirical results have confirmed the time delay effects, thus providing the case company and relevant accounting information users with a useful insight into understanding the amount of time delayed in accounting results.

Table 8-1 summaries the research objective, research questions, research issues, research developments and their related chapters in this thesis.

Table 8-1. Research objective, research question, research issues and research developments

Research objective or research question	Research issue	Research development	Related chapter
Research Objective: To develop an intelligent system-based approach to accounting method selection.	How to construct the approach and what methodology can be used for addressing the accounting method selection from a decision support perspective.	An intelligent system-based approach to accounting method selection.	Chapter 3
RQ1. How to model business factors and accounting results that are relevant to the accounting method type under evaluation? In the empirical study conducted, the accounting method type under evaluation is the exploration costing accounting method with two accounting method alternatives, the full cost (FC) and successful efforts (SE) methods.	What business activities does the exploration costing's method correspond to?	Identification of upstream activity of the case company.	Chapter 4
	What business factors are involved in the case company's relevant business actives?	Identification of business factors relevant to exploration activities of the case company.	Chapter 4
	What items in the accounting results can be affected by the exploration costing accounting method alternatives?	Identification of accounting items to be affected by identified business factors of the case company.	Chapter 4
	How to model the relationships between the identified business factors and affected accounting results?	NN modelling experimented on various model training settings as a part of NN module.	Chapter 5

Table 8-1. Research objective, research question, research issues and research developments (continued)

Research objective or research question	Research issue	Research development	Related chapter
RQ2. How to obtain the accounting results under an unused accounting method alternative for a given accounting method type? In the empirical study conducted, the unused accounting method alterative for the evaluation period is FC.	How to predict the accounting results under an unused accounting method, FC, given the effect of the accounting method in use, SE, on the accounting results for the evaluation period?	Obtained the best performing NN model for predicting accounting results under the unused accounting method alternatives as a part of NN module.	Chapter 5
RQ3. How to evaluate applicable accounting method alternatives and identify the most suitable accounting method for a given accounting method type with respect to a company's strategic goals? In the empirical study conducted, FC and SE are the applicable alternatives for exploration costing accounting method.	What are the evaluation criteria to be used to reflect a company's strategic goals?	Identification of the strategic goals and KPIs of the case company.	Chapter 4
	How to best weight the evaluation criteria to reflect a company's best possible operational condition for the accounting method to achieve its strategic goal?	Optimal criteria weighting using fuzzy weights as a part of the MCDM module.	Chapter 5
	How to obtain performance ratings for the accounting method alternatives, namely FC and SE, with respect to the identified evaluation criteria?	Evaluation of accounting method alternatives with respects to the identified criteria as a part of the MCDM module.	Chapter 5

Table 8-1. Research objective, research question, research issues and research developments (continued)

Research objective or research question	Research issue	Research development	Related chapter
RQ3. How to evaluate applicable accounting method alternatives and identify the most suitable accounting method for a given accounting method type with respect to a company's strategic goals? In the empirical study conducted, FC and SE are the applicable alternatives for exploration costing accounting method.	How to aggregate the criteria weights and performance ratings to obtain an overall performance value for each accounting method alternative?	MCDM simple additive score aggregation as a part of the MCDM module.	Chapter 5
RQ4. How to evaluate and select the best accounting method combination for multiple accounting method types? In the empirical study conducted, two accounting method types considered are the exploration costing accounting method and the inventory accounting method.	How to model two accounting method types for predicting accounting results?	Identification of inventory activities and affected accounting items. NN modelling for exploration costing and inventory.	Chapter 6
	How to evaluate alternative accounting method combinations?	Identification of strategic goals and KPIs. MCDM evaluation of the accounting method alternatives for exploration costing and inventory.	Chapter 6
	What are the interacting effects of exploration costing accounting method and inventory accounting method in selecting the most suitable accounting methods?	Evaluation of accounting method alternatives for inventory individually. Comparison of relative performances.	Chapter 6

Table 8-1. Research objective, research question, research issues and research developments (continued)

Research objective or research question	**Research issue**	**Research development**	**Related chapter**
Are there time delay effects on accounting results?	How to examine time delay given the empirical data and NN models of the relationship between business factors and accounting results?	The new method using different time alignments between business factors and accounting results in NN model training.	Chapter 7

8.2 Research contributions

This research makes significant conceptual, methodological and empirical contributions in addressing the accounting method evaluation and selection as a decision problem.

The original contribution of this research to knowledge lies in the fact that it addresses the accounting method selection problem from a novel perspective. The accounting method selection problem has been identified as crucial and channelling by academic researchers and partitioners. Although existing studies and current best practices hypothesise or theorise why a particular accounting method is selected, the issue of how to make a good accounting method selection remains unaddressed. This is mainly because no specific methodology has been developed for evaluating accounting method alternatives. To address this unresolved issue, this research develops a new intelligent system-based approach for evaluating accounting method alternatives in terms of their performance on a company's strategic goals in a rational and informed manner.

Methodologically, the proposed approach contributes to the accounting method selection problem in two aspects:

(a) This research develops an innovative approach to the accounting method selection problem. A unique characteristic of such a decision problem is that the available accounting results are produced by the accounting method in use. The accounting results that would have been produced by unused accounting method alternatives are unobtainable or unavailable for the accounting method evaluation. Based on the mechanism of the accounting information processing, modelling the relevant business factors and accounting results is new for its purpose. Additionally, instead of building separate NN models for different accounting methods, the proposed approach includes the accounting method under evaluation as an input, together with relevant business factors as inputs in NN modelling. With this innovative modelling, the trained NN models are capable of predicting the accounting results under an unused accounting method alternative.

(b) This research develops a new method for examining the time delay effects of business transactions on accounting results. By training NN models using different time alignments between the business factors and the accounting results, different time delay intervals can be examined. The most probable time delay interval on accounting results can be identified. The knowledge of the amount of time delay is of significance to the users of accounting results.

Empirically, this research contributes to practical accounting method selection in three aspects:

(a) This research effectively supports the accounting method selection problem for the case company. The outcomes of the empirical study conducted identify the most suitable accounting methods and provide new supporting evidence for the case company's current selection of successful effort (SE) and weighted average (WA) for the two accounting method types of exploration costing and inventory, respectively. Additionally, the identified business factors and affected accounting results that are relevant to the accounting method under investigation are of significance for the case company to gain new insights into understanding the accounting method selection problem.

(b) The evaluation of two accounting method types provides empirical evidence for examining the interacting effects of the two accounting method types. This research outcome confirms the interacting effects on accounting method selection. It also confirms the notion in accounting choice research that multiple means are available for companies to achieve their goals through the accounting method selection for purposefully influencing accounting results.

(c) As a pioneering study in accounting research to empirically examine the time delay effect of business transactions on accounting results, the empirical result of this research confirms the time delay effect and provides the case company with a useful insight into understanding the amount of time delayed in its accounting results.

8.3 Limitations and future research

The empirical studies conducted may be limited by the availability and accessibility of the operating and accounting data. The accounting results under each accounting method alternative are essential for modelling accounting results using neural network (NN) models for evaluating accounting method alternatives. To obtain actual accounting results under an unused accounting method alternative by redoing the accounting records is costly or infeasible in most cases. NN modelling requires such data. Hence, the accounting method types that can be evaluated may be limited to the accounting method types that have been actually used in the past. Hence, the examinable interactive effects between different accounting method types may also be limited.

In future research, the interactive effects of multiple accounting method types can be further investigated. With the availability of data, the intelligence system-based approach could be used to examine the effects of the accounting method alternatives on the achievement of a company's strategic goals and to evaluate various accounting method alternatives under different settings.

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Appendix A

Table A-1. Data table of proved reserves and production for liquids, natural gas and hydrocarbons at period end

Year	Quarter	Proved reserves of liquids (mmbbl)	Proved reserves of natural gas (bcf)	Proved reserves of hydrocarbons (mmboe)	Liquids production (mmbbl)	Natural gas production (bcf)	Hydrocarbons production (mmboe)
2018	4	3,183	17,324	6,356	885	5,358	1,867
2018	3	3,183	17,324	6,356	886	5,008	1,803
2018	2	3,183	17,324	6,356	881	5,359	1,863
2018	1	3,183	17,324	6,356	885	5,358	1,867
2017	4	3,262	17,290	6,430	832	5,254	1,795
2017	3	3,262	17,290	6,430	885	5,012	1,803
2017	2	3,262	17,290	6,430	827	5,152	1,771
2017	1	3,262	17,290	6,430	832	5,254	1,795
2016	4	3,230	18,462	6,613	906	5,184	1,856
2016	3	3,230	18,462	6,613	864	4,616	1,710
2016	2	3,230	18,462	6,613	852	4,709	1,715

Table A-1. Data table of proved reserves and production for liquids, natural gas and hydrocarbons at period end (continued)

Year	Quarter	Proved reserves of liquids (mmbbl)	Proved reserves of natural gas (bcf)	Proved reserves of hydrocarbons (mmboe)	Liquids production (mmbbl)	Natural gas production (bcf)	Hydrocarbons production (mmboe)
2016	1	3,230	18,462	6,613	890	4,718	1,754
2015	4	3,372	14,302	5,975	998	4,868	1,884
2015	3	3,372	14,302	5,975	868	4,582	1,703
2015	2	3,372	14,302	5,975	903	4,676	1,754
2015	1	3,372	14,302	5,975	860	4,596	1,697
2014	4	3,077	14,808	5,772	888	4,284	1,648
2014	3	3,077	14,808	5,772	812	4,197	1,576
2014	2	3,077	14,808	5,772	813	4,234	1,584
2014	1	3,077	14,808	5,772	822	4,182	1,583
2013	4	3,079	14,442	5,708	816	417	1,577
2013	3	3,079	14,442	5,708	851	4,402	1,653
2013	2	3,079	14,442	5,708	845	4,410	1,648
2013	1	3,079	14,442	5,708	818	4,290	1,600
2012	4	3,084	14,190	5,667	912	4,584	1,747
2012	3	3,084	14,190	5,667	891	4,545	1,718

Table A-1. Data table of proved reserves and production for liquids, natural gas and hydrocarbons at period end (continued)

Year	Quarter	Proved reserves of liquids (mmbbl)	Proved reserves of natural gas (bcf)	Proved reserves of hydrocarbons (mmboe)	Liquids production (mmbbl)	Natural gas production (bcf)	Hydrocarbons production (mmboe)
2012	2	3,084	14,190	5,667	856	4,394	1,656
2012	1	3,084	14,190	5,667	867	4,480	1,683
2011	4	3,134	15,582	5,940	896	4,345	1,678
2011	3	3,134	15,582	5,940	793	3,773	1,473
2011	2	3,134	15,582	5,940	793	3,867	1,489
2011	1	3,134	15,582	5,940	899	4,356	1,684
2010	4	3,415	16,198	6,332	1,049	5,021	1,954
2010	3	3,415	16,198	6,332	948	4,203	1,705
2010	2	3,415	16,198	6,332	980	4,319	1,758
2010	1	3,415	16,198	6,332	1,011	4,615	1,816
2009	4	3,377	16,262	6,209	1,073	4,668	1,886
2009	3	3,377	16,262	6,209	957	4,139	1,678
2009	2	3,377	16,262	6,209	986	4,290	1,733
2009	1	3,377	16,262	6,209	1,013	4,398	1,779
2008	4	3,243	17,214	6,242	1,079	4,449	1,854

Table A-1. Data table of proved reserves and production for liquids, natural gas and hydrocarbons at period end (continued)

Year	Quarter	Proved reserves of liquids (mmbbl)	Proved reserves of natural gas (bcf)	Proved reserves of hydrocarbons (mmboe)	Liquids production (mmbbl)	Natural gas production (bcf)	Hydrocarbons production (mmboe)
2008	3	3,243	17,214	6,242	1,015	4,302	1,764
2008	2	3,243	17,214	6,242	998	4,442	1,772
2008	1	3,243	17,214	6,242	1,012	4,503	1,796
2007	4	3,127	16,549	6,010	1,048	4,401	1,815
2007	3	3,127	16,549	6,010	975	3,927	1,659
2007	2	3,127	16,549	6,010	1,026	4,082	1,736
2007	1	3,127	16,549	6,010	1,030	4,061	1,734
2006	4	3,457	16,897	6,400	1,079	4,121	1,796
2006	3	3,457	16,897	6,400	1,041	3,834	1,709
2006	2	3,457	16,897	6,400	1,056	3,974	1,748
2006	1	3,457	16,897	6,400	1,143	3,920	1,827
2005	4	3,748	17,501	6,796	1,132	3,885	1,806
2005	3	3,748	17,501	6,796	1,104	3,319	1,714
2005	2	3,748	17,501	6,796	1,107	618	1,725

Table A-2. Data table of average sale price for liquids, natural gas and hydrocarbons and accounting method applied for exploration costing and inventory at period end

Year	Quarter	Liquids average sale price	Natural gas average sale price	Hydrocarbons average sale price	Accounting method for exploration costing	Accounting method for inventory
2018	4	61.17	4.50	42.34	1	1
2018	3	69.99	5.73	51.85	1	1
2018	2	69.17	4.52	47.62	1	1
2018	1	61.17	4.50	42.34	1	1
2017	4	48.65	3.60	33.42	1	1
2017	3	48.03	3.80	35.14	1	1
2017	2	45.29	3.45	32.05	1	1
2017	1	48.65	3.60	33.42	1	1
2016	4	44.56	3.50	32.95	1	1
2016	3	40.82	3.14	29.70	1	1
2016	2	40.58	3.11	29.30	1	1
2016	1	29.69	3.31	24.09	1	1
2015	4	38.68	4.06	31.68	0	1
2015	3	43.97	4.45	34.57	0	1

Table A-2. Data table of average sale price for liquids, natural gas and hydrocarbons and accounting method applied for exploration costing and inventory at period end (continued)

Year	Quarter	Liquids average sale price	Natural gas average sale price	Hydrocarbons average sale price	Accounting method for exploration costing	Accounting method for inventory
2015	2	55.60	4.63	41.96	0	1
2015	1	48.26	5.11	38.28	0	1
2014	4	66.44	6.65	53.45	0	1
2014	3	92.61	6.49	66.39	0	1
2014	2	100.63	6.90	72.25	0	1
2014	1	99.40	7.47	71.49	0	1
2013	4	101.00	7.26	74.43	0	1
2013	3	101.39	7.24	71.90	0	1
2013	2	93.25	7.35	68.65	0	1
2013	1	102.32	7.18	72.10	0	1
2012	4	101.38	7.48	74.04	0	1
2012	3	96.43	6.72	69.48	0	1
2012	2	101.46	6.96	72.02	0	1

Table A-2. Data table of average sale price for liquids, natural gas and hydrocarbons and accounting method applied for exploration costing and inventory at period end (continued)

Year	Quarter	Liquids average sale price	Natural gas average sale price	Hydrocarbons average sale price	Accounting method for exploration costing	Accounting method for inventory
2012	1	111.54	7.33	78.14	0	1
2011	4	100.42	7.13	72.58	0	1
2011	3	104.42	6.45	73.88	0	1
2011	2	108.59	6.34	76.39	0	1
2011	1	95.36	5.99	66.62	0	1
2010	4	76.72	6.75	59.55	0	1
2010	3	70.37	5.67	53.63	0	1
2010	2	72.33	5.81	55.06	0	1
2010	1	70.93	5.73	54.28	0	1
2009	4	68.42	5.20	52.24	0	1
2009	3	62.69	5.20	49.54	0	1
2009	2	54.43	5.03	44.20	0	1
2009	1	42.09	7.06	41.46	0	1

Table A-2. Data table of average sale price for liquids, natural gas and hydrocarbons and accounting method applied for exploration costing and inventory at period end (continued)

Year	Quarter	Liquids average sale price	Natural gas average sale price	Hydrocarbons average sale price	Accounting method for exploration costing	Accounting method for inventory
2008	4	46.47	8.36	47.11	0	1
2008	3	99.77	9.13	80.00	0	1
2008	2	105.02	7.78	80.32	0	1
2008	1	85.72	6.80	65.64	0	1
2007	4	81.32	6.10	62.13	0	1
2007	3	70.95	5.14	54.38	0	1
2007	2	64.58	5.06	50.82	0	1
2007	1	54.39	2.30	45.12	0	1
2006	4	54.85	5.39	45.53	0	1
2006	3	65.20	5.44	52.21	0	1
2006	2	64.33	5.15	51.24	0	1
2006	1	56.27	5.23	46.71	0	1
2005	4	52.26	4.85	43.53	0	0

Table A-2. Data table of average sale price for liquids, natural gas and hydrocarbons and accounting method applied for exploration costing and inventory at period end (continued)

Year	**Quarter**	**Liquids average sale price**	**Natural gas average sale price**	**Hydrocarbons average sale price**	**Accounting method for exploration costing**	**Accounting method for inventory**
2005	3	48.03	4.38	40.24	0	0
2005	2	48.03	4.38	40.24	0	0

Table A-3. Data table of price and traded volume of company share and oil futures, interests of USD and EUR and exchange rate at period end

Year	Quarter	Share price quarter average	Share traded volume	Future price quarter average	Future traded volume	USD interests %	EUR interests %	USD/EUR exchange rate quarter average
2018	4	33.7017	614.8233	63.4500	58.2100	2.2200	0.2500	1.1414
2018	3	37.4567	319.8400	72.9467	46.4000	1.9200	0.2500	1.1629
2018	2	36.8667	584.9267	71.2700	59.1800	1.7400	0.2500	1.1922
2018	1	34.6400	478.5100	65.0975	53.6200	1.4500	0.2500	1.2289
2017	4	32.8200	432.3967	58.5475	51.8500	1.2000	0.2500	1.1778
2017	3	31.4367	472.4200	50.3033	60.8000	1.1500	0.2500	1.1755
2017	2	31.8850	671.1733	49.4292	58.8600	0.9500	0.2500	1.1008
2017	1	31.3967	752.7133	53.6800	48.6700	0.7000	0.2500	1.0661
2016	4	29.3867	1,113.9700	49.9433	51.7700	0.4500	0.2500	1.0857
2016	3	30.5100	758.5600	45.7700	49.2500	0.4000	0.2500	1.1169
2016	2	30.7317	1,258.5230	45.9933	49.4700	0.3700	0.2500	1.1290
2016	1	28.2417	731.9367	34.3408	49.2700	0.3600	0.2833	1.1021
2015	4	32.1350	646.4200	44.3950	38.4700	0.1600	0.3000	1.0933

Table A-3. Data table of price and traded volume of company share and oil futures, interests of USD and EUR and exchange rate at period end (continued)

Year	Quarter	Share price quarter average	Share traded volume	Future price quarter average	Future traded volume	USD interests %	EUR interests %	USD/EUR exchange rate quarter average
2015	3	33.1200	762.8700	49.6500	37.6300	0.1400	0.3000	1.1190
2015	2	36.8950	1,000.7070	60.3117	33.9700	0.1200	0.3000	1.1068
2015	1	34.6433	843.3633	52.2708	38.2300	0.1100	0.3000	1.1270
2014	4	40.3067	852.4200	75.4083	33.0100	0.1000	0.3000	1.2500
2014	3	50.5483	456.3233	100.3233	26.7700	0.0900	0.3667	1.3229
2014	2	51.5383	413.9767	106.0325	24.4200	0.0900	0.6333	1.3726
2014	1	47.1033	527.4300	103.6392	23.7400	0.0700	0.7500	1.3705
2013	4	48.1183	403.1267	102.9825	24.9900	0.0900	0.8333	1.3607
2013	3	45.1133	539.3467	107.4933	26.8600	0.0800	1.0000	1.3235
2013	2	45.5833	738.0667	98.3775	29.1000	0.1200	1.1667	1.3061
2013	1	48.1550	1,519.7300	103.3700	23.8100	0.1400	1.5000	1.3202
2012	4	46.3033	1,206.9230	99.0242	24.9600	0.1600	1.5000	1.2971
2012	3	42.9183	1,176.4730	99.9367	26.5300	0.1400	1.5000	1.2526

Table A-3. Data table of price and traded volume of company share and oil futures, interests of USD and EUR and exchange rate at period end (continued)

Year	Quarter	Share price quarter average	Share traded volume	Future price quarter average	Future traded volume	USD interests %	EUR interests %	USD/EUR exchange rate quarter average
2012	2	42.0183	1,398.6070	101.4725	29.4000	0.1500	1.7500	1.2839
2012	1	45.3417	1,373.0230	110.7183	28.0700	0.1000	1.7500	1.3118
2011	4	41.3050	2,285.9630	100.5942	28.4600	0.0700	2.0000	1.3482
2011	3	40.1633	3,444.7870	100.2317	32.4900	0.0800	2.2500	1.4128
2011	2	48.6517	1,830.4470	110.0900	32.9600	0.0900	2.0000	1.4438
2011	1	47.4183	1,760.2230	100.4692	30.9200	0.1600	1.7500	1.3652
2010	4	43.4617	1,486.4670	85.6308	28.3300	0.1900	1.7500	1.3584
2010	3	40.8533	1,311.5270	76.4058	29.2800	0.1900	1.7500	1.2926
2010	2	41.3333	1,685.2000	78.8300	32.3600	0.1900	1.7500	1.2773
2010	1	47.5817	977.3400	77.3008	27.9500	0.1300	1.7500	1.3833
2009	4	50.8700	1,195.5700	75.2517	27.3500	0.1200	1.7500	1.4780
2009	3	47.4533	1,112.0370	68.4458	24.7700	0.1600	1.7500	1.4275
2009	2	45.1817	1,433.9200	59.0725	21.7100	0.1800	1.9167	1.3656

Table A-3. Data table of price and traded volume of company share and oil futures, interests of USD and EUR and exchange rate at period end (continued)

Year	Quarter	Share price quarter average	Share traded volume	Future price quarter average	Future traded volume	USD interests %	EUR interests %	USD/EUR exchange rate quarter average
2009	1	41.3367	2,013.0600	44.4050	21.4300	0.1800	2.8333	1.3104
2008	4	44.9283	2,021.5430	61.2392	21.0600	0.5100	3.6667	1.3215
2008	3	64.1783	1,680.8300	119.9358	23.4400	1.9400	5.2500	1.5085
2008	2	76.4950	1,325.6130	121.2908	25.4900	2.0900	5.0000	1.5631
2008	1	67.1533	1,797.5500	96.8733	23.3100	3.1800	5.0000	1.5003
2007	4	71.3250	1,148.0430	89.8800	22.3200	4.5000	5.0000	1.4495
2007	3	70.3433	1,317.8100	75.0825	19.2000	5.0700	5.0000	1.3735
2007	2	68.6267	823.5600	66.6475	18.4800	5.2500	5.0000	1.3483
2007	1	63.4850	971.4567	59.5092	20.2500	5.2600	4.7500	1.3137
2006	4	63.0567	711.2367	60.8533	14.9900	5.2500	4.4167	1.2941
2006	3	60.1267	638.0600	71.1725	10.7000	5.2500	4.0833	1.2743
2006	2	59.0833	928.7300	70.7292	11.2200	4.9100	3.7500	1.2611
2006	1	58.0030	755.2533	63.4158	10.7000	4.4600	3.5000	1.2031

Table A-3. Data table of price and traded volume of company share and oil futures, interests of USD and EUR and exchange rate at period end (continued)

Year	**Quarter**	**Share price quarter average**	**Share traded volume**	**Future price quarter average**	**Future traded volume**	**USD interests %**	**EUR interests %**	**USD/EUR exchange rate quarter average**
2005	4	55.0360	787.8733	59.3800	9.0900	3.9800	3.0833	1.1923
2005	3	57.3893	613.6900	62.9050	10.3600	3.4600	3.0000	1.2216
2005	2	51.6747	555.8667	53.1917	9.2701	2.9400	3.0000	1.2587

Table A-4. Data table of affected accounting items at period end

Year	Quarter	Total assets	Total liabilities	Total equity	Revenue	Gross profit	Operating income
2018	4	139,798.50	79,481.30	60,317.21	23,037.82	5,460.85	1,683.66
2018	3	143,230.70	84,086.46	59,144.22	23,147.03	7,045.96	4,010.15
2018	2	141,112.00	80,920.30	60,191.71	22,470.97	6,232.53	3,147.27
2018	1	140,527.10	81,240.29	59,286.77	22,207.96	6,434.86	2,948.85
2017	4	129,903.10	75,559.42	54,343.70	24,565.17	7,651.55	5,014.09
2017	3	136,196.10	81,454.16	54,741.95	18,549.76	4,370.94	51,172.95
2017	2	129,590.20	75,773.21	53,817.01	17,360.82	3,670.37	619.24
2017	1	133,428.80	76,805.00	56,623.84	19,749.55	5,235.78	2,249.69
2016	4	137,821.50	79,076.53	58,744.97	18,264.92	4,707.91	2,278.28
2016	3	133,906.60	77,945.91	55,960.70	15,130.73	3,254.26	214.27
2016	2	138,196.40	79,114.92	59,081.47	15,487.95	3,323.28	248.51
2016	1	135,669.30	77,653.15	58,016.18	13,852.88	2,623.41	-354.13
2015	4	149,673.00	90,078.98	59,594.06	3,430.89	-169.61	-5,342.34
2015	3	160,865.30	92,803.08	68,062.20	20,962.50	4,589.48	67.87
2015	2	164,125.80	93,470.58	70,655.20	24,680.43	5,797.59	435.84
2015	1	176,773.60	99,794.01	76,979.59	27,482.72	6,396.34	1,750.62

Table A-4. Data table of affected accounting items at period end (continued)

Year	Quarter	Total assets	Total liabilities	Total equity	Revenue	Gross profit	Operating income
2014	4	194,353.00	111,658.50	82,694.42	34,051.16	5,905.89	-988.26
2014	3	192,346.10	107,392.60	84,953.45	35,623.29	8,429.80	3,422.08
2014	2	192,156.30	108,118.40	84,037.84	37,566.74	8,741.11	3,093.41
2014	1	192,503.20	106,985.30	85,517.83	40,241.99	9,634.62	4,996.84
2013	4	183,758.30	102,667.00	81,091.38	36,400.71	9,123.46	460.83
2013	3	182,563.50	99,625.39	82,938.14	39,431.02	9,092.74	4,375.48
2013	2	179,672.30	98,908.87	80,763.38	36,891.68	6,972.20	1,905.31
2013	1	194,720.50	108,522.50	86,197.97	41,470.98	9,455.00	5,064.33
2012	4	179,592.30	98,937.10	80,655.19	44,374.84	12,143.95	3,250.21
2012	3	194,716.60	114,325.40	80,391.18	40,814.77	10,619.74	6,213.57
2012	2	193,426.80	111,727.90	81,698.94	38,634.86	9,283.18	3,631.32
2012	1	190,386.00	107,363.00	83,023.00	43,885.73	13,016.93	8,334.05
2011	4	199,372.30	115,177.60	84,194.76	39,409.54	8,499.59	2,808.39
2011	3	194,503.60	112,868.50	81,635.13	37,052.69	10,824.56	6,377.23
2011	2	188,047.10	107,889.00	60,720.04	35,907.37	10,203.96	5,459.59
2011	1	179,097.50	101,361.70	77,735.82	39,340.89	11,860.09	7,388.65

Table A-4. Data table of affected accounting items at period end (continued)

Year	Quarter	Total assets	Total liabilities	Total equity	Revenue	Gross profit	Operating income
2010	4	175,010.50	101,003.70	74,006.78	38,294.88	10,268.75	4,079.82
2010	3	161,814.30	91,993.84	69,820.46	29,560.35	9,293.89	5,264.60
2010	2	164,365.40	91,154.88	73,210.50	29,544.50	9,874.96	5,493.18
2010	1	171,798.80	96,508.56	75,290.29	34,773.36	11,140.68	6,665.29
2009	4	163,905.90	99,652.53	64,253.40	32,774.63	12,287.04	3,314.03
2009	3	140,913.40	76,122.05	64,791.35	27,353.92	7,049.28	4,118.00
2009	2	152,776.90	89,193.29	63,583.60	25,796.29	8,720.90	3,957.99
2009	1	134,942.40	70,956.38	63,986.05	31,053.23	7,544.55	4,695.73
2008	4	171,503.90	106,138.50	65,365.35	32,930.41	8,165.43	473.06
2008	3	142,457.00	74,494.26	67,962.71	42,438.63	12,260.94	9,380.13
2008	2	170,435.80	106,029.20	64,406.54	42,371.37	14,006.05	8,576.20
2008	1	134,613.30	71,802.13	62,811.14	42,408.38	13,320.22	8,995.51
2007	4	139,101.70	83,674.87	55,426.78	37,686.30	-2,906.75	8,307.20
2007	3	115,534.20	55,587.91	59,946.24	27,741.06	27,741.06	5,791.42
2007	2	106,752.20	49,737.15	57,015.00	26,628.39	7,713.26	5,449.97
2007	1	98,819.85	42,370.64	56,449.21	28,706.03	8,450.81	6,319.44

Table A-4. Data table of affected accounting items at period end (continued)

Year	Quarter	Total assets	Total liabilities	Total equity	Revenue	Gross profit	Operating income
2006	4	110,919.90	61,899.44	49,020.42	27,626.64	9,532.48	4,667.26
2006	3	91,212.30	37,148.18	54,064.12	25,987.01	7,935.44	6,021.44
2006	2	106,311.60	58,794.61	47,516.99	26,048.18	9,128.61	6,008.71
2006	1	57,555.12	7,568.07	49,987.05	28,371.55	9,229.42	6,479.37
2005	4	104,393.30	58,492.59	45,900.66	29,530.88	-17,209.60	-10,509.80
2005	3	55,595.40	7,777.50	47,817.90	21,181.64	21,181.64	4,923.92
2005	2	96,802.73	54,552.46	42,250.26	19,969.16	6,243.75	4,432.27

Appendix B

Table B-1. Model prediction performance for inventory accounting method selection

Model training setting No.	Accounting method type	Data scaling	NN architecture	Training technique	MAPE	MAE
M1	Inventory	Original data	SLP	N	13.28%	4,638.80
M2				D	7.49%	4,171.41
M3				V	16.80%	5,839.78
M4				D&V	6.57%	2,130.74
M5			MLP	N	15.53%	6,362.37
M6				D	21.58%	7,827.65
M7				V	17.98%	5,094.11
M8				D&V	21.14%	6,600.94
M9			RNN	N	11.00%	9,543.83
M10				D	19.97%	10,064.38
M11				V	10.83%	3,577.45
M12				D&V	16.74%	7,877.85
M13			LSTM	N	10.37%	8,809.04
M14				D	11.01%	9,194.12
M15				V	10.87%	3,614.03
M16				D&V	10.88%	3,618.22
M49		Ratio scaling	SLP	N	4.45%	0.3864
M50				D	4.42%	0.4260
M51				V	8.15%	0.5711
M52				D&V	5.79%	0.5144

Table B-1. Model prediction performance for inventory accounting method selection (continued)

Model training setting No.	Accounting method type	Data scaling	NN architecture	Training technique	MAPE	MAE
M53	Inventory	Ratio scaling	MLP	N	8.83%	0.6990
M54				D	9.78%	0.8017
M55				V	5.32%	0.3946
M56				D&V	6.24%	0.4462
M57			RNN	N	15.06%	0.8539
M58				D	16.74%	0.7721
M59				V	39.75%	2.3405
M60				D&V	35.55%	1.8547
M61			LSTM	N	12.03%	0.6716
M62				D	13.18%	0.6628
M63				V	44.31%	2.3916
M64				D&V	29.06%	1.8928