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A Study on Motor Vehicle Manufacturers

Qinqin Zeng

Delft University of Technology

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Dedicated to my family,
my love.

“綠陰不減來時路，添得黃鸝四五聲”

曾畿 《三衢道中》

Preface

“鱼知水恩，乃幸福之源” literally means “Joys of a fish start with its gratitude towards water”. Along with this Confucius wisdom, I always feel so grateful to everyone in my life. As a lucky fish who will complete the Ph.D. journey in TU Delft, I would like to express my sincere gratitude to all those whose support has made my journey joyful.

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It is so nice having you along this journey. I wish you all the best!

Well, lucky fish, it is time for another journey.

Qinqin Zeng

Delft, the Netherlands

Content

Chapter 1

Introduction

This dissertation introduces new methods for performance measurement to benchmark motor vehicle manufacturers from economic and environmental perspectives. The research background motivates the necessity of this dissertation followed by the problem statements, the research objective and the relevance to bridge the research gap in the research field. This section motivates that company performance measurement methods with consistent analysis and benchmark techniques for motor vehicle manufacturers to cope with environmental concerns are missing.

1.1 Research background

This section introduces the research background of this dissertation, focusing on the fields of company performance measurement, motor vehicle manufacturers, and company performance measurement from economic and environmental perspectives.

1.1.1 Performance from both an economic perspective and an environmental perspective

Topics about company performance measurement have a long history. Since the late 1980s, several classical integrated company performance frameworks have been developed such as the balanced scorecard as the first generation of company performance measurement, strategy maps as the second generation (Neely et al., 2003). The concept of the third generation of performance measurement has been proposed with emphasize on the adoption of non-financial indicators and intangible indicators. Taking into account non-financial indicators and intangible indicators, there are several studies in the motor vehicle manufacturing sector. For instance, an average value leverage factor is proposed as a performance measurement for car companies from a stability-value leverage perspective (Beelaerts van Blokland et al., 2019). Company performance measures from an inventory perspective are proposed for truck companies (Zeng & Beelaerts van Blokland, 2018). Six sub-indicators are integrated into an overall performance index for suppliers in the automotive industry (Chahid et al., 2014).

An environmental perspective helps stakeholders, such as shareholders, government regulators, consumers and employees, to pay more attention to companies' environmental performance. Current performance analysis from an environmental performance is mostly at the national level or even broader levels, such as the System of Environmental-Economic Accounting. Studies on company performance analysis from both an economic perspective

and an environmental perspective are insufficient in terms of consistent performance measures and quantitative performance analysis techniques.

1.1.2 Motor vehicle manufacturing

The life cycle of a vehicle consists of three stages including production stage, use stage, and end-of-life stage (Del Pero et al., 2018). The production stage, also called the manufacturing stage, consists of mining, ingot production, material production, part production and vehicle assembly (Hakamada et al., 2007). Vehicles' manufacturing has a great impact on the environment since it consumes a significant amount of natural resources and generates undesirable wastes such as CO_2, CO, SO_2, HC, NOX, VOC and PM10. For instance, more than 95% of water consumption along the life cycles of Volkswagen's three car models is consumed in the production phase (Berger et al., 2012).

This dissertation focuses on the manufacturing stage for motor vehicle manufacturers (MVMs). MVMs make a profit with input including materials, resources and energy, and output including vehicles, components, and various pollutants. In 2018, around 91.5 million vehicles were produced worldwide (Statista, 2019). Along with this production, a large volume of CO_2 has been emitted, which contributed around 73% to global greenhouse gas (GHG) (PBL Netherlands Environmental Assessment Agency, 2018). It is estimated that up to 16% of global man-made CO_2 emissions come from motor vehicles' production (International Organization of Motor Vehicle Manufacturers, 2019).

Instead of exclusively focusing on improving economic performance, such as improving profitability, MVMs are expected to take a long-term view in contributing toward sustainable development. From the 1980s onwards, the vast majority of MVMs have adopted an active attitude towards the reduction of the environmental impact of their production processes (Orsato & Wells, 2007). Nowadays, there are more and more MVMs integrating environmental concerns into their daily production. They participate in environmental preservation projects and release environmental policies regarding developing eco-friendly products (Audi AG, 2018), reducing over-consumption of energy and reducing GHG emissions. For MVMs, it is essential to create a bigger market share of zero-emission or low emission vehicles. According to the "cap and trade" principle of EU ETS, holders will be rewarded if they actively reduce carbon emissions to certain amounts during their production. Otherwise, they will be fined if they generated excessive carbon emissions. Manufacturers have to get aware of the potential risks such as the carbon tax and the bills due to excessive carbon emissions.

There is a positive relationship between stakeholder pressure and the implementation of environmental practices (Betts et al., 2015). For investors and financial institutions in the investment world, there has been a change in thinking from avoiding MVMs that have a negative impact on the environment to investing in companies that have positive environmental policies. As one of the first international asset management companies, Robeco together with RobecoSAM published "The Big Book of SI" in 2018. Here "SI" is short for sustainability investing which indicates investors take environmental protection to a high level by making it tangible and measurable. Stakeholders such as suppliers are becoming more knowledgeable about products' environmental impact. A firm can be seriously damaged if suppliers withdraw from it (He et al., 2011). Nonprofit organizations, such as Greenpeace in the Netherlands (Greenpeace International, 2018), take inventive actions for reducing resource over-consumption and they take action against companies that damage the environment.

1.1.3 Company performance measurement in the past and in the following fiscal years

Benchmarking is an important instrument for the effective management of organizations to determine system performance (Ho & Wu, 2006). Emerging business improvement methodologies, such as the total quality management, involve an element of benchmarking (Moffett et al., 2008). Benchmarking has been deployed (Madsen et al., 2017) within industries including manufacturing (Hong et al., 2012), education (Lau et al., 2018) and construction (Kim & Huynh, 2008). Performance benchmarking involves a comparison of measures (Adebanjo & Mann, 2008). It is crucial to choose those relevant economic performance measures and environmental performance measures that meet the conditions for MVMs.

Several indices have been used to assess MVMs combining their economic performance and environmental performance. For instance, the well-known Dow Jones Sustainability Indices World rates companies based on 24 factors from the economic, environmental and social dimensions. However, this index is only available for companies that rank the top 10% in their industries. MVMs that rank outside of the top 10% is not qualified to refer to this index. This dissertation focuses on a measurement method that can be applicable for any potential MVM. As the basis of the measurement method, company performance data need collecting and analyzing. Data at the company level generally is discrete in a series of periods. This type of data is classified as time-series data. Time series analysis can be used in business applications for forecasting a quantity into the future and explaining its historical patterns. Effective trend analysis of time series data can assist decision-makers to better understand the trend of company performance in the complex business environment.

1.1.4 Summary of research background

There is a call for MVMs to develop a method to measure their company performance from both an economic perspective and an environmental perspective. Benchmarking has been recognized as one of improvement techniques in the world (Al Nuseirat et al., 2019). In order to benchmark different MVMs, a time series data of their company performance need collecting. How to generate historical data as well as the trend data in the future is crucial. This dissertation focuses on company performance measurement methods for MVMs to measure their historical performance as well as the future performance from economic and environmental perspectives.

1.2 Problem statements

Several studies are in line with the concept of the third generation of company performance measurement. However, currently, there are three problems as follows.

1) For MVMs, environmental impacts can be measured in terms of resource consumption, emissions or environmental damage (Hahn et al., 2010). However, different MVMs adopt different performance measures. For instance, as one of the leading MVMs, Audi AG has adopted specific indicators to measure environmental impact reduction in production since 2011. The indicators are the average change (on a per-unit basis) of carbon dioxide (CO_2) emissions, energy, freshwater, organic solvents, wastewater, and waste. MVMs such as Bayerische Motoren Werke AG focus on five aspects in terms of the improvement in resource consumption and emissions from vehicle production. The five aspects include energy consumption, CO_2 emissions, waste for disposal, water consumption, process wastewater and solvent

emissions. In summary, one current problem in the field of company performance measurement is that there is a lack of a standard and consistent company performance measures from economic and environmental perspectives.

2) To quantify the multidimensional concept, performance analysts use composite indicators (CIs). A number of CIs have been elaborated in publications such as the tool book "Handbook on Constructing Composite Indicators" (Organisation for Economic Cooperation and Development, 2004) and "Handbook on Constructing Composite Indicators" (Joint Research Centre-European Commission, 2008). The majority of CIs focus on certain financial measures. The advantages of these financial measures are that they are easy to use and understand (Joo et al., 2009). As mentioned in Section 1.1.2, MVMs are expected to take a long-term view in contributing toward sustainable development. A literature survey on the existing CIs identified only seven articles that are utilized in the motor vehicle manufacturing sector. Among the seven articles, there are only two articles with CIs considering an environmental perspective. In summary, there is a lack of rigorous quantitative methods for measuring the comprehensive picture of MVMs' performance from economic and environmental perspectives.

3) Accurate trend analysis can enhance policymakers to better predict the trend of company performance. Forecasting is very important "in a firm's major decision-making" (Luo et al., 2018, pp. 334). So far, much concentration is on the historical performance and on the things that have already happened (Unahabhokha et al., 2007). Trend analysis of company performance mainly rely on experts' judgment and some financial data for decision-making. In other words, there is a lack of trend performance analysis for the following fiscal years.

Based on the problem statement analysis above, a research gap has been identified. A method to analyze the historical as well as the future company performance, with consistent measures and rigorous techniques, for MVMs is missing. The following section presents the research objective in this dissertation.

1.3 Research objective

The objective of this research is to develop a new company performance measurement method. This method is expected to solve the three current problems in the field of company performance measurement by taking MVMs' specific background into consideration. 1) Firstly, this method is with consistent company performance measures from economic and environmental perspectives. 2) Secondly, this method is with rigorous quantitative methods for measuring the multidimensional company performance. Specifically, the method is mathematically constructed with transparency in generating time series data. The dataset is built based on data which is available from public documents. 3) Thirdly, this method can provide a trend value for benchmarking the future company performance of MVMs in the following fiscal years.

1.4 Dissertation relevance

The relevance of this dissertation is presented from the viewpoints of a scientific nature and a societal nature respectively.

1.4.1 Scientific relevance

Most studies on company performance measurement focus on assessing the economic aspect with financial indicators relying on experts' scoring. An investigation of current problems during constructing compositor indicators (CIs) has a scientific impact on providing a state-of-the-art in CIs to performance analysts. This dissertation studies how company performance is measured with a new method that is especially suitable in the context of motor vehicle manufacturers (MVMs). This dissertation can distinguish itself from other studies in the field of company performance measurement in terms of 1) new company performance measures for MVMs from both an economic perspective and an environmental perspective, 2) applicable techniques to construct a new composite indicator to measure the company performance, and 3) trend analysis for the following three fiscal years. The development of this method is based on publicly available data. This dissertation is expected to work as the basis for the fourth generation of company performance measurement with new measures and methods.

1.4.2 Societal relevance

The approach for measuring the environmental performance is societally relevant for MVMs regarding reducing energy consumption, water consumption and CO_2 emissions during vehicles' production. According to the "cap and trade" principle of EU ETS, holders have to pay for the excessive carbon emissions during their production. The trend data generated in this dissertation is helpful for MVMs to get aware of the potential risks due to excessive carbon emissions fines and carbon tax bills. "The entry price of €10 per ton from 2021 is much too low, the price will stabilize on the market and can then rise to €120 to 130 per tonne, which many people demand." says the influential German economist Jens Südekum (FD, 2019). Better environmental performance is beneficial for MVMs with lower production costs as well as with a high reputation for sustainable development. In addition, better environmental performance may bring more support from organizations that take inventive actions for reducing resource overconsumption such as Greenpeace in the Netherlands.

The case study has societal relevance providing available statistics for trend analysis to statistical organizations. Statistics generated in this dissertation can be integrated as a modular into the statistic network in the organization such as the International Organization of Motor Vehicle Manufacturers and the European Environment Agency. The historical data generated by the new composite indicator of company performance over the fiscal year 2008 to 2017 is useful for the historical analysis of MVMs. The trend data based upon the forecasts over the fiscal years 2018 to 2020 can enhance policymakers to better predict the trend of different MVMs' performance and make decisions to avoid unexpected policy consequences. Data generated in this dissertation has practical relevance with stakeholders in the investment world such as asset management organizations. For sustainability-themed investments, the data helps the stakeholders identify the MVMs that are with positive environmental policies.

The approach developed for delivering a new composite indicator of company performance has practical relevance for setting up restrictions for MVMs. In addition, the comprehensive benchmarking from economic and environmental perspectives provides insights for MVMs to improve their performance, which is not obvious to observe from raw data.

1.5 Summary

This chapter has introduced the research background of this dissertation. A research gap in the research field has been presented, that is, a company performance measurement method with consistent measures and rigorous techniques from economic and environmental perspectives for MVMs is missing. In order to narrow down this research gap, the research objective in this dissertation has been proposed, that is, to develop a new company performance measurement method for MVMs to measure and benchmark their company performance from economic and environmental perspectives. The relevance of this dissertation has been listed from the viewpoints of a scientific nature and a societal nature. In order to achieve the research objective, a research design will be presented in the following chapter.

Chapter 2

Research Design

As mentioned in Section 1.2 in the previous chapter, there are three main problems in the field of company performance measurement. The first problem is that there is a lack of consistent measures of company performance measures from economic and environmental perspectives. The second problem is that there is a lack of rigorous quantitative methods for measuring the comprehensive picture of MVMs' performance from economic and environmental perspectives. The third problem is that there is a lack of the trend analysis of company performance for the following fiscal years. This dissertation aims to develop a new company performance measurement method for MVMs to measure their historical performance as well as the future performance from economic and environmental perspectives. In general, Chapter 2 is where literature is reviewed. In this dissertation, Chapter 2 presents a research design, providing the research scope, research questions and the approaches to solving the questions.

2.1 Research scope

This dissertation has focus on motor vehicle manufacturers for two main reasons as follows.

1) The motor vehicle manufacture is of economic significance and "is one of the largest manufacturing activities in the world" (Sánchez & Pérez, 2005, pp. 689). This industry is "an engine of industrial development, provider of technological capability, and generator of inter-industrial linkages" (Olugu & Wong, 2012, pp.376). This research, with a focus on this industry, can be beneficial to motor vehicle manufacturers and the other manufacturing industries in general.

2) Under the pressure from EU ETS (European Commission, 2018), the European Parliament (European Parliament, 2018), and etc, manufacturers have to consider greenhouse gas (GHG) emissions reductions during their production processes. The motor vehicle manufacturing industry itself is "one of the most resource-intensive industrial systems in the world" (Mildenberger & Khare, 2000, pp. 208). In return, a large volume of CO_2 has been emitted, which contributed around 73% to global greenhouse gas (PBL Netherlands Environmental Assessment Agency, 2018). It is estimated that up to 16% of global man-made CO_2 emissions comes from the production of motor vehicles (International Organization of Motor Vehicle Manufacturers, 2019). It is high time for motor vehicle manufacturers to raise awareness from an environmental perspective.

Prior to developing the new company performance measurement method, this section is going to set up a scope statement. This section defines the scope of the terms including motor vehicles, motor vehicle manufacturers, and company performance from economic and environmental perspectives.

2.1.1 Motor vehicles

The North American Industry Classification System (abbreviated as NAICS) is a classification of business sectors by type of economic activity. Various specific sectors such as the transportation equipment-manufacturing sector are included in 2017 NAICS Sectors (United States Census Bureau, 2017). According to the classification by 2017 NAICS, the motor vehicle manufacturing sector (code: 3361) consists of two sub-sectors, including the automobile and light-duty motor vehicle manufacturing (code: NAICS 33611) and the heavy-duty truck manufacturing sector (code: NAICS 33612). The International Organization of Motor Vehicle Manufacturers (OICA) is the world association of the national automobile industry federations. Founded in 1919 in Paris, OICA is committed to the global harmonization of safety, environmental standards, and fuel efficiency, and this organization represents the common interests of the global auto industry. OICA is considered as the voice speaking on automotive issues in world forums (Organization of Motor Vehicle Manufacturers, 2017). This dissertation refers to the information from NAICS and OICA to get the scope of motor vehicles and the scope of motor vehicle manufacturers.

The term motor vehicles used in this dissertation pertains to the vehicles including passenger cars, light commercial vehicles, heavy trucks, buses and coaches. According to the definitions from OICA and from Glossary for Transport Statistics, different types of vehicles in this dissertation are defined as follows:

- Passenger cars are motor vehicles with at least four wheels, used for the transport of passengers, and comprising no more than eight seats in addition to the driver's seat.
- Light commercial vehicles are motor vehicles with at least four wheels, used for the carriage of goods. Maximum authorized mass depends on national and professional definitions with the limit (ranging from 3.5 to 7 tonnes).
- Heavy trucks are vehicles intended for the carriage of goods. Maximum authorized mass is over the limit (ranging from 3.5 to 7 tonnes) of light commercial vehicles.
- Buses and coaches are used for the transport of passengers, comprising more than eight seats in addition to the driver's seat, and having a maximum mass over the limit (ranging from 3.5 to 7 tonnes) of light commercial vehicles.

2.1.2 Motor vehicles manufacturers

The term motor vehicle manufacturers (MVMs) used in this dissertation pertains to manufacturers that are primarily engaged in the design and manufacture of motor vehicles including passenger cars, light commercial vehicles, heavy trucks, buses, and coaches. There are different categories when it comes to the dominant MVMs. For instance, fourteen MVMs have been identified dominant in the global automotive market. As shown in Figure 2.1, the MVMVs include Ford, Daimler, Toyota, Nissan, Renault, PSA, Volkswagen, GM, FCS, TATA, Honda, BMW Group, Greely and Hyundai.

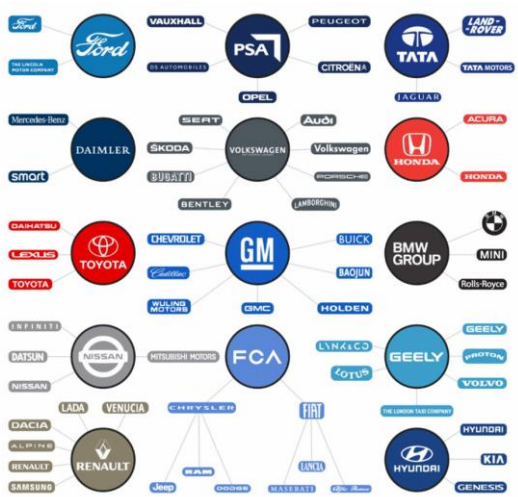


Figure 2.1: Dominant MVMs in the global automotive market (Business Insider, 2018)

Fifty MVMs have been identified as top MVMs in terms of the production volume by OICA. The MVMs include Toyota, Volkswagen, Hyundai, General Motors, Ford, Nissan, Honda, Fiat, Renault, PSA, Daimler, BMW, Mazda, Mitsubishi, Tata, Suzuki, Saic, Changan, Baic, Dongfeng Motor, Geely, Great Wall, Fuji, Chery, Anhui JAC automotive, Iran Khodro, Isuzu, Mahindra, FAW, Saipa, BYD, Brilliance, Guangzhou auto industry, Hunan Jiangnan, Chongqing Lifan motor co., Avtovaz, China national heavy-duty truck, Haima cars, Ashok Leyland, Paccar, Shannxi, South east (Fujian), Changfeng, GAZ, Rongcheng huatai, Ximen King Long, Proton, Zhengzhou Yutong, Chengdu Dayun and Eicher (Organization of Motor Vehicle Manufacturers, 2017). The 14 MVMs listed in Business Insider have been included in the 50 MVMs in OICA. The scope of MVMs in this dissertation is shown in Figure 2.2.

Figure 2.2: Scope of motor vehicle manufacturers

2.1.3 Company performance from economic and environmental perspectives

The term company performance from economic and environmental perspectives pertains to how well an MVM performs from an economic perspective and an environmental perspective.

The economic performance of companies can be defined as "an assessment for an organization of its success in areas related to its assets, liabilities and overall market strength. Many business operators take regular stock on either a formal or less formal basis of the general economic performance of their company to make sure that it remains on the right track financially" (Business dictionary, 2019).

Company environmental performance can be defined as "the organization's performance with respect to their environmental responsibilities" (Yang et al., 2011, pp. 252). Energy, water, greenhouse gas emissions, toxic releases and spills (Poser et al., 2012; Eilola, 2017) can be used in environmental performance. Screening companies use different criteria for environmental performance. For instance, KLD Research & Analytics, Inc. conducts environmental analysis based on criteria including products and services, operations and management. This dissertation exclusively includes criteria that are measurable and their data are publicly available.

2.2 Research questions

The main research question of this dissertation is

How to measure company performance with composite indicators from economic and environmental perspectives for MVMs?

As presented in Section 1.2, a method to measure the company performance from economic and environmental perspectives, with consistent measures and rigorous techniques for MVMs, is missing. To narrow down this research gap, the objective of this research is to develop a new company performance measurement method. This method is expected to solve the three current problems in the field of company performance measurement concerning MVMs' specific background. The main research question can be answered through proposing a new company performance measurement method, specifically by developing 1) consistent company performance measures from economic and environmental perspectives, 2) rigorous quantitative methods for measuring the multidimensional company performance, and 3) trend analysis models for benchmarking company performance of MVMs in the following fiscal years.

The main research question is broken into five sub research questions (SRQs):

SRQ_1: What is the state-of-art in current composite indicators of company performance for MVMs?

According to the Glossary of Statistical Terms, a composite indicator (CI) is "formed when individual indicators are compiled into a single index, on the basis of an underlying model of the multidimensional concept that is being measured" (Organization for Economic Cooperation and Development, 2007, pp. 125). As mentioned in Section 1.2, the majority of CIs are at broader levels rather than at the company level. It is necessary to identify and analyze the CIs that are utilized in companies. In order to answer SRQ_1, Chapter 3 will conduct a literature review on current CIs of company performance, focusing on 1) which techniques that are used for constructing the CIs, and 2) which business sectors these CIs have been utilized in practice and how about CIs' utilization in the motor vehicle manufacturing sector.

SRQ_2: What company performance measures can be applied to construct CIs of MVMs' performance from economic and environmental perspectives?

During the development of CIs, identifying relevant measures is a crucial phase (Freudenberg, 2003). However, as mentioned in Section 1.2, there is a lack of consistent measures of company performance measures from economic and environmental perspectives. As a result, different MVMs adopt different performance measures. It is necessary to identify consistent measures for different MVMs as the input for constructing CIs. In general, identifying and validating the underlying indicators can be undertaken through an extensive literature review. In order to answer SRQ_2, Chapter 4 will identify measures based on literature review, relevant documents, and guidelines for MVMs.

SRQ_3: What methods are used to construct the CI, for generating the historical company performance data for MVMs?

The historical company performance means the company performance in the previous or past fiscal years. To quantify the multidimensional company performance, performance analysts use CIs. It is crucial to understand the techniques for constructing CIs. There are various kinds of techniques for constructing CIs. If properly conceived, CIs can work as an effective statistical tool for calculating and analyzing company performance. However, CIs can "send misleading policy messages if poorly or misinterpreted constructed" (Joint Research Centre-European Commission, 2008, pp. 13).

There are several phases in constructing CIs. In order to answer SRQ_3, Chapter 5 will construct an index of company performance during the fiscal year 2008 to 2017. The development of the index will focus on five phases including the phase for selecting measures, the phase for normalizing the measures, the phase for weighing the measures, the phase for aggregating individual measures into a single one, and the phase for post analyzing the CIs.

SRQ_4: Given the information of MVMs' historical performance, what methods can be used to generate their future performance data for the following fiscal years?

Effective trend analysis can aid decision-makers to plan for the future by understanding how changes in inputs affect outcomes. Current studies focus more on measures for the historical company performance. As mentioned in Section 1.2, there is a lack of trend company performance analysis for the following fiscal years. Accurate forecasts require more work than simply multiplying data from the historical company performance.

In order to answer SRQ_4, Chapter 6 will build autoregressive integrated moving average models to generate trend performance data for the following three fiscal years. The minimum Akaike information criteria value will be used to identify the model of the best fit. Trend analysis accuracy of the models will be tested by the mean absolute percentage error.

SRQ_5: How to realize the visualization of company performance data of MVMs?

Currently, several tools are being adopted to rank or rate companies. The majority involves a third party who can collect the data, make the comparison and provide feedback but on a confidential basis (Managing Innovation, 2019). In addition, the tools only target at top companies, which means that not every MVM is qualified to be included. This dissertation aims to contribute with the new company performance measurement method that is accessible for potential users to use. In order to answer SRQ_5, Chapter 7 will develop a measurement tool. The tool comprises a set of programs and databases developed using SQL, JavaScript and Preprocessor Hypertext. The tool will be tested with random inputs, which can indicate whether the measurement tool is an accessible and feasible tool for any MVM to measure its company performance.

2.3 Research approaches

In order to address the main research question as well as the five sub research questions, a new composite indicator of company performance needs constructing from economic and environmental perspectives for MVMs. For obtaining the knowledge of the state-of-art in current CIs for MVMs, literature in this field needs reviewing. For generating quantitative data of the company performance, data analysis techniques are required. As presented in Section 2.1.2, the top fifty MVMs in terms of the production volume by OICA will be used as an intensive study about the MVMs in general. For visualizing the data that are generated in this research, an online measurement tool will be developed via a website. Therefore, in this dissertation, it is necessary to adopt four approaches, including 1) literature review, 2) data analysis, 3) case study, and 4) web development.

2.3.1 Literature review

To identify and discuss the eligible literature referencing topics of the state-of-the-art in this dissertation, one of the approaches is to review the existing literature. The literature review in this dissertation is based on the preferred reporting items by Moher et al. (2009) and the guidelines as proposed by Keele (2007). Moher et al. (2009) proposed a checklist of items to include when reporting a systematic review or meta-analysis. Items such as eligibility criteria, information sources, search, data collection process, and summary measures are included. Keele (2007, pp. 6) summarized three main phases in a literature review: planning the review, conducting the review and reporting the review. In this dissertation, literature is reviewed in light of the following topics: 1) company performance measurement, 2) stakeholder theory, 3) environment management, 4) trend analysis, and 5) benchmarking.

2.3.2 Data analysis for the development of composite indicators

In order to conduct data analysis on company performance, quantitative measurement techniques are required. As listed in Figure 2.3, this dissertation focuses on five phases for developing CIs, including the phase for selecting measures, the phase for normalizing the measures, the phase for weighing the measures, the phase for aggregating individual measures into a single one, and the phase for post analyzing the CIs.

There are various kinds of techniques for each phase. Multi-criteria decision-making (MCDM) is one of widely used methodologies in fields like business and economy (Mardani et al., 2015; Rabbani et al., 2014). During the development of CIs, commonly used MCDM techniques include Analytic Hierarchy Process (Saaty, 1987), Analytic Network Process (Saaty, 1996), VlseKriterijumska Optimizacija I Kompromisno Resenje (Duckstein & Opricovic, 1980), Grey Relational Analysis (Deng, 1982), Technique for Order of Preference by Similarity to Ideal Solution (Lai et al., 1994), Non-compensatory Multi-criteria (Cook et al., 1988), Decision Aid for Multi-Attribute Evaluation Using Imprecise Weight Estimates (Jessop, 2014), Best-Worst Method (Rezaei, 2016) and Decision-Making Trial and Evaluation Laboratory by the Science and Human Affairs Program of Battelle Memorial Institute of Geneva.

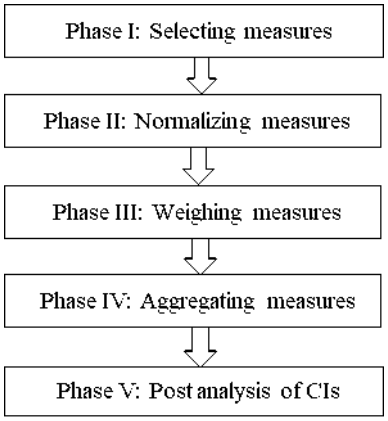


Figure 2.3: Phases during the development of CIs (source: author)

Subjectivity and imprecision always exist during decision-making processes (Zimmermann, 2000). In general, for weighing measures and calculating the CIs, detailed data is extracted from sample companies' annual financial reports, sustainability reports and global reporting initiative reports. If detailed data is unavailable, researchers need to use MCDM techniques or totally rely on subjective scoring for weighing measures. In this case, the inherent subjectivity or ambiguous information during the weighing process needs to be handled. Fuzzy theories, also called fuzzy logic (Klir & Yuan, 1995) can be utilized to provide an inference structure for relatively precise deductions (Grabisch, 1996).

Besides, statistical-based techniques or mathematics-based techniques are used in quantitative research. Commonly used statistical-based tools include Correlation Analysis (Dodge, 2006), Factor Analysis (Kim et al., 1978), Panel Analysis (Blundell and Bond, 1998), Descriptive Statistics (Dodge, 2006) and Regression Analysis (Rawlings et al., 2001). Commonly used mathematics-based techniques include Data Envelopment Analysis (Seiford & Thrall, 1990), Structural Equation Model (Jöreskog & Sörbom, 1993), Equal Weighting (Einhorn & Hogarth, 1975), Shannon Entropy Technique (Shannon, 1948), Monte Carlo Simulation by (Mooney, 1997), linear programming and logistic regression.

Based on the feature of the dataset in this dissertation, regression analysis and Shannon Entropy technique will be used for weighing measures and min-max based normalization will be developed for normalizing measures.

2.3.3 Case study

This dissertation adopts the case study method because the case study is a preferred method when the how-to-do question is being asked about a phenomenon within some real-life context (Yin, 2017). A case study can be defined as an intensive study about a person, a group of people or a unit, which is aimed to generalize over several units. In a case study, the focus is based on an especially unit (Jacobsen et al., 2002). A case study is a history of a past or current phenomenon, drawn from multiple sources of evidence. The case study method allows the questions of why, what and how, to be answered with a relatively full understanding of the nature and complexity of the complete phenomenon (Benbasat et al., 1987). It can include data from direct observation and systematic interviewing as well as from public and private archives.

Dul and Hak (2007) state that the case study research strategy can be used for analyzing practical business problems. In order to give a methodological framework to design case studies with scientific rigor, Dul and Hak propose processes for different kinds of case study

research (Dul & Hak, 2007, pp. 38). This dissertation refers to this case study process by Dul and Hak (2007) to develop new company performance measurement models to generate the data of company performance. A model-building approach will be integrated in the next sections.

2.3.4 Web development

In order to enable readers with insights, a website is developed for visualizing this research. The web development in this dissertation can provide an online tool for society to use. The online tool comprises a set of programs and databases developed by the structured query language (SQL), JavaScript and Preprocessor Hypertext (PHP). PHP is a server-side web programming language used for web development, easy to integrate with web pages, and it is with open source (Gosselin, 2006). MySQL is commonly used in conjunction with PHP scripts to create powerful and dynamic server-side applications (Welling & Thomson, 2005). Data of company performance for different MVMs can be generated as outputs.

2.3.5 Model building approach

As mentioned in Section 2.3.3, a model-building approach will be integrated. This section presents a model-building approach that is based on the four research approaches from Section 2.3.1, 2.3.2, 2.3.3 and 2.3.4. As shown in Figure 2.4, the first column lists the five sub research questions SRQ_1 to SRQ_5. In order to answer the questions, the four approaches are provided in the second column. The content in both the first column and the second column has been presented in Chapter 2. Content from Chapter 3 to Chapter 7 answers the research questions with respective approaches. For instance, in order to answer SRQ_3, a literature review will be conducted on the art-of state in composite indicators of company performance. Quantitative models will be developed with data analysis techniques and with data collected from the case study MVMs.

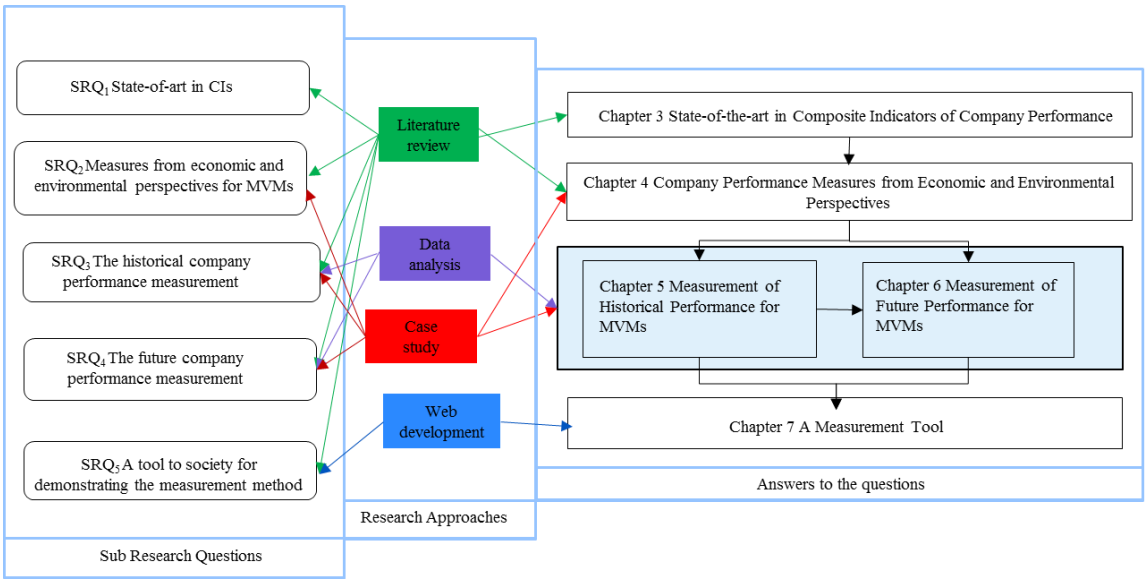


Figure 2.4: Model-building flowchart in this research

2.4 Structure of this dissertation

As shown in Figure 2.5, Chapter 2 presents the research scope in this dissertation, the main research question as well as the sub-questions. The approaches that will be adopted to solve the questions are introduced.

Chapter 3 provides an understanding of company performance measurement for MVMs. A literature survey on composite indicators of company performance measurement is performed. This chapter is based on a publication to *Performance Improvement Quarterly*.

Chapter 4 proposes a preliminary model of company performance measurement from economic and environmental perspectives for MVMs. All the measures are with publicly available data. This chapter is based on a publication to *Journal for the Advancement of Performance Information and Value*, and a publication on the 5_{th} International Conference on Industrial Engineering and Applications.

Chapter 5 develops a quantitative approach of company performance measurement for MVMs, with an index I_{MVM} as an outcome. The index I_{MVM} is assessed through a benchmark against several criteria. This chapter is based on an under-review manuscript to *International Journal of Productivity and Performance Management*, and a publication on the 25_{th} International Annual European Operations Management Association Conference.

Chapter 6 develops an approach to generating the trend I_{MVM} data in the following fiscal years by autoregressive integrated moving average models. The minimum AIC value is used to identify the model of the best fit. The trend analysis accuracy of the ARIMA models is tested by the mean absolute percentage error with the horizon period h=4. This chapter is based on a publication to *Benchmarking: An International Journal*, and a publication on the 26_{th} International Annual European Operations Management Association Conference.

Chapter 7 visualizes the research via a website developed using JavaScript and Hypertext Preprocessor. An online calculator is set up with eleven measures as inputs. Data of company performance from economic and environmental perspectives are as outputs. The outputs are compared with fifteen leading MVMs. The weaknesses of MVMs can be pointed out through real-time graphs.

Chapter 8 concludes that a company performance index can be constructed to generate the company performance data from economic and environmental perspectives for MVMs. The data is useful for benchmarking MVMs from economic and environmental perspectives. It concludes the answers to the main research question, the answers to sub-questions, and the contributions obtained during the course of this research. To conclude, the recommendations for further research are reflected.

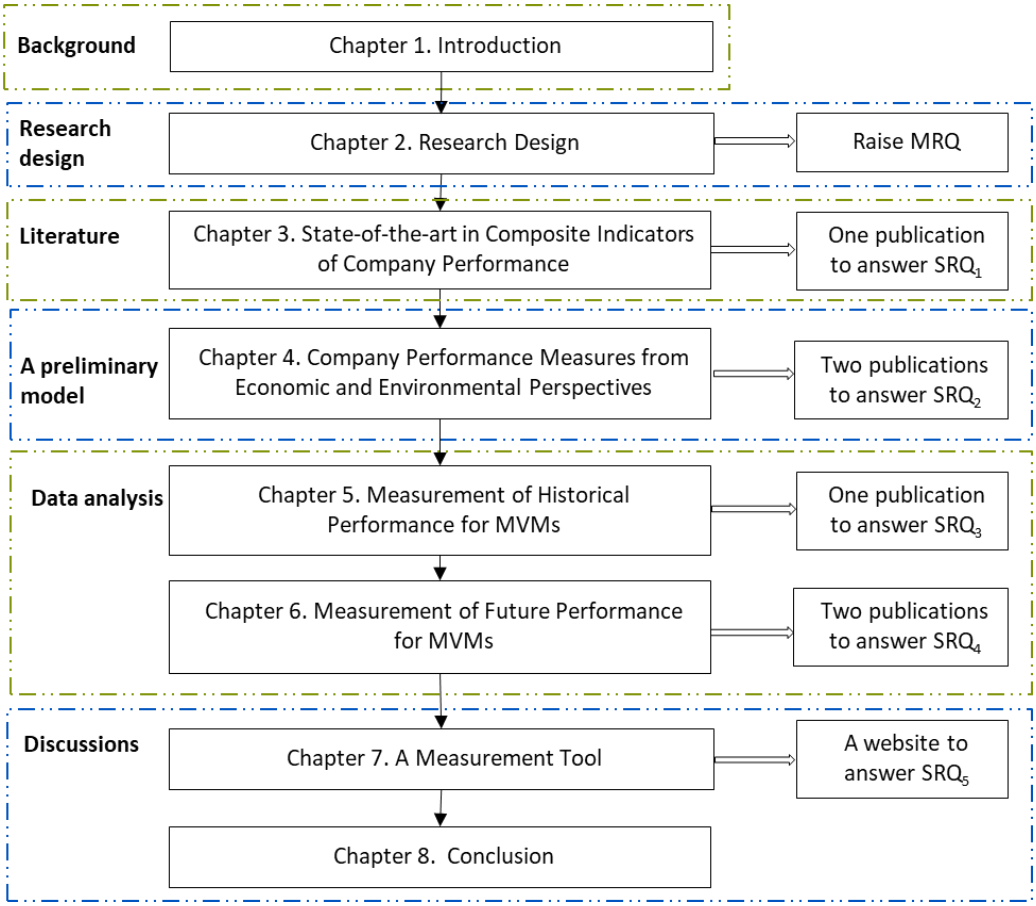


Figure 2.5: The structure of this dissertation

Chapter 3

State-of-the-art in Composite Indicators of Company Performance

3.1 Introduction

The previous chapter brought up the main research question and sub research questions in Section 2.2. In order to answer the first sub research question, this chapter reviews the state-of-the-art in composite indicators of company performance.

This chapter is organized as follows. Section 3.2 presents an understanding of company performance measurement by introducing the first generation, the second generation, and the third generation of company performance measurement. Section 3.3 develops a literature search strategy on composite indicators (CIs) of company performance that have been utilized in business sectors. Section 3.4 reviews the literature in terms of the techniques used for constructing the CIs. Section 3.5 consists of discussions of the general problems during the development of CIs, and discussions of the specific problems during the development of CIs in the motor vehicle manufacturing sector. Section 3.6 and Section 3.7 summaries and concludes this chapter respectively. Section 3.8 presents the reflection on this chapter, raising awareness of company performance measurement from both an economic perspective and an environmental perspective. This provides motivations for Chapter 4.

Section 3.2, Section 3.3, Section 3.4, Section 3.5 and Section 3.6 are from:

Zeng, Q., Beelaerts van Blokland, W. W. A., Santema, S. and Lodewijks, G. (2020), Composite indicators of company performance: a literature survey. *Performance Improvement Quarterly*， Published as Early View 1-34.

3.2 Company performance measurement

The term "performance" is widely used in all fields of management. Performance is defined as a notion that is used to assess the quality of individual and collective efforts (Corvellec, 2018). The specific meaning that performance takes in an organization is suggested as the result of extensive discussions between the various managers or decision-makers of the organization (Neely et al, 2007). Company performance measurement is fundamental for decision-makers to monitor performance and to solve management problems. Traditionally, financial performance is considered as company performance. For instance, the returns on capital employed and market to book value (De Wet & Du Toit, 2007) were employed as company

performance indicators. Return on assets (Hagel III et al., 2010) and cash flow return on investment (Aust, 2010) were considered as "the best way" to measure company performance. In addition, multiple measures such as the combination of the market to book value, company size and return on capital (Adeneye, 2015) were employed as company performance measures.

Financial analysis systems such as DuPont System are used to measure company performance. Due to the complex global business environment, company performance has evolved into the integration of both financial and non-financial indicators. Since the late 1980s, academics and practitioners have tried to improve methods of measuring company performance by developing concepts such as activity based costing (Cooper and Kaplan, 1987). Several comprehensive company performance frameworks have been developed as the first generation of company performance measurement, including the balanced scorecard (Kaplan & Norton, 1995), the performance prism (Neely & Adams, 2002) and the Skandia's Navigator (Edvinsson, 1997). The frameworks supplement the traditional financial measures with non-financial measures. Meanwhile, one challenge showed up, namely, how to link and integrate all of the individual measures from different perspectives. As a response to this challenge, the second generation turned to address the dynamic of value creation by investigating transformations of resources. Several company performance measurement frameworks have been developed and applied, mainly including strategy maps (Kaplan & Norton, 2000), success maps (Neely et al., 2002) and intellectual capital navigator models (Roos et al., 2001). However, these frameworks have a fundamental weakness. There is no ability to link the business-oriented methodology to real free cash flow, which is the cornerstone of market valuation (Pike & Roos, 2001). In order to seek clarity between business orientated and financially orientated company performance measurement from broader perspectives, the third generation of company performance measurement was proposed with emphasize on the cash flow consequences of the non-financial and intangible activities within companies (Neely et al., 2003).

3.2.1 The first generation of company performance measurement

Since the 1980s, there have been criticisms stating that accounting measures are "lagging indicators". As a result, "the measures do not provide much guidance for what must be done differently" (Eccles & Pyburn, 1992, pp. 41). Academics and practitioners began to seek new ways of measuring company performance. Some researchers tried to improve methods of measuring financial performance by developing and applying concepts such as activity-based costing. Other researchers tried to supplement traditional financial measures with non-financial measures. Several comprehensive frameworks have been developed such as the balanced scorecard (BSC), the performance prism and the Skandia's Navigator. The BSC integrates four perspectives in terms of financial, customer, internal business, innovation and learning aspects. An example of the BSC is shown in Figure 3.1.

Despite the widespread use of the first generation of company performance measurement, there are several shortcomings since they are static and fail to illustrate adequately the linkages between different performance measures. For instance, the shortcomings of BSC are identified as follows: 1) suppliers are excluded and regulators and competitors are ignored (Marr & Adams, 2004), 2) environmental and community or social issues/aspects are missing (Brignall, 2002). Therefore, frameworks such as the performance prism have been developed which adopt a broader perspective on stakeholders. However, other complex issues arise such as who are the key stakeholders and what do they want and need, what strategies do companies have to put in place to satisfy these needs, and what do companies expect from the stakeholders in return.

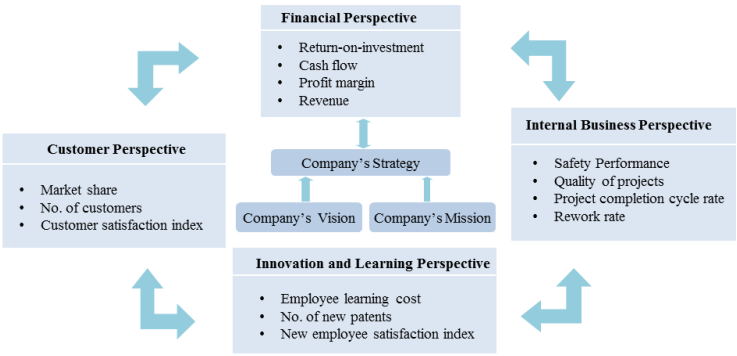


Figure 3.1: An example of the balanced scorecard system

3.2.2 The second generation of company performance measurement

The issues mentioned above have been addressed by the second generation of company performance measurement. This measurement uses strategy maps (Kaplan & Norton, 2000), success maps (Neely & Adams, 2002) to take into account the dynamic nature of performance and the transformation processes linking objectives and resources. The reliance on success and failure maps provides a flexible structure that enables companies to map everything that is important to them in their success maps. However, the second generation of company performance measurement does not attempt to link the business-orientated methodology to real free cash flow. This fundamental shortcoming provides the onset for the development of the third generation of company performance measurement.

3.2.3 The third generation of company performance measurement

The third generation requires companies to seek greater clarity about the linkages between the non-financial and intangible dimensions of company performance and the cash flow consequences. There are three fundamental criteria for developing the third generation (Pike & Roos, 2001): 1) appropriateness and adequacy, 2) information adequacy, and 3) practicality and organizational alignment.

In summary, as shown in Figure 3.2, the evolution of company performance measurement started from a pure financial-biased framework. The first generation achieved through supplementing the traditional financial measures with non-financial measures. The second generation addressed the dynamic of value creation by investigating transformations of resources. Both the first generation and the second one have gained appropriateness in how they reflect the realities in companies. The third generation emphasizes the business-orientated methodology to real free cash flow activities. This dissertation focuses on quantitative company performance measurement from economic and environmental perspectives, which will be addressed as the basis for the fourth generation of company performance measurement.

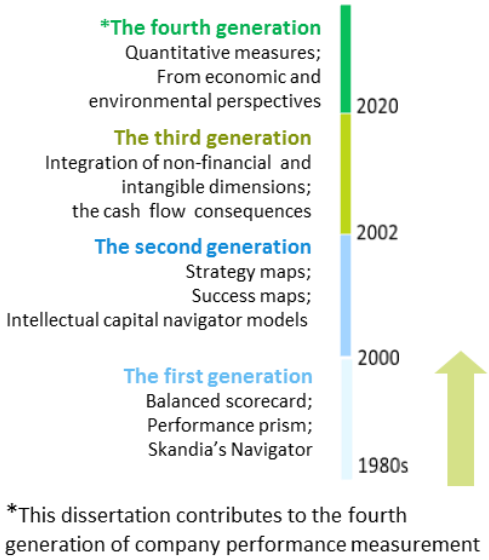


Figure 3.2: Demonstration of the four generations of company performance measurement methods

3.3 Composite indicators

A composite indicator may be defined a single index which "is formed when individual indicators are compiled into a single index, on the basis of an underlying model of the multidimensional concept that is being measured" (Organization for Economic Cooperation and Development, 2007, pp. 125). In recent years, CIs have increasingly been accepted as a useful tool for benchmarking, performance comparisons, policy analysis and public communication in different fields (Zhou et al., 2006). For developing a CI, ten phases have been suggested in the checklist, including a theoretical framework, data selection, imputation of missing data, multivariate analysis, normalization, weighing and aggregation, uncertainty and sensitivity analysis, back to the data, links to other indicators, and visualization of the results (Joint Research Centre-European Commission, 2008). The idea of CIs is so attractive that a large volume of publications has been devoted to this subject. However, the majority of CIs derived are on social and environmental issues, and at macro levels, such as at the national level or the regional level (Zeng et al., 2018). Composite indicators that have been utilized at the company level in specific business sectors such as the manufacturing sector are relatively limited.

The following section comprises a literature survey on existing CIs of company performance measurement methods. There are two underlying motivations to write this section. 1) Provide an up-to-date literature survey on the existing CIs at the company level. 2) By analyzing the references retrieved, the authors aim to identify the current problems during CIs' construction in the motor vehicle manufacturing sector, which can benefit practitioners with a more transparent implementation of constructing CIs. With a better understanding about how CIs work in monitoring company performance, stakeholders such as financial institutions can effectively benchmark company performance. A clear literature survey method is demanded as the very first step in the literature survey processes. Keele (2007, pp. 6) summarized three main steps in a literature review: planning the review, conducting the review and reporting the review. In this dissertation, developing questions is specified in the planning the review step. The search processes are specified in conducting the review step. The search result is presented in reporting the review step.

3.3.1 Planning the reference search

This section tries to answer the first sub research question: what the state-of-art in current CIs of company performance for MVMs is. This dissertation has a focus on the motor vehicle manufacturing sector. This dissertation conducts a literature review on current CIs of company performance, focusing on 1) which techniques that are used for constructing the CIs, and 2) which business sectors these CIs have been utilized in practice, specifically, how about CIs' utilization in the motor vehicle manufacturing sector.

Which techniques are used for constructing the composite indicators?

It is crucial to understand the techniques for constructing composite indicators (CIs). There are various kinds of techniques for constructing CIs. If properly conceived, CIs can work as an effective statistical tool for calculating and analyzing performance. However, CIs can "send misleading policy messages if poorly or misinterpreted constructed" (Joint Research Centre-European Commission, 2008, pp. 13).

A crucial role is played by the concept of weighing the variables (Munda & Nardo, 2005). In addition, Freudenberg (2003) discussed other crucial phases including the phase for identifying and developing relevant measures, the phase for standardizing measures to allow comparisons, the phase for weighing measures and groups of measures, and the phase for conducting sensitivity tests on the robustness of aggregated measures.

This dissertation focuses on five phases including Phase I for selecting measures, Phase II for normalizing measures, Phase III for weighing measures, Phase IV for aggregating individual measures into a single index, and Phase V for the post analysis of the CIs. In order to answer SRQ_1, the techniques used in the CIs will be identified in Section 3.4.

Given the CIs identified, which business sectors have these CIs been utilized in practice and how about CIs' utilization in the motor vehicle manufacturing sector?

The construction of CIs cannot be directly generalized from one sector to another sector. Measures as well as their weights vary from one sector to another. This is in line with the statement that performance measurement needs to be based on sectors exclusively due to reasons such as sector gaps (Yildiz et al., 2011). In order to SRQ_1, the literature review in terms of the techniques used during the five phases and in terms of the CIs' utilized sectors is conducted in the following subsections.

3.3.2 Conducting the reference search processes

Keywords search

In this dissertation, literature is reviewed in light of the following topics: 1) company performance measurement and 2) composite indicator. Keywords are collected based on the research question and the two sub-questions. This process entailed keyword searches for composite indicators; index; indices; company performance; performance measurement; company assessment and performance indicator. The keyword search queries are listed in Table 3.1.

Table 3.1: Keyword search queries

	Combine with **AND**	
Combine with **OR**	*company performance*	*composite indicator*
	*performance measure**	*index*
	*performance assess**	*indices*

This section takes two stages as the literature search strategy. Stage I involves fourteen criteria that are used to include potential studies. Stage II involves three criteria that are used to exclude the ineligible results from Stage I.

Fourteen criteria in Stage I

As shown in Table 3.2, the first three criteria C_1, C_2 and C_3 mean collecting potential references via the three sources. Although there are many sources that could be used for the literature search, this section focuses on Web of Science core collection, Scopus and Google Scholar. Web of Science Core Collection indexes primary journals and article citations in several databases spanning a wide range of disciplines (UK Libraries, 2019). Scopus and Google Scholar are chosen because 1) they cover the world's scientific and scholarly literature comprehensively (Aksnes & Sivertsen, 2019), and 2) they represent major competitors to Web of Science in the field of bibliometric (Yang & Meho, 2006).

C_4 in Table 3.2 indicates that the literature search dates back to the year 2004, considering 2004 is the year when 1) Google Scholar was launched and 2) the most accepted concept of the composite indicator was presented at the OECD Committee on Statistics (Organization for Economic Cooperation and Development, 2007, pp.5).

C_5 - C_7 in Table 3.2 mean articles are full papers published in academic journals. In other words, the documents type for Web of Science core collection is *Article,* for Google Scholar is *Article*, and for Scopus is *Articles.*

C_8 - C_{10} in Table 3.2 indicate the field tags where keywords are retrieved. The field tags for Web of Science core collection is *In Title,* for Google Scholar is *anywhere in the article,* and for Scopus is *In Abstract title, Abstract, keywords.*

C_{11} in Table 3.2 means the language of the articles is English.

C_{12} - C_{13} in Table 3.2 indicate the research subject/area of the literature search. This dissertation is in the field of company performance management and measurement. Therefore, for Web of Science core collection, the research subject/area includes scoped as Mathematics; Operations research management science; Business economics; Social issues; Mathematical methods in social sciences. For Scopus the research subject/area includes Mathematics; Business, Management and Accounting; Decision Sciences; Multidisciplinary; Social Science; Economics, Econometrics and Finance.

C_{14} in Table 3.2 indicates that for Web of Science core collection, the literature search can be scoped further by setting up the Web of Science Categories as Mathematics applied; Mathematics interdisciplinary applications; Mathematics; Statistics probability; Operations research management science; Economics; Multidisciplinary sciences; Business; Business finance; Management; Social sciences mathematical methods; Ecology; Social issues.

In summary, for Web of Science Core Collection, the inclusion criteria include C_1, C_4, C_5, C_8, C_{11}, C_{12} and C_{14}. For Google Scholar, the inclusion criteria include C_2, C_4, C_6, C_9 and C_{11}. For Scopus, the inclusion criteria include C_3, C_4, C_7, C_{10}, C_{11} and C_{13}.

Three exclusion search criteria in Stage II

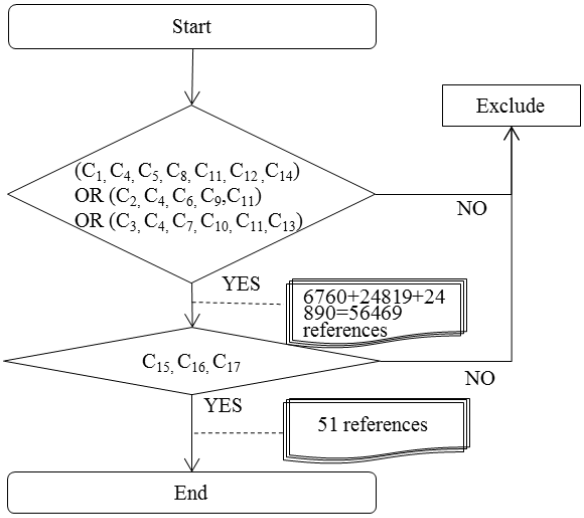
In Stage II, the search results after Stage I need double-checking by excluding 1) C_{15}: the article that is a duplicate reference from EndNote. In other words, articles that are overlapped in Web of Science core collection, Scopus or Google Scholar, 2) C_{16}: when looked into its full text, the article mentions the CI which is not utilized in sectors at the company level, and 3) C_{17}: articles, such as Digalwar et al. (2015), focusing on developing theoretical frameworks rather than focusing on quantitative models for constructing CIs. The information of the seventeen criteria are shown in Table 3.2.

Table 3.2: Criteria for reference search

Stage	Content	Criterion
I	Database	C_1 Web of Science Core Collection C_2 Google Scholar C_3 Scopus
	Time Span	C_4 From 2004 to 2018
	Document Types	C_5 Article C_6 Articles C_7 Article
	Search Keywords from	C_8 In Title C_9 Anywhere in the article C_{10} In Abstract title, Abstract, keywords
	Language	C_{11} English
	Research/ Subject Areas	C_{12} Mathematics; Operations research management science; Business economics; Social issues; Mathematical methods in social sciences C_{13} Mathematics; Business, Management and Accounting; Decision Sciences; Multidisciplinary; Social Science; Economics, Econometrics and Finance
	Web of Science Categories	C_{14} Mathematics applied; Mathematics interdisciplinary applications; Mathematics; Statistics probability; Operations research management science; Economics; Multidisciplinary sciences; Business; Business finance; Management; Social sciences mathematical methods; Ecology; Social issues
II	Exclusion	C_{15} Duplication Checking with EndNote C_{16} Articles with CIs that are not utilized in sectors at the company level C_{17} Articles that are not focusing on quantitative models or techniques for constructing CIs.

3.3.3 Reporting the search results

The search result is shown in Figure 3.3. After Stage I with the inclusion criteria C_1 - C_{14}, this dissertation searched 56469 potential articles. After Stage II with the exclusion criteria C_{15} - C_{17}, this dissertation finally identifies 51 individual articles with CIs that are utilized in sectors at the company level. Twenty-five articles are from Web of Science Core Collection, eleven articles are from Google Scholar and fifteen articles are from Scopus.



Note: The meaning of C_1 to C_{17} refer to Table 3.3

Figure 3.3: Search results with two stages

To answer the question "which techniques are used for constructing the CIs", a search result with the information of the CIs, the authors with the publication year, and the CI's utilized context is listed in Table 3.3.

Table 3.3: Search results: the name of the CIs, the authors with the publication year, and the CIs' utilized context

No.	Name of the CI	Author (Year), Source[a]	The CI's utilized context
1	An airline safety index	Chang and Yeh (2004), C_1	Four major airlines in China
2	A knowledge management performance index	Lee et al. (2005), C_1	One hundred one firms in Korea
3	A financial performance index	Sohn et al. (2007), C_1	One thousand one hundred fifty-two firms in Korea
4	A Governance Index	Chen et al. (2007), C_1	Three thousand two hundred thirty-three firms in China
5	A sustainability performance index	Singh et al. (2007), C_1	A steel company in India
6	An air force logistics management index	Yoon et al. (2008), C_1	Airforce sector in Korea
7	A hierarchical assessment index	Grimaldi and Cricelli, (2009), C_1	-[b], -[c]
8	A total performance index	Hwang et al. (2009), C_3	Thirty-five commercial banks in China
9	Packaging Recycling Index	Qalyoubi-Kemp (2009), C_2	Commercial packaging companies, in the USA
10	A fuzzy intellectual capital index	Kale (2009), C_1	Construction firms, in Turkey
11	A socially responsible property investment index	Newell (2009), C_3	Eleven property companies in UK
12	A transparency index	Cheung et al. (2010), C_2	One hundred companies in China
13	An over index of suppliers	Amrina and Yusof (2010), C_2	Automotive SEM[d] companies in Malaysia

14	A leanness index	Singh et al. (2010), C_2	An automobile company in India
15	Global corporate social responsibility rate	Focacci (2011), C_3	Three companies, - [c]
16	An average value leverage index	Beelaerts van Blokland et al. (2012), C_2	Aircraft manufacturers, engine manufacturers and large suppliers, - c
17	A sustainability index	Zhou et al. (2012), C_3	A brewery, - [c]
18	A metafrontier non-radial Malmquist CO_2 emission performance index	Zhang and Choi (2013), C_2	Two hundred fifty-nine fossil fuel power plants in China
19	A corporate performance index	Erbetta et al. (2013), C_3	Three hundred twenty companies in ten sectors in Italy
20	A ranking index	Blancas et al. (2013), C_2	The fast-food franchising sector in Spain
21	An overall performance index of suppliers	Chahid et al. (2014), C_3	Automotive companies in Morocco
22	An integrated lean index	Wong et al. (2014), C_2	A semiconductor manufacturing company in Malaysia
23	A psychosocial risk indicator	Bergh et al. (2014), C_3	An oil and gas company in Norway
24	A sustainability assessment index	Garbie (2014), C_3	An aluminum manufacturing company in Sultanate of Oman
25	A scheduling performance evaluation index	Liu et al. (2014), C_3	Baoyun Logistics Company in China
26	A circular economy efficiency composite index	Ma et al. (2014), C_3	Private steel enterprises in China
27	A sustainability performance index	Mohamed et al. (2015), C_3	Food process manufacturers in China and Malaysia
28	A sustainable supply chain performance index	Gopal and Thakkar (2015), C_3	An automobile company in India
29	A sustainability index	Salvado et al. (2015), C_3	An automotive company in Portugal
30	An efficiency assessment index	Zanella et al. (2015), C_3	Hydropower plants in Brazil
31	Lean transaction cost efficiency indicators	de Jong and Beelaerts van Blokland (2015), C_3	An aircraft maintenance repair and overhaul service company, - [c]
32	A sustainability index	Harik et al. (2015), C_3	Six food manufacturing companies, -
33	A social and environmental disclosure index	Monica and Gagan (2015), C_1	Forty-one companies in India
34	An automotive supplier selection weighted Index	Ayağ and Samanlioglu (2016), C_1	Automotive suppliers in Turkey
35	A performance evaluation model	Li and Zhao (2016), C_1	5 thermal power plants in China
36	A multiple criterion appraisement index	Sahu et al. (2016), C_1	- [b], - [c]
37	A sustainable business excellence index	Metaxas et al. (2016), C_1	An insulating materials manufacturer, - [c]
38	A corporate governance index	Nerantzidis (2016), C_1	- [b], in Greece
39	Corporate Social Responsibility index	Paredes-Gazquez et al. (2016), C_1	Seventy-four companies from twenty-three countries

40	A sustainability reporting index	Garg (2017), C_1	Seventeen food and agro-products companies in India
41	A product liability index	Seo and Bae (2017), C_1	Forty manufacturers in eleven sectors in Korea
42	A dynamic Luenberger indicator	Mendola and Volo (2017), C_1	One hundred three commercial banks and two hundred sixty-five cooperative Shinkin banks, in Japan
43	A performance index of risk and governance structure	Tinggi et al. (2017), C_1	Three hundred ninety companies, in Malaysia
44	A competitiveness assessment index	Zhang et al. (2017), C_1	An aviation & aerospace manufacture in China
45	A corporate sustainability index	Kocmanova et al. (2017), C_1	Two hundred eleven manufacturing companies in Czech
46	An average value leverage factor	Beelaerts van Blokland et al. (2019), C_2	Vehicle manufacturers, - [c]
47	A sustainable circular index	Azevedo, Godina, and Matias (2017), C_1	Manufacturing companies, -
48	A composite indicator of corporate sustainability	Engida et al. (2018), C_2	Companies in the European food and beverages sector, - [c]
49	A multidimensional innovation index	Pereira et al. (2018), C_1	Metalworking SMEs, in Portugal
50	A composite leading indicator	Rubio-Romero et al. (2018), C_1	A company responsible for the public collection and delivery of solid urban waste in Spain
51	A green index	Rita et al. (2018), C_1	Eight SEMsd, - [c]
Note: a--- Database source. C_1 stands for Web of Science Core Collection; C_2 stands for Google Scholar; C_3 stands for Scopus; b---unclear information of sectors in the article; c--- unclear information of the geographical distribution in the article; d--- SEMs means small and medium-sized enterprises.			

Based on the results in Table 3.3, analysis on the techniques that are used for constructing the indices is presented in Section 3.4. The analysis on the business sectors these CIs have been utilized in practice, especially in the motor vehicle manufacturing sector, is presented in Section 3.5.

3.4 Techniques used during Phase I to Phase V for constructing composite indicators

As presented in section 3.2.1, this dissertation focuses on five phases for developing CIs. Phase I is selecting measures, Phase II is normalizing the measures, Phase III is weighing measures, Phase IV is aggregating individual measures into one single index, and Phase V is the post analysis of the CIs derived. To answer "which techniques are used for constructing the CIs", this section identifies the techniques as shown in Figure 3.3.

3.4.1 Phase I - Selecting measures

Phase I is selecting measures for constructing CIs. In general, identifying and validating the underlying indicators can be undertaken through an extensive literature review. Besides, there are three main techniques as follows. In the survey, 31 articles adopt a literature review, 16 articles adopt interviews or surveys, 5 articles adopt content analysis, and 4 articles adopt the Delphi technique. The technique, the references that applied the technique and the proportion the technique makes up in the 51 references are shown in table 3.4.

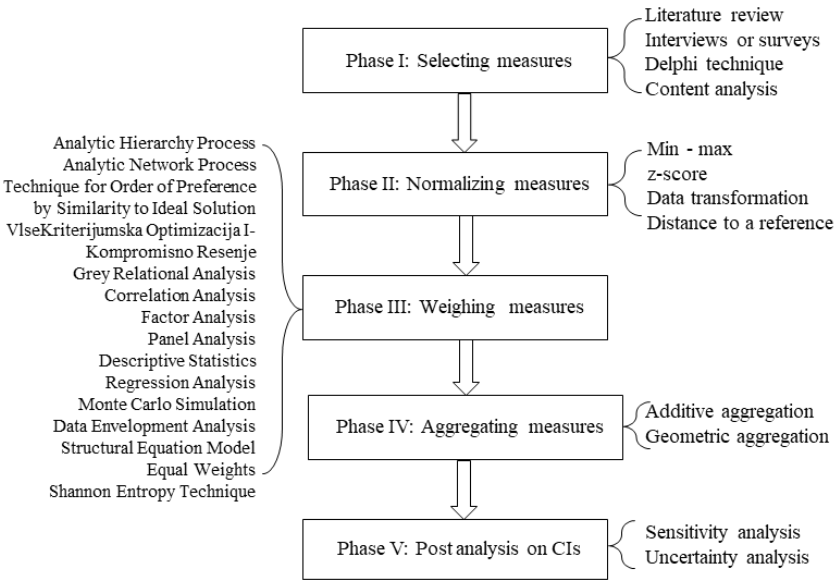


Figure 3.3: Techniques during CIs' construction (source: author)

- **The Delphi technique.** The Delphi technique is a formalized technique of communication (Dalkey & Helmer, 1963). It is designed to extract the maximum amount of unbiased information from a panel of experts (Chan et al., 2001), which could be used to assess uncertainty in a quantitative manner. The Delphi technique can also be used to weigh measures.
- **Interviews or surveys.** Interviews or surveys are used to get more information for choosing the underlying indicators, and afterwards the consistency of the results obtained from this process needs to be verified. The Cronbach Coefficient Alpha (Cronbach, 1951) is often used to measure internal consistency. The MegaStat application can be used for calculating the coefficient.
- **Content analysis.** It is used for identifying the underlying measures, by referring to some documents from companies' annual reports, Global Reporting Initiative, the ISO 14031and etc. Value stream mapping and the cognitive mapping can be included in this technique.

3.4.2 Phase II - Weighing measures

Phase II is weighing measures for constructing CIs. Weights are often used as measures of perceived importance of the subgroup to the system (Burgass et al., 2017). In the phase of weighing measures, there are two categories, namely, MCDM methods and indirect explication (including mathematic-based techniques and statistic-based techniques). The commonly used statistic-based techniques are listed in Table 3.5, and the others are listed as follows.

- **Analytical hierarchy process (AHP)** method (Saaty, 1987). Fourteen references outof the 51 articles adopted this technique, including Chen et al. (2007); Grimaldi and Cricelli (2009); Amrina and Yusof (2010); Chahid et al. (2014); Wong et al. (2014); Garbie (2014); Gopal and Thakkar (2015); Salvado et al. (2015); Harik et al. (2015); Metaxas et al. (2016); Nerantzidis (2016); Seo and Bae (2017); Zhang et al. (2017); Rita et al. (2018). Verify the pairwise comparison with the consistency ratio (CR) as follows, where *CI* is the consistency index, $\lambda_{\max}$ is the maximum eigenvalue and n is the size of the matrix, and the CR value must be less than 0.10.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{3.1}$$

$$CR = \frac{CI}{RI} \tag{3.2}$$

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{3.1}$$

$$CR = \frac{CI}{RI} \tag{3.2}$$

Table 3.4: A list of selecting measures techniques with the references

No.	Technique, proportion	References
1	Literature review, 60.78%	Chang and Yeh (2004); Lee et al. (2005); Chen et al. (2007); Singh et al. (2007); Yoon et al. (2008); Grimaldi and Cricelli, (2009); Qalyoubi-Kemp (2009); Kale (2009); Newell (2009); Beelaerts van Blokland et al. (2012); Erbetta et al. (2013); Blancas et al. (2013); Wong et al. (2014); Bergh et al. (2014); Garbie (2014); Liu et al. (2014); Zanella et al. (2015); de Jong and Beelaerts van Blokland (2015); Harik et al. (2015); Sahu et al. (2016); Metaxas et al. (2016); Nerantzidis (2016); Paredes-Gazquez et al. (2016); Garg (2017); Seo and Bae (2017); Mendola and Volo (2017); Tinggi et al. (2017); Zhang et al. (2017); Beelaerts van Blokland et al. (2019); Azevedo et al. (2017); Rubio-Romero et al. (2018).
2	Interviews or surveys, 31.37%	Chang and Yeh (2004); Lee et al. (2005); Yoon et al. (2008); Hwang et al. (2009); Kale (2009); Wong et al. (2014); Bergh et al. (2014); Ma et al. (2014); Harik et al. (2015); Nerantzidis (2016); Garg (2017); Seo and Bae (2017); Zhang et al. (2017); Azevedo et al. (2017); Pereira et al. (2018); Rubio-Romero et al. (2018).
3	Content analysis, 9.80%	Salvado et al. (2015); de Jong and Beelaerts van Blokland (2015); Monica and Gagan (2015); Azevedo et al. (2017); Rita et al. (2018).
4	Delphi technique, 7.84%	Nerantzidis (2016); Seo and Bae (2017); Azevedo et al. (2017); Rubio-Romero et al. (2018).
Notes: the Proportion is calculated as the number of the references for each technique divided by 51 which is the number of total articles.		

- **Analytical network process (ANP)** method (Saaty, 1996). Two references out of the 51 articles adopted this technique, including Wong et al. (2014); Ayağ and Samanlioglu (2016). A supermatrix W, where w_{21} is a vector that represents the impact of the goal on the criteria, W_{32} is a matrix that represents the impact of criteria on each of the alternatives, I is the identity matrix, and entries of zeros corresponding to those elements that have no influence.

$$W = \begin{bmatrix} 0 & 0 & 0 \\ w_{21} & 0 & 0 \\ 0 & W_{32} & 0 \end{bmatrix} \tag{3.3}$$

Table 3.5: References in terms of weighing techniques with statistical techniques

No.	Technique, proportion	References
1	Correlation analysis, 17.65%.	Chen et al. (2007); Hwang et al. (2009); Newell (2009); Beelaerts van Blokland et al. (2012); Liu et al. (2014); de Jong and Beelaerts van Blokland (2015); Paredes-Gazquez et al. (2016); Zhang et al. (2017); Beelaerts van Blokland et al. (2019)
2	Factor analysis, 9.80%	Lee et al. (2005); Sohn et al. (2007); Yoon et al. (2008); Garg (2017); Kocmanova et al. (2017)
3	Panel analysis, 5.88%	Cheung et al. (2010); Mendola and Volo (2017); Tinggi et al. (2017)
4	Descriptive statistic, 5.88%	Qalyoubi-Kemp (2009); Cheung et al. (2010); Rubio-Romero et al. (2018)
5	Relationship analysis, 3.92%	Beelaerts van Blokland et al. (2012); Monica and Gagan (2015)
6	Principal component analysis, 1.96%	Engida et al. (2018)
	Notes: the Proportion is calculated as the number of the references for each technique divided by 51 which is the number of total articles.	

- **Technique for order preference by similarity to ideal solution (TOPSIS)** method **(**Lai et al., 1994). Two references out of the 51 articles adopted this technique, including Sahu et al. (2016); Metaxas et al. (2016). The similarity to the worst condition C_j can be calculated as below.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \quad i = 1, 2, ..., m; \quad j = 1, 2, ..., n \tag{3.4}$$

$$t_{ij} = r_{ij} \times w_j \tag{3.5}$$

$$w_j = \frac{W_j}{\sum_{k=1}^{n} W_k} \tag{3.6}$$

$$A^+ = \left\{ t_i^+ \middle| \max_j t_{ij} \left(\text{benefit}\right) \& \min_j t_{ij} \left(\text{cost}\right) \right\} \tag{3.7a}$$

$$A^- = \left\{ t_i^- \middle| \min_j t_{ij} \left(\text{benefit}\right) \& \max_j t_{ij} \left(\text{cost}\right) \right\} \tag{3.7b}$$

$$S_j^+ = \sqrt{\sum_{i=1}^{n} \left(t_{ij} - t_i^+\right)^2} \tag{3.8a}$$

$$S_j^- = \sqrt{\sum_{i=1}^{n} \left(t_{ij} - t_i^-\right)^2} \tag{3.8b}$$

$$C_j = \frac{S_j^-}{S_j^+ + S_j^-} \tag{3.9}$$

Where $R=\left[r_{ij}\right]_{m\times n}$ is the normalized evaluation matrix $X=\left[x_{ij}\right]_{m\times n}$. t_{ij} represents the weighted normalised decision matrix; W_j represents the original weight given to the indicator v_j. A^+ is the best alternative and A^- is the worst alternative. $S_j^{+:}$ represents the L2 distance between the target alternativeand the best condition A^+ and S_j^- represents the L2 distance between the target alternativeand the worst condition A^-.

- **VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)** method (Duckstein & Opricovic, 1980). Li and Zhao (2016). adopted this technique. The VIKOR index can be calculated as below.

$$f_{ij}=\frac{SN_i^j}{\sqrt{\sum_{i=1}^{m}(SN_i^j)^2}}\quad i=1,2,...,m;\quad j=1,2,...,n \tag{3.10}$$

$$A^*=\left\{\min f_{ij}\,\middle|\,i=1,2,...,m\right\}=\left\{f_1^*,f_2^*,...,f_j^*,...,f_n^*\right\} \tag{3.11a}$$

$$A^-=\left\{\max f_{ij}\,\middle|\,i=1,2,...,m\right\}=\left\{f_1^-,f_2^-,...,f_j^-,...,f_n^-\right\} \tag{3.11b}$$

$$S_i=\sum_{j=1}^{n}w_j\left(f_j^*-f_{ij}\right)/\left(f_j^*-f_j^-\right) \tag{3.12}$$

$$R_i=\max_j\left[w_j\left(f_j^*-f_{ij}\right)/\left(f_j^*-f_j^-\right)\right] \tag{3.13}$$

$$Q_l=\alpha\left[\frac{s_i-s^*}{s^--s^*}\right]+\left(1-\alpha\right)\left[\frac{R_i-R^*}{R^--R^*}\right] \tag{3.14}$$

Where $X=\left[SN_{ij}\right]_{m\times n}$ represents the structure of the decision matrix. f_{ij} is the normal quality loss of jth attribute in the ith alternative. A^* represents the ideal solution and A^- represents the negative ideal solution. w_j is the weight of the jth objective function. α is a weighing factor, and $\alpha \in [0, 1]$.

- **Grey relational analysis (GRA)** method (Deng,1982). One reference out of the 51 articles adopted this technique, that is, Li and Zhao (2016). The grey relational grade can be calculated as below.

$$x_{ij}=\frac{y_{ij}-\underline{y_j}}{\overline{y_j}-\underline{y_j}} \tag{3.15a}$$

$$x_{ij}=\frac{\overline{y_j}-y_{ij}}{\overline{y_j}-\underline{y_j}} \tag{3.15b}$$

$$x_{ij}=1-\frac{\left|y_{ij}-y_j^*\right|}{\mathrm{Max}\left\{\overline{y_j}-y_j^*,y_j^*-\underline{y_j}\right\}} \tag{3.15c}$$

$$\Delta_{ij}=\left|x_{0j}-x_{ij}\right| \tag{3.16}$$

$$\Delta_{\min}=\mathrm{Min}\left\{\Delta_{ij},i=1,2,...,m;\quad j=1,2,...,n\right\} \tag{3.17a}$$

$$\Delta_{\max} = \text{Max}\left\{\Delta_{ij}, i = 1, 2, ..., m; \quad j = 1, 2, ..., n\right\} \tag{3.17b}$$

$$\gamma\left(x_{0j}, x_{ij}\right) = \frac{\Delta_{\min} + \varsigma\Delta_{\max}}{\Delta_{ij} + \varsigma\Delta_{\max}} \tag{3.18}$$

$$\Gamma\left(X_0, X_i\right) = \sum_{j=1}^{n} w_j \gamma\left(x_{0j}, x_{ij}\right) \tag{3.19}$$

Where i represents alternatives (i=1, 2,…,m) and j represents for attributes (j=1,2,…,n). y_{ij} represents the performance value of attribute j of alternative i. $\overline{y_j}$: represents the maximum value from {y_{ij} , i = 1, 2, . . . , m} and $\underline{y_j}$ represents the minimum value from {yij , i = 1, 2, . . . , m}. $\gamma\left(x_{0j}, x_{ij}\right)$ is the grey relational coefficient between x_{oj} and x_{ij}. ζ is the distinguishing coefficient, and $\zeta \in [0, 1]$. w_j represents the weight of attribute j and usually depends on decision-makers' judgments or the structure of the proposed problem; the function (3.15a) is for the "the larger the better" attributes; the function (3.15b) is for the "the smaller the better" attributes; the function (3.15c) is for the "the closer to the desired value the better" attributes.

- **Data envelopment analysis (DEA)** method (Seiford & Thrall, 1990). Nine references out of the 51 articles adopt this technique, including Zhou et al. (2012); Zhang and Choi (2013); Erbetta et al. (2013); Blancas et al. (2013); Zanella et al. (2015); Paredes-Gazquez et al. (2016); Seo and Bae (2017); Kocmanova et al. (2017); Engida et al. (2018). Charnes-Cooper-Rhodes (CCR) model for the relative efficiency of the selected entity k (Martić et al., 2009) can be calculated as follows.

$$\max \quad h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \tag{3.20}$$

The following three constraints:

$$\frac{\sum_{r=1}^{s} u_r y_r}{\sum_{i=1}^{m} v_i x_i} \le 1, \; j = 1, 2, ..., j_k, ..., n \tag{3.21}$$

$$u_r \ge \varepsilon, r = 1, 2, ..., s \tag{3.22}$$

$$v_i \ge \varepsilon, r = 1, 2, ..., m \tag{3.23}$$

Where x_{ij} represents the observed magnitude of i type input for entity j ($x_{ij} > 0$, $i = 1, 2, ..., m$, $j = 1, 2, ..., n$). y_r represents the observed magnitude of r-type output for entity j ($y_{rj} > 0$, $r = 1, 2, ..., s$, $j = 1, 2, ..., n$). v_i is the weights to be determined for input I; m is the number of inputs. u_r is the weights to be determined for output r. s is the number of outputs, h_k represents the relative efficiency of the entity k. n is the number of entities and ε represents a small positive value.

- **Equal weights** (Einhorn and Hogarth, 1975). Three references out of the 51 articles adopted this technique, including Chen et al. (2007); Zhou et al. (2012); Beelaerts van

Blokland et al. (2019). Equal weighting could imply the recognition of equal status for all indicators. Alternatively, it could be the result of insufficient knowledge of causal relationships.

- **Shannon entropy** (Shannon, 1948). One reference out of the 51 articles adopted this technique, that is, Li and Zhao (2016). The Shannon entropy is calculated as follows.

$$H(X)=\sum_{i=1}^{n} p(x_i)I(x_i)=\sum_{i=1}^{n} p(x_i)\log_b \frac{1}{p(x_i)}=-\sum_{i=1}^{n} p(x_i)\log_b p(x_i) \tag{3.24}$$

Where b is the base of the logarithm used. Common values of *b*are 2, Euler's number *e*, and 10 (Schneider, 2007). p_{ij} is the relative frequency of x_{ij}. d_j is the degree of diversification. w_j represents the weight of measure *j* for manufacturer *i*, $w_j \in (0,1)$ and $\sum w_j=1$.

- **Fuzzy logic.** To handle the inherent subjectivity and incompletely defined data, the fuzzy set theory, which is also called as fuzzy logic (Werro, 2016), is adopted. As a mathematical theory first introduced by Zadeh in 1965, its key idea is that an element has a degree of membership in a fuzzy set that is defined by a membership function (Taha & Rostam, 2011). The fuzzy set can be $\tilde{a}=\{(x, \mu_{\tilde{a}}(x)), x\in R, \mu_{\tilde{a}}(x)\in [0, 1]\}$, where *x* is a point in the universe, $\mu_{\tilde{a}}$ for the membership function of $\tilde{a}$, and $\mu_{\tilde{a}}(x)$ for the degree of *x* attributed to $\tilde{a}$. The membership function can be the trapezoidal function, the triangular membership function etc. Each fuzzy set corresponds to a linguistic variable, such as those associated with the nine-point scale by Saaty. A commonly adopted function is the triangular membership function. As shown in equation (3.25), this function is with computational simplicity for decision-makers (Moon & Kang, 2001), where a^l, a^m and a^u denote the smallest possible value, the most promising value, and the largest possible value respectively, $a^l \le a^m \le a^u$.

$$\mu_{\tilde{a}}(x)=\begin{cases}(x-a^l)/(a^m-a^l), & a^l \le x \prec a^m \\ 1, & x=a^m \\ (a^u-x)/(a^u-a^m), & a^m \prec x \le a^u \\ 0, & \text{otherwise}\end{cases} \tag{3.25}$$

- Other techniques such as structural equation modeling technique. Four references out of the 51 articles adopted this technique, including Sohn et al. (2007); Yoon et al. (2008); Mohamed et al. (2015); Kocmanova et al. (2017). Paredes-Gazquez et al. (2016) generated 10,000 random draws of input factor combinations through a Monte Carlo simulation (Mooney, 1997) for the construction of a composite index for measuring social outcomes in the electric utility industry.

3.4.3 Phase III - Normalizing measures

Phase III is normalizing measures for constructing CIs. Data of measures are often in different formats and they need normalizing to the same scale for aggregation (Jacobs et al., 2004). This allows a comparison of disparate indicators within a single framework (Burgass et al., 2017). Normalization techniques include (Saisana & Saltelli, 2011):

- Min-Max normalization, which is also known as re-scaling by minimum method. It normalizes indicators within a given range, such as [0, 1], by subtracting the minimum value and dividing by the range.
- Standardization, which is also known as z-score normalization. It converts indicators to a continuous measure with a mean of zero and a standard deviation of one.
- Other techniques such as data transformation based on given values, ratio-scale methods, the percentages of annual differences over consecutive years and the distance to a reference. Besides, there are several non-linear normalization techniques such as logarithm function, expectation function and arc-tangent function.

As shown in Table 3.6, there are 9 articles with an explanation of the normalization process; while the remaining 42 articles are without clear normalization process. Basically, there are three categories of measures. One category is that the higher value the measure has, the better the performance in terms of the measure is. The second category is that the lower value the measure has, the better performance in terms of the measure is. The last category is that there is a nominal value for the measure to be the best. Among the 51 articles, there are 6 articles taking into account different categories of measures.

Table 3.6: References distribution in terms of normalization techniques

No.	Technique, source, and proportion	Reference(s)	Function
1	Min-max normalization; Dodge (2006). Proportion: 9.80%	Focacci (2011); Zhou et al. (2012); Salvado et al. (2015); Harik et al. (2015); Azevedo et al. (2017)	$r_{ij} = \frac{x_{ij} - \text{Min}(x_j)}{\text{Max}(x_j) - \text{Min}(x_j)}$
2	z-score normalization; Zill, Wright, and Cullen (2011). Proportion: 5.88%	Singh et al. (2007); Hwang et al. (2009); Zhou et al. (2012)	$r_{ij} = \frac{x_{ij} - \text{Mean}(x_j)}{\text{Stdev}(x_j)}$
3	Data transformation based on given values; Dodge (2006). Proportion: 3.92%	Beelaerts van Blokland et al. (2012); Ma et al. (2014)	$r_{ij} = \frac{x_{ij}}{x}$ or $r_{ij} = \frac{x}{x_{ij}}$
4	Distance to a reference; Hope and Parker (1995). Proportion: 1.96%	Zhou et al. (2012)	$r_{ij} = \frac{x_{ij}}{x_{ij}^{\text{Benchmark}}}$ or $r_{ij} = \frac{x_{ij}^{\text{Benchmark}}}{x_{ij}}$
5	Percentages of annual differences over consecutive years; Nardo et al. (2004). Proportion: 1.96%	Zhou et al. (2012)	$r_{ij} = \frac{x_{ij}^{t} - x_{ij}^{t-1}}{x_{ij}^{t-1}}$ or $r_{ij} = \frac{x_{ij}^{t-1} - x_{ij}^{t}}{x_{ij}^{t-1}}$
Notes: r_{ij} represents the normalized value of the measure j for manufacturer i (i= 1,2,3, ..., m); j is the measure and j= 1,2,3, ..., n; x is for a given value; $x_{ij}^{\text{Benchmark}}$ is the an external benchmark value; x^{t}_{ij} and x^{t-1}_{ij} are the x_{ij} values in the fiscal year t and $t-1$ respectively; the Proportion is calculated as the number of the references for each technique divided by 51 which is the number of total articles.			

3.4.4 Phase IV - Aggregating measures

Phase IV is aggregating individual measures into CIs. Following the phases of weighing and normalizing indicators, aggregation techniques are needed to integrate those individual indicators into a bigger picture. The quality and reliability of a CI depend heavily on the underlying aggregation phase. The choice of aggregation method can be a source of model error and subjective judgment uncertainty as it can fundamentally alter how the CI performs.

Two alternatives for aggregation have gained attention in the CI literature: the additive method of aggregation and the geometric aggregation (Burgass et al., 2017). The additive method of aggregation involves a summation of weighted and standardized measures. This method is useful when all individual indicators have the same measurement unit, while geometric aggregations are better suited if the modeler wants some degree of non-compensability (Joint Research Centre-European Commission, 2008, pp. 32).

To develop a CI for measuring company performance, a simple additive aggregation function is always used for aggregation (Lee & Yu, 2013). The simple additive weighing (SAW) method is easy to understanding for non-experts (Zhou et al., 2006). Although this method is widely used in the development of a CI (Saisana and Tarantola, 2002), it assumes preference independence, which Nardo et al (2005) define as 'given the sub-indicators, a simple additive aggregation function exists if and only if these indicators are mutually preferentially independent'. SAW does not consider that the interaction among measures can cause redundancy (Grabisch, 1996). Developing a CI by simply adding the weights of these measures can lead to an incorrect estimation.

The other option is the geometric aggregation such as the weighted product (WP) method. Geometric aggregation entails partial compensability. This aggregation method is a dimensionless analysis, appropriate for measures with the use of different ratio or interval scale. It is frequently used at the national level. It is emphasized that countries need to focus more on increasing the weak measure with the lowest score in order to improve their overall tanking position.

Ebert and Welsch (2004) showed that the WP method is theoretically superior to the SAW method during the development of CIs. Considering the cardinality characteristic of CIs, Zhou et al. (2006) found that the WP method seems to be a better choice compared to several other MCDA methods. The techniques and references are shown in Table 3.7.

3.4.5 Phase V - Post analysis of composite indicators

Phase V is the post analysis of the CIs. The post analysis is performed to assess the robustness of the CIs derived in terms of the normalization scheme, the imputation of missing data (Saisana et al., 2005), the aggregation technique and so on. Sensitivity analysis is a powerful tool for gauging the robustness and increasing its transparency of CIs derived. Sensitivity analysis is an integral part of model development and involves an analytical examination of input parameters to aid in model validation (Hamby, 1995). The variance-based technique can be used as a technique for sensitivity analysis. In this research, only Wong, Ignatius, and Soh (2014) and Rita et al. (2018) have performed the post analysis phase.

Table 3.7: References distribution in terms of aggregation techniques

No.	Technique, source	References	Function
1	The additive method of aggregation such as the SAW method; Keeney and Raiffa (1993) Proportion: 33.33%	Sohn et al. (2007); Chen et al. (2007); Yoon et al. (2008); Hwang et al. (2009); Newell (2009); Amrina and Yusof (2010); Focacci (2011); Beelaerts van Blokland et al. (2012); Zhou et al. (2012); Chahid et al. (2014); Ma et al. (2014); Harik et al. (2015); Ayağ and Samanlioglu (2016); Nerantzidis (2016); Beelaerts van Blokland et al. (2019); Azevedo et al. (2017)	$CI_i = \sum_{j=1}^{n} w_j r_{ij}$
2	Geometric aggregation such as the WP method; Bouyssou and Vansnick (1986). Proportion: 5.88%	Zhou et al. (2012); Erbetta et al. (2013); Blancas et al. (2013)	$CI_i = \prod_{j=1}^{n} (r_{ij})^{w_j}$
Notes: r_{ij} represents the normalized value of the measure j for manufacturer i (i= 1,2,3, ..., m); j is the measure and j= 1,2,3, ..., n; w_i is the weights of the measure j; the Proportion is calculated as the number of the references for each technique divided by 51 which is the number of total articles.			

3.4.6 Sub conclusion

As stated in Section 2.1, this dissertation has focus on motor vehicle manufacturers. Different MVMs can assign different significance levels for different company performance measures. As a statistical-based technique, regression models are estimated to retrieve the relative weights of the indicators (Competence Centre on Composite Indicators and Scoreboards, 2019). As a measure of uncertainty in information, Shannon's concept is capable of being deployed as a weighing calculation method (Shemshadi et al., 2011). Despite the technique of equal weights is easy to use, this research will adopt regression analysis and Shannon entropy technique to weigh measures.

Different MVMs can generate different data in terms of their company performance. Company performance measures, such as the profit or inventories size, can be negative. In this case, this raw data of the measures is inapplicable for potential aggregations such as power functions. To enable this research with potential aggregations, the data needs converting into eligible base numbers in power functions. In this dissertation, a modified min-max function will be developed for normalizing measures. Simple additive aggregations do not consider that the interaction among measures can cause redundancy. In this dissertation, the geometric mean will be used for aggregating individual measures into a multiplicative index.

3.5 Utilized sectors of the composite indicators

To answer which business sectors these CIs have been utilized in practice, this section lists the CIs' utilized sectors, specifically the CIs that have been utilized in the motor vehicle manufacturing sector. Table 3.8 lists the distribution of the reference in terms of the CIs' utilized sectors. This dissertation identified 25 articles that mention the specific CI's utilized sector. Fourteen articles have not mentioned the specific applied sector, and two articles have been applied into multiple sectors.

Table 3.8: The distribution of the reference in terms of the CIs' utilized sectors

No.	Code (NAICS)	Sector	References
1	3361	Motor Vehicle Manufacturing	Amrina and Yusof (2010); Singh et al. (2010); Chahid et al. (2014); Gopal and Thakkar (2015); Salvado et al. (2015); Ayağ and Samanlioglu (2016); Beelaerts van Blokland et al. (2019).
2	3364	Aerospace Product and Parts Manufacturing	Chang and Yeh (2004); Yoon et al. (2008); Beelaerts van Blokland et al. (2012); Beelaerts van Blokland (2015); Zhang et al. (2017).
3	311	Food Manufacturing	Blancas et al. (2013); Mohamed et al. (2015); Harik et al. (2015); Garg (2017); Engida et al. (2018).
4	2211	Electric Power Generation, Transmission and Distribution	Zhang and Choi (2013); Zanella et al. (2015); Li and Zhao (2016)
5	3311	Iron and Steel Mills and Ferroalloy Manufacturing	Singh et al. (2007); Ma et al. (2014)
6	5221	Depository Credit Intermediation	Hwang et al. (2009); Mendola and Volo (2017)
7	3121	Beverage Manufacturing	Zhou et al. (2012);Engida et al. (2018)
8	5619	Other Support Services-packing	Qalyoubi-Kemp (2009)
9	2362	Nonresidential Building Construction	Kale (2009)
10	5313	Activities Related to Real Estate	Newell (2009)
11	3344	Semiconductor and Other Electronic Component Manufacturing	Wong et al. (2014)
12	2111	Oil and Gas Extraction	Bergh et al. (2014)
13	3313	Alumina and Aluminum Production and Processing	Garbie (2014)
14	5416	Management, Scientific, and Technical Consulting Services-logistics	Liu et al. (2014)
15	3261	Plastics Product Manufacturing	Metaxas et al. (2016)
16	3323	Architectural and Structural Metals Manufacturing	Pereira et al. (2018)
17	5621	Waste Collection	Rubio-Romero et al. (2018)
18	Mutiple sectors		Erbetta et al. (2013); Seo and Bae (2017); Engida et al. (2018)

The distribution in terms of the CIs' geographical utilization areas is listed in Table 3.9. Ten articles have not mentioned the specific geographical area information. Gopal and Thakkar (2015) conducted a case study in both China and in Malaysia. Garg (2017) conducted case studies in 23 countries. The most distributed continent is Asia, especially with China as the biggest distribution geographical area. The second biggest distribution is in Europe with six articles. There are two articles applied in companies in America and one article in Africa.

3.5.1 Composite indicators in the motor vehicle manufacturing sector

This dissertation identifies seven articles with CIs in the motor vehicle manufacturing sector. Table 3.10 lists the name of the CIs developed in the seven references and the techniques used for constructing CIs.

Table 3.9 References distribution in terms of CIs' geographical utilization areas

Continent	Country	Reference(s)
Asia	China	Chang and Yeh (2004); Chen et al. (2007); Hwang et al. (2009); Cheung et al. (2010); Zhang and Choi (2013); Liu et al. (2014); Ma et al. (2014); Li and Zhao (2016); Kocmanova et al. (2017)
	India	Singh et al. (2007); Singh et al. (2010); Gopal and Thakkar (2015); Monica and Gagan (2015); Garg (2017)
	Korea	Lee et al. (2005); Sohn et al. (2007); Yoon et al. (2008); Seo and Bae (2017)
	Malaysia	Amrina and Yusof (2010); Wong et al. (2014); Wong et al. (2014)
	Turkey	Kale (2009); Ayağ and Samanlioglu (2016)
	Sultanate of Oman	Garbie (2014)
	Japan	Mendola and Volo (2017)
Europe	The United Kingdom	Newell (2009)
	Italy	Erbetta et al. (2013)
	Norway	Bergh et al. (2014)
	The Netherlands	de Jong and Beelaerts van Blokland (2015)
	Greece	Nerantzidis (2016)
	Czech	Kocmanova et al. (2017)
America	The United States of America	Qalyoubi-Kemp (2009)
	Brazil	Zanella et al. (2015)
Africa	Morocco	Chahid et al. (2014)
Unclear		Grimaldi and Cricelli, (2009); Focacci (2011); Zhou et al. (2012); Harik et al. (2015); Sahu et al. (2016); Metaxas et al. (2016); Beelaerts van Blokland et al. (2019); Azevedo et al. (2017); Engida et al. (2018); Pereira et al. (2018)

3.5.2 Benchmark the indices

In order to overcome the seven general problems presented in Section 3.5.1, eight benchmark items are listed as follows.

- I_1: with an environmental perspective, considering that this research has a focus on an environmental perspective;
- I_2: with concerns about different categories of measures considering there are measures belonging to "the lower value the measure has, , the better performance it has" such as the measure CO_2 emissions, and there are measure belonging to "the higher value the measure has, the better performance it has" such the measure profitability;
- I_3: with specific normalization technique(s), considering the phase for normalizing measures to allow comparisons is a crucial step for constructing CIs (Freudenberg, 2003);
- I_4: with concerns about preference independence between measures, considering independency between factors exist in the realistic problems;

Table 3.10: The references with CIs in the motor vehicle manufacturing sector

Reference	Name of the CI	Technique(s)
Amrina and Yusof (2010)	An over index of suppliers	Literature review, surveys, AHP, SAW
	$S_k = \sum_{i=1}^{M}\sum_{j=1}^{Ni} W_i w_{ij} R_{ijk}$, where S_k is the overall score of k supplier; W_i is the relative weight of i criterion; W_{ij} is the relative weight of *j* sub-criterion belonging to *i* criterion; R_{ijk} is rating criterion of *k* supplier for *j* sub-criterion of *i* criterion; *M* is total number of criteria; N_i is total number of sub-criterion belonging to *i* criterion.	
Singh et al. (2010)	A leanness index	Fuzzy logic, Questionnaires
	$L_I(\mu) = L_A(\mu)/A + L_B(\mu)/B + L_C(\mu)/C + L_D(\mu)/D + L_E(\mu)/E + L_F(\mu)/F$, where $L_I(u)$ is the value of leanness; *A, B, C, D, E, F* are the crisp values from the triangular fuzzy functions $\bar{A}$= (80,100,100), $\bar{B}$=(60,80,100), $\bar{C}$=(40,60,80), $\bar{D}$=(20,40,60), $\bar{E}$ = (0,20,40), and $\bar{F}$ = (0,0,20) respectively, μ=(0,1).	
Chahid et al. (2014)	An overall performance index of suppliers	AHP, Performance Measurement Questionnaire, SAW
	$GP = 100*\left(0.09P_{Cc} + 0.17P_{Qs} + 0.43P_{Ma} + 0.05P_{Ab} + 0.02P_{Oi} + 0.23P_{Tdb}\right)$,where *GP* is the a global performance; C_c is the number of customer complaints/ one million hours delivered; Q_s is (non- conformities total/ parts supplied)*1 million/ one million hours delivered; M_a is the ratio between the actual production time and the total time available; Ab is the number of hours missed/ one million hours delivered; O_i is the number of occupational injuries/ one million hours delivered; and T_{db} is the average number of days of training per employee/one million hours delivered.	
Gopal and Thakkar (2015)	A sustainable supply chain performance index	AHP, Fuzzy logic, Liberatore score, signal-to-noise ratio and life cycle assessment polygon technique
	CSSCPI= SILS*SIS/N, where CSSCPI is composite sustainable supply chain performance index; SILS is the value from sub-index based on Liberatore score method for computing weights of qualitative indicators; and SIS/N is the value form sub-index based on signal to noise ratio method for computing weights of quantitative indicators.	
Salvado et al. (2015)	A sustainability index	AHP, min-max, content analysis
	$I_{C\_SUST_j} = f\left[W_{i1}\times\left(I_{i1}\right)j, W_{i2}\times\left(I_{i2}\right)j, W_{i3}\times\left(I_{i3}\right)j\right]$, where I_{C_SUSTj} is the total sustainability index for each company; W_{i1}, W_{i2}, W_{i3} are the weights for each considered sub-index; $(I_{is})_j$ is the value of the indicator *i* associated to the 3 dimensions of sustainability for company *j*.	
Ayağ and Samanlioglu (2016)	An automotive supplier selection weighted index	ANP, Fuzzy logic, SAW
	$D_{ia} = \sum_{j=1}^{J}\sum_{k=1}^{Kja} P_{ja} A^D_{kja} A^I_{kja} S_{ikja}$, where D_{ia} is the product of the desirability index, P_{ja} is the relative importance weight of dimension *j* on determinant a; A^D_{kja} is the relative importance weight for attribute-enabler *k* of dimension *j*, and determinant *a* for the dependency (D) relationships between attribute-enabler's component levels; A^I_{kja} is the stabilized relative importance weight for attribute-enabler k of dimension *j*, and determinant a for the independency (I) relationships within attribute-enabler's component level; S_{ikga} is the relative impact of concept alternative *i* on attribute-enabler *k* of dimension *j* of concept selection network; K_{ja} is the index set of attribute-enablers for dimension *j* of determinant *a*; and *J* is the index set for attribute *j*.	
Beelaerts van Blokland et al. (2019)	A value leverage factor	Literature review, Correlation analysis, SAW
	AVL=($R_{R\&D/C \text{ versus } P/C}$ + $R_{R\&D/C \text{ versus } R/C}$ + $R_{P/C \text{ versus } P/C}$)/3, where AVL is the vaverage R value by a linear least squares correlation analysis between three measures, including turnover per capita (T/C), profit per capita (P/C) and R&D expenditure per capita(R&D/C).	

- I_5: with fuzzy logic or grey theory to tackle inherent subjectivity, considering the inherent subjectivity needs handling, where fuzzy logic or grey theory is widely used;
- I_6: with objective weighing techniques, considering this research has a focus on quantitative data analysis;
- I_7: with clear aggregation procedure, considering the phase for aggregating measures into one index is a crucial phase for constructing CIs (Freudenberg, 2003);
- I_8: with a post-analysis phase, considering this research aims to construct the index transparently, and the post-analysis is a crucial phase for constructing CIs (Freudenberg, 2003).

Accordingly, the distribution of items in the seven references is shown in Table 3.11. There are two articles with CIs including an environmental perspective. Based on the literature review, opinions from a team of three experts, Gopal and Thakkar (2015) proposed 18 sub environmental indicators. The indicators include qualitative indicators (including the availability of collection centers, utility utilization, implementation of environmental regulations, supplier commitment on overall environmental aspects, product to be disposed to landfill or incinerate) and quantitative indicators (including total waste, percentage of suppliers having ISO Certification). Based on ISO 14031 and G4 of the Global Reporting Initiative, Salvado et al. (2015) proposed four quantitative sub-environmental indicators, including the rate of non-hazardous waste, rate of hazardous waste, amount of water consumed per year in industrial processes, and amount of energy used per year. There are two articles with clear normalization techniques and concerns about different categories of measures, which make their calculation more transparent and easier to understand.

Table 3.11: The distribution of criteria in the references

Items / Reference	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
Amrina and Yusof (2010)	×	×	×	×	×	×	√	×
Singh et al. (2010)	×	×	×	×	√	×	√	×
Chahid et al. (2014)	×	×	×	×	×	×	√	×
Gopal and Thakkar (2015)	√	√	√	×	√	√	√	×
Salvado et al. (2015)	√	√	√	×	×	×	×	×
Ayağ and Samanlioglu (2016)	×	×	×	√	√	×	√	×
Beelaerts van Blokland et al. (2019)	×	×	×	×	-	√	√	×
Note: √ means the reference satisfies the benchmark item; × means the reference dissatisfies the benchmark item; - means it is unnecessary to satisfy that benchmark item in the context of the reference.								

There is only one article taking into account the preference of independence between measures. It adopted the ANP method, which allows dependency between factors and is more suitable to the real problems when being compared with AHP (Saaty, 2004). There are six articles involving subjective scoring, but just three of them with the adoption of fuzzy logic to handle the subjectivity and imprecision for weighing measures. There are six articles with clear aggregation procedures, but none of these articles conducts the sensitivity analysis or uncertainty analysis on the CIs derived.

Based on the analysis above, this dissertation identified two current problems during the development of CIs in the motor vehicle manufacturing sector, namely, 1) a lack of consistent

company performance measures from an environmental perspective, 2) a lack of rigorous quantitative methods for measuring this performance.

3.6 Summary

This chapter conducted a literature survey on the existing composite indicators of company performance measurement for MVMs. Firstly, three generations of company performance measurement have been introduced in Section 3.2. Then, the literature in terms of the techniques used for constructing the CIs has been reviewed in Section 3.3 and discussed in Section 3.4. The analysis of the business sectors where these CIs have been utilized, specifically in the motor vehicle manufacturing sector, is presented in Section 3.5. Besides, the problems during the development of CIs have been discussed.

3.7 Conclusion

This chapter focused on answering the first sub research question in this dissertation, that is, what is the state-of-art in current composite indicators of company performance for MVMs. This chapter answered this sub research question by conducting a literature survey. Totally, this chapter identified 51 current CIs utilized in industry. As to the techniques used for constructing the CIs, there are 29 specific individual techniques as shown in Figure 3.3. As to the CIs' utilized sectors, as shown in Table 3.8, there are 17 specific sectors. The motor vehicle manufacturing sector is the most studied sector. This chapter answered this sub research question by analyzing the 51 CIs that utilized in industry.

3.8 Reflection

Two current problems during the development of CIs in the motor vehicle manufacturing sector have been identified. There is a lack of a standard definition of company performance from an environmental perspective, and there is a lack of rigorous quantitative methods for measuring this performance. The discussions in each of the corresponding phases can be helpful guidance of developing a scientific approach for constructing new CIs. This can generate a more transparent implementation during the development of CIs, and a better understanding of how CIs work in monitoring or benchmarking company performance.

Based on the findings and the limitations in this chapter, three recommendations are provided for developing the next generation of company performance measurement method. 1) In line with the statement by (Abdallah & Alnamri, 2015), this chapter has found out that there is a lower rate of the adoption of non-financial indicators in business practice. It is suggested to define and measure company performance from an environmental perspective. 2) It is necessary and can be interesting to put more concentration on the post analysis for the CIs, which can help gauge the robustness of the CI and improve its transparency. 3) There are unpredictable issues when it comes to constructing CIs for companies, such as the financial crises. It can be interesting to analyze how CIs contribute as a method to predict the trend of the company performance, which has not been discussed yet.

Therefore, the next chapter will focus on identifying the measures as basis for the next generation of company performance measurement method. An environmental perspective will be highlighted. Chapter 5 will focus on constructing the index with a post analysis phase. Chapter 6 will focus on the trend analysis on the index of company performance for different MVMs.

Chapter 4

Company Performance Measures from Economic and Environmental Perspectives

4.1 Introduction

As discussed in the previous chapter, there is a call for a new generation of company performance measurement method with environmental concerns. In this dissertation, the new generation is addressed as the fourth generation of company performance measurement. As a response to the second sub research question, this chapter identifies company performance measures from economic and environmental perspectives.

This chapter is organized as follows. Section 4.2 presents an understanding of company performance measurement by introducing the concept of the basis for the fourth generation of the company performance measurement method. Section 4.3 and Section 4.4 identify economic measures and environmental measures respectively from stakeholders. Accordingly, Section 4.5 develops a preliminary model of company performance measurement from an economic perspective and from an environmental perspective. The preliminary model is proposed based on a literature review, public documents and guidelines for MVMs. Section 4.6 and Section 4.7 summaries and concludes this chapter respectively. Section 4.9 presents the reflection on this chapter.

Section 4.2 and Section 4.3 are from Zeng, Q., Beelaerts van Blokland, W.W.A. (2018). Exploring Company Performance Measurement for Truck Manufacturers. *Journal for the Advancement of Performance Information and Value*, 10(1), 102-124.

Section 4.4 is from Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C., and Lodewijks, G. (2018). Company Performance Measurement for Automobile Companies: a composite indicator from an environmental perspective. In 5th International Conference on Industrial Engineering and Applications (pp. 391-395). Singapore, Singapore.

4.2 Concept of the fourth generation of company performance measurement method

Growing concerns on the environmentally sustainable development call for data analysis from economic and environmental perspectives. To access the economic performance and environmental performance of different countries, the System of Environmental-Economic

Accounting has performed data analysis via analytical applications. Unlike such data analysis that is at the national level or even broader global levels, this dissertation focuses on economic and environmental performance analysis at the company level.

4.2.1 Four sources to identify measures

It is crucial to choose measures to quantify company performance. In order to answer the second sub research question, this dissertation refers to four sources as follows to identify measures for quantifying MVMs' performance from economic and environmental perspectives.

Source 1: stakeholder theory

Stakeholder theory suggests that a firm needs to deal with the interests of its stakeholders (Donaldson & Preston 1995) and go beyond shareholders' interests to include other stakeholders (Pullman & Wikoff, 2017). Researchers and practitioners have shown interest in stakeholder orientation which leads to better organizational performance (He et al., 2011). In terms of company performance from economic and environmental perspectives, key stakeholders of MVMs consist of customers, business partners, owners, employees, investors, government, non-government organizations (NGOs) and non-profit organizations (NPOs). The concerns of the main stakeholders of MVMs from economic and environmental perspectives, as listed in Table 4.1, can be helpful in identifying company performance measures from economic and environmental perspectives.

Table 4.1: Stakeholders of MVMs and their concerns from economic and environmental perspectives

Label	Stakeholders	Concerns
S_1	Customers	Product price, product quality, after sales service, response time
S_2	Employees	Safe and healthy working condition, remuneration packages, quality of life, welfare measures
S_3	Business partners	Procurement policies, green supply chain management, information exchange
S_4	Financial organizations	Financial information, repayments, loans, environmental policies
S_5	NGOs/NPOs, Governments	Regional contribution activities, donations activities, product footprint, revenue and tax distribution, contribution to GDP, environment compliance, environmental preservation projects
S_6	Owners	Profitability, revenue, stock price, grievances and complaints, corporate governance, management of risk

Source 2: literature in the automotive industry

There are studies with company performance measures for automotive companies. For instance, three measures are proposed to quantitatively compare car companies from a stability-value leverage perspective (Beelaerts van Blokland et al., 2019). Different company measures are proposed from different perspectives, such as from an inventory perspective for truck manufacturers (Zeng & Beelaerts van Blokland, 2018), from a global perspective (Chahid et al., 2014), and from an environmental perspective (Jabbour et al., 2013; Zeng et al., 2018; Plank & Teichmann, 2018).

Source 3: documents released from the industry

This dissertation conducts data analysis based on released data of the identified measures. This dissertation collects data from annual reports from MVMs, including financial reports, sustainability reports, environmental reports, and corporate social responsibility reports.

Source 4: documents released by organizations

Besides the documents released by companies in the automotive industry, in order to get data of the measures, this dissertation refers to publications by authoritative organizations as well. G4 Guidelines from Global Reporting Initiative provides available data of environmental measures such as the amount of water consumption and energy consumption. ISO 14031 guidelines are applicable to all companies regardless of their application sectors. The guidelines give guidance on the use of environmental performance evaluation within an organization.

4.2.2 Requirements for developing the measurement method

In line with the first generation, the second generation and the third generation of company performance measurement, this dissertation aims to develop the basis for the fourth generation of company performance measurement method with five requirements as follows.

- It is with measures from both an economic perspective and an environmental perspective.
- It is developed for MVMs by taking the specific background into consideration.
- The measurement is based on publicly available data.
- It is mathematically constructed with transparency in generating time series data.
- It provides a trend based upon forecasts for benchmarking the future performance of MVMs in the following fiscal years.

4.3 Economic measures from S_1, S_2, S_3 and S_6

Several company performance indicators drive company performance from an economic perspective. Greenley and Foxall (1998) maintain that orientation to stakeholders, including consumers, shareholders and employees, is positively related to business performance. There are five measures mainly from stakeholders including S_1, S_2, S_3, and S_6. Each measure is denoted with its impact direction, where impact "+" denotes the measure, which satisfies "the higher its value is, the better the result is" and "-" denotes the measure which satisfies "the lower its value is, the better the result is ".

Suppliers, as important as customers, are one of the primary stakeholders (Preston, 1995; Clarkson, 1995). A firm will be seriously damaged if suppliers withdraw from it (He et al., 2011). Suppliers are identified as one of the key stakeholders by Donaldson and Preston (1995), Freeman et al. (2004), Harrison and Freeman (1999). Taking into account the concerns from S_1 customers, S_2 employees and S_3 business partners especially suppliers, a value-leverage perspective has been identified to measure the flow of products through the processes from an operation performance perspective (Beelaerts van Blokland et al., 2012). To express the value leverage capabilities, there are three indicators including turnover per employee (T/E), profit per employee (P/E), research and development expenditure per employee (R&D/E).

4.3.1 V_1 - Market share

Competition performance is one important aspect of company performance (Harrison-Walker, 2001; Laitinen, 2002). Market share is frequently used to measure competition performance (Tseng et al., 2009). S_6 owners or shareholders concern more about the measure market share that represents the percentage of gross sales or production volume by the company in the worldwide market (Kozmetsky & Yue, 1998; Murphy et al., 1996). Increasing market share is the ultimate goal of any business marketing plan. It is mainly about taking competitive advantages to gain customers from established competitors. Market share is used to give a general idea of the size of a company in relation to its market, which can be defined, by the sample company's production volume divided by the total production volume of all the sample companies over a specified period (Kozmetsky & Yue, 1998; Tseng et al., 2009). It is calculated as in equation (4.1). This measure satisfies "the higher its value is, the better the result is", so it is with the impact "+".

$$V_1 = \frac{Ni[\#]}{\sum_{i=1}^{n} Ni[\#]} \times 100\% \tag{4.1}$$

Where: *N* is for the motor vehicle production volume of the company *i*; I is for the MVMs (*i*=1, 2,…, n); n is for the size of sample manufacturers.

4.3.2 V_2 - Cash flow margin

Operating cash flow margin matters to S_3 business partners. It is a measure of a company's liquidity. Business partners are concerned whether they will be paid the amount promised to them at the date that was promised to them. If the value of operating cash flow margin is less than 1, business partners may reason that the company has generated less cash in the period than it needs to pay off its short-term liabilities.

In the manufacturing industry, four indicators provide appropriate measures of financial performance: earnings profitability, capital structure, market value, and the cash turnover ratio (Tseng et al., 2009). The cash turnover ratio indicates a firm's efficiency in its use of cash for generating net sales and gives a measure of the company's liquidity (Murphy et al., 1996). It is calculated as in equation (4.2). This measure satisfies "the higher its value is, the better the result is", so it is with the impact "+".

$$V_2 = \frac{CFO[\$]}{NS[\$]} \times 100\% \tag{4.2}$$

Where: *CFO* is for cash flows from operating activities; *NS* is for net sales.

4.3.3 V_3 - Profit per employee (P/E)

Profitability is proved as the best indicator to identify how the company is doing as respect to satisfying their shareholders (Sinkey Jr and Nash, 1993), and it is a common measure of performance for the company (Doyle, 1994). Net profit is traditionally regarded as the most comprehensive reflection of a company's profitability. Unlike net profit, net profit margin (net margin) is expressed as a percentage rather than as an absolute amount, which makes it possible for net profit margin to be regarded as benchmarks to companies regardless of their differences in size. By tracking increases and decreases in its net profit margin, the truck company can self-assess its financial health and forecast profits based on revenue. Summarily,

the net profit margin can give a more accurate view of how profitable a company is. In this dissertation, the measure on a per-employee basis is used. It is calculated as in equation (4.3). This measure satisfies "the higher its value is, the better the result is", so it is with the impact "+".

$$V_3 = \frac{P[\$]}{E[\$]} \tag{4.3}$$

Where: *P* is for pre-tax operating profit; *E* is for the number of employees.

4.3.4 V_4 - Research and Development expenditure per employee (R&D/E)

Technology is a relevant aspect of corporate change and corporate success (Zegveld, 2004), which has contributed a lot by its being created and applied towards production processes or towards the companies' management systems. The automotive industry itself is technology-intensive. New products, improving traditional dimensions such as safety and comfort while curbing polluting emissions, are always encouraged (Wells, 2010). Even though a large-scale commercialization phase with innovative vehicles or motor components seems still far (Hildermeier, 2016; Lanzini, 2018), the motor vehicle industry is introducing in the market products with innovative technologies such as Internet connection, AddiDrive Assist, electrical drive and vehicle networking technology. The measure research and development expenditure per capita focuses on innovation within a company, and co-innovation with suppliers in the development process for new vehicles (Beelaerts van Blokland et al., 2019).

In this dissertation, the measure on a per-employee basis is used. Research and development (R&D) expenditure per employee is defined as a unique technology or smart and original process, supported by intellectual property in cooperation with co-innovation parties, based upon the customer demand. It reflects the R&D focus of a company and can be used to measure the commitment made by companies in developing new technologies and products. Its degree is a significant indicator of future technological development, output, and productivity. It can be represented by R&D expenditure per employee. It is calculated as in equation (4.4). This measure satisfies "the higher its value is, the better the result is", so it is with the impact "+".

$$V_4 = \frac{R\&D[\$]}{E[\$]} \tag{4.4}$$

Where: *R&D* is for research and development expenditure.

4.3.5 V_5 - Inventory turnover

Another concern to S_6 owners or shareholders as well as S_3 suppliers is the inventory turnover. It is a financial indicator used in accounting to understand how long it takes a business to convert its inventory to cash. Inventory turnover is regarded as the most commonly used metric for inventory performance measurement, as it reflects the overall efficiency of the supply chain, from S_2 suppliers to S_1 customers (Rabinovich et al., 2003). Originating from the Toyota production system, lean production has evolved as a best-practice strategy over time. Lean production has been widely applied beyond the automotive industry (Womack et al., 1990). Besides creating value, lean production also focuses on eliminating waste. Ohno has identified seven types of waste, and excess inventory is one type of waste within a company, which should be eliminated (George et al., 2006). In accounting, inventory consists

of raw materials inventory, work-in-progress inventory and finished goods inventory. Inventory is an important asset for a company; Inventory is one of the primary sources of revenue generation and subsequent earnings for the company's shareholders (Virender, 2010).

Inventory turnover is defined by a ratio showing how many times a company has sold and replaced inventory during a given period. Inventory turnover can be calculated as sales divided by average inventory. It also can be calculated as the cost of goods sold divided by average inventory. Sales include a mark-up over cost, so its calculation inflates inventory turnover. For greater accuracy, inventory turnover is calculated as the cost of goods sold divided by average inventory (Zeng & Beelaerts van Blokland, 2018). It is calculated as in equation (4.5). This measure satisfies "the higher its value is, the better the result is", so it is with the impact "+".

$$V_5 = \frac{COGS_t[\$]}{0.5 \times (I_t + I_{t-1})[\$]} \tag{4.5}$$

Where: COGS represents cost of goods sold; *t* represents the fiscal year (*t*=0, 1,…,T); *I* represents the inventory size.

4.4 Environmental measures from S_3, S_4, S_5 and S_6

There is more than profitability to an MVM. More and more MVMs get to participate in environmental preservation. There is an urgent need to concern the environmental-related indicators of company performance for manufacturers. Environmental impacts can be measured in terms of resource consumption, emissions or environmental damage. For instance, Audi AG have adopted environmental measures including the average change (on a per-unit basis) of carbon dioxide (CO_2) emissions, energy, freshwater, organic solvents, wastewater and waste.

It is suggested that environmental management needs to be based on a systemic approach incorporating environmentally conscious strategy at every level of the organization (Jabbour, 2010). This dissertation exclusively includes measures that are with publicly available. In other words, although some measures can be identified from literature, they will not be used in this dissertation due to their data unavailability. For instance, Plank and Teichmann (2018) proposed measures including information on kilograms of carbon dioxide emitted for the production, water consumption in liters for the production and information on the length of the transportation route. The length of the transportation route will be excluded in this dissertation, since it is not feasible to get accurate data information on this measure.

Measures are identified from an environmental perspective taking into account concerns mainly from S_3 business partners, S_4 financial organizations and S_5 governments, NGOs or NPOs. Three measures are taken into account including 1) water consumption, 2) energy consumption and 3) CO_2 emissions. The reasons why the three measures are chosen are as follows.

- Vehicle production requires a large volume of water, usually through in-house parts production and painting operations. Access to affordable water has been identified as one of the most important issues at risk through companies' activities. Water consumption can be regarded as an indicator of the company's impact on water resources (Harik et al., 2015).

- The increasing use of energy-saving techniques is a recent trend in motor vehicle manufacture. Motor vehicle manufacturing consumes a large volume of energy during the production process (Afgan et al., 2000).
- CO_2 emissions contribute around 70% of the whole global GHG, which leads to severe consequences such as global warming.

In general, the three measures are with available data while others are not. Data of the three measures can be collected individually from publicly available documents. Note that this dissertation does not analyze the relationship among the three measures.

4.4.1 V_6 - Water consumption per vehicle produced (WC/N)

Access to affordable water has been identified as one of the most important issues at risk through companies' activities. Water consumption can be regarded as an indicator of the company's impact on water resources (Harik et al., 2015). In this dissertation, the figure is calculated as: the amount of water consumption = ∑(freshwater consumption externally sourced + groundwater intake + rainwater utilization amount + surface water from lakes, rivers, and ocean). For manufacturers that do not report the direct data of water consumption such as Nissan Motor Company, this figure can be measured by the difference between the amount of water intake (or water input or water withdraw) and water discharge.

The unit cubic meter (m^3) is used for water consumption because 1) it is a base unit from the International System of Units and 2) the majority of leading manufacturers report water resource data in this unit. Water consumption on a per- unit (auto vehicles produced) basis is adopted as a measure. It is calculated as in equation (4.6). This measure satisfies "the lower its value is, the better the result is", so it is with the impact "-".

$$V_6 = \frac{WC\left[m^3\right]}{N_i\left[\#\right]} = \frac{WI - WD\left[m^3\right]}{N_i\left[\#\right]} \tag{4.6}$$

Where: N is for the production volume; i is for the manufacturer; N_i is for the volume of auto vehicles produced from the manufacturer i; WC is for water consumption; WI is for water input and WD is for water discharge.

4.4.2 V_7 - Energy consumption per vehicle produced (EC/N)

The increasing use of energy-saving techniques is a trend in motor vehicle manufacture. Nevertheless, motor vehicle manufacturing consumes a large volume of energy during the production process (Afgan et al., 2000). Energy consumption (Molina-Azorín et al., 2009) on a per-unit (auto vehicles produced) is adopted as a measure, namely energy consumption per vehicle produced. This figure is made up of the electricity, the energy from renewable energy sources, heating (including district heating), combustion gases for production processes, and externally supplied refrigeration (source: G4—EN3 Power consumption within the organization).

The unit Megawatt-hours (MWh) is used for water consumption because 1) watt is a derived unit from the International System of Units and 2) the majority of leading manufacturers report energy resource data in MWh. It is calculated as in equation (4.7). This measure satisfies "the lower its value is, the better the result is", so it is with the impact "-".

$$V_7 = \frac{EC[MWh]}{N_i[\#]} \tag{4.7}$$

Where: *EC* is for energy consumption.

4.4.3 V_8 - CO_2 emissions per vehicle produced (CO_2E/N)

CO_2 emissions on a per-unit (auto vehicles produced) are adopted as a measure. In this dissertation, the figure is calculated as: the amount of CO_2 emissions =∑(direct CO_2 emissions + indirect CO_2 emissions). Direct CO_2 emissions are from business activities, as defined by the GHG Protocol (examples: combustion of fuel oil at manufacturing plants). Indirect CO_2 emissions are from a company's use of energy, as defined by the GHG Protocol (examples: purchased electrical energy used by a manufacturing plant or office (source: G4—EN15 and G4—EN16 Direct and Indirect GHG emissions). Manufacturers report the emissions-related data in multiple units. For instance, Honda does it in the metric ton, Toyota does it in ton and Daimler does it in kilogram. Metric ton (t) is adopted as the unit for CO_2 emissions considering 1) metric ton is a unit accepted for use with International System of Units, 2) the majority of manufacturers report emissions data in this unit and 3) this unit is used in EU ETS, which is the world's biggest carbon market. It is calculated as in equation (4.8). This measure satisfies "the lower its value is, the better the result is", so it is with the impact "-".

$$V_8 = \frac{CE[t]}{N_i[\#]} \tag{4.8}$$

Where: *CE* is for CO_2 emissions.

4.5 A preliminary model with eight measures

Accordingly, a preliminary model of the company performance measurement method for MVMs is developed in Figure 4.1. It consists of eight measures and each measure is denoted with its impact direction. Measures on a per-employee basis are used for V_3 and V_4. Here, the term "Employee" refers to any person who is regularly employed by the company or consolidated subsidiaries or affiliated companies worldwide at a salary and is enrolled in the active employment rolls of the company or a subsidiary. It excludes part-time employees or apprentices. For the data of R&D expenditure and the data of the cost of goods sold, their absolute values are used.

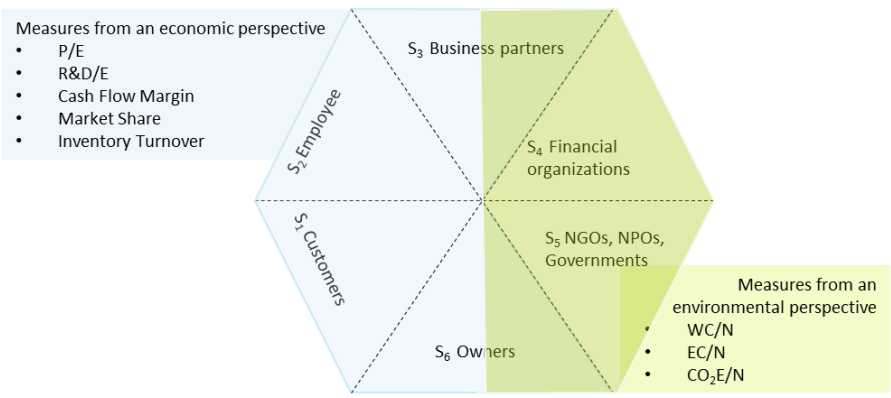


Figure 4.1 The preliminary model of company performance for MVMs

4.6 Summary

Chapter 4 identified company performance measures from economic and environmental perspectives. An understanding of company performance measurement was presented in Section 4.2 by introducing the concept of the basis for the fourth generation of the company performance measurement method. Economic measures and environmental measures were identified from stakeholders in Section 4.3 and Section 4.4 respectively. Accordingly, a preliminary model of company performance measurement was developed in Section 4.5 from economic and environmental perspectives. The preliminary model was proposed based on a literature review, public documents and guidelines for MVMs.

4.7 Conclusion

This chapter has focused on answering the second sub research question in this dissertation, that is, what company performance measures can be applied to construct CIs of MVMs' performance from economic and environmental perspectives. Analysis has been conducted to identify measures from an economic perspective and from an environmental perspective, referring to four sources including stakeholder theory, literature in the automotive industry, documents released from industry and documents about MVMs by organizations. Accordingly, a preliminary framework with eight measures has been built from economic and environmental perspectives.

As shown in Figure 4.1, five measures are from an economic perspective, including profit per employee, research and development expenditure per employee, cash flow margin, market share and inventory turnover. An environmental perspective during vehicles' production has been highlighted. Three measures are from an environmental perspective, including water consumption per vehicle produced, energy consumption per vehicle produced and CO_2 emissions per vehicle produced. This preliminary model has made a response to the recommendations in the previous chapter. This chapter has answered this sub research question by proposing this preliminary model of company performance measurement.

4.8 Reflection

The preliminary model developed in this chapter is new in terms of identifying eight company performance measures. All the eight measures are with publicly available data. The eight measures give an insight into quantifying company performance from both an economic perspective and an environmental perspective for MVMs. This preliminary model is the basis for the fourth generation of company performance measurement. With the eight measures, a new index of company performance measurement will be constructed. The next chapter will focus on integrating the eight measures in this preliminary model into one single composite indicator with techniques that are suitable to the background of MVMs.

Chapter 5

Measurement of Historical Performance for MVMs

5.1 Introduction

The preliminary model is ready from the previous chapter. In order to answer the third sub research question, this chapter focuses on constructing a composite indicator to quantify MVMs' performance from economic and environmental perspectives. This index will be consistent with the five requirements as mentioned in section 4.2.2.

This chapter is organized as follows. Section 5.2 presents specific considerations for MVMs. In section 5.3, techniques are identified for constructing the I_{MVM}, according to three considerations in section 5.2. Data is collected from fifteen MVMs over the recent ten fiscal years (FYs), that is, from FY2008 to FY2017. A sensitivity analysis with the simple additive weighing method is performed to analyze how different aggregation methods affect the final value. Section 5.4 demonstrates how to implement the method to construct the index. Section 5.5 assesses the index I_{MVM} through a benchmark against seven benchmark items. The construction of the I_{MVM} satisfies all of its six applicable benchmark items while the other three indices do not. The results indicate that the new measurement is effective for MVMs to measure their company performance from economic and environmental perspectives. Section 5.6 presents a discussion on MVMs' environmental performance in terms of water consumption, energy consumption and CO_2 emissions in FY2017. Section 5.7 and Section 5.8 summaries and concludes this chapter respectively. Section 10 presents the reflection on this chapter, raising awareness of CO_2 emissions in vehicles' production.

Section 5.2, Section 5.3, Section 5.4, Section 5.5 and Section 5.6 are from the work:

Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C. and Lodewijks, G. Company performance measurement with environmental concerns: an index for motor vehicle manufacturers (under review). *International Journal of Productivity and Performance Management*

Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C. and Lodewijks, G. (2018) Measuring company performance from an environmental perspective: a composite indicator for truck manufacturers. On the 25th International Annual European Operations Management Association Conference: Budapest, Hungary.

5.2 Three considerations for MVMs

The purpose of this chapter is to construct the index I_{MVM} based on the preliminary model. This index will be constructed with the five requirements in Section 4.2.2. Based on literature and the public available reports of manufacturers, this dissertation identifies three considerations as follows.

- **Consideration 1.** There are two different categories of impact for the eight measures. For instance, the measure profit per employee satisfies "the larger its value is, the better the result gets" while the measure energy consumption per vehicle produced satisfies "the smaller its value is, the better the result gets ". Therefore, there will be different functions for normalizing measures of the two categories respectively.

- **Consideration 2.** There are measures that have negative values. For instance, the measure profit per employee in FY2008 in Audi AG was $76,477, while it was negative $121,280 for General Motors. In this case, the value is inapplicable for aggregations such as power functions. In order to be able to adopt potential aggregations, the values are qualified as a base number in power functions.

- **Consideration 3.** A complete compensability between the eight measures is not desirable (Joint Research Centre-European Commission, 2008, pp. 19). For instance, we disagree that high cash flows from operating activities can compensate for a loss of available water.

5.3 The development for I_{MVM} measurement by five phases

The development of constructing the index I_{MVM} consists of five phases. As shown in Figure 5.1, during Phase I, develop a conceptual framework of company performance. During Phase II to Phase IV, construct I_{MVM} using regression analysis for weighing measures, a linear procedure based on min-max normalization for normalizing measures, and a geometric aggregation for aggregating individual measures into a multiplicative index. During Phase V, a sensitivity analysis is used to analyze the robustness of I_{MVM}.

5.3.1 Phase I and Phase II – The preliminary model and regression analysis

Phase I develops a conceptual framework of company performance with measures and their measures. This part has been done with the preliminary model in section 4.4. As a determinant of firm performance (Kuncová et al., 2016), firm size has three proxies: total sales, total assets and market capitalization (Dang et al., 2018). Market capitalization is a more appealing measure, since it is a market-oriented and forward-looking measure of size and economic relevance for a company (Bryan, 2007). Besides, market capitalization is calculated by multiplying a company's shares outstanding by the current market price of a single share, which means it is not subject to managers' influence on profit figures and investment decisions. Market capitalization is used as a proxy of company size for manufacturers, with the calculation in equation (5.1). "n_{MS}" represents the number of a company's outstanding shares and "SP_t" for the current share price of a single share.

$$\text{Market Capitalization}[\$] = n_{MS}[\#] * SP_t[\$] \tag{5.1}$$

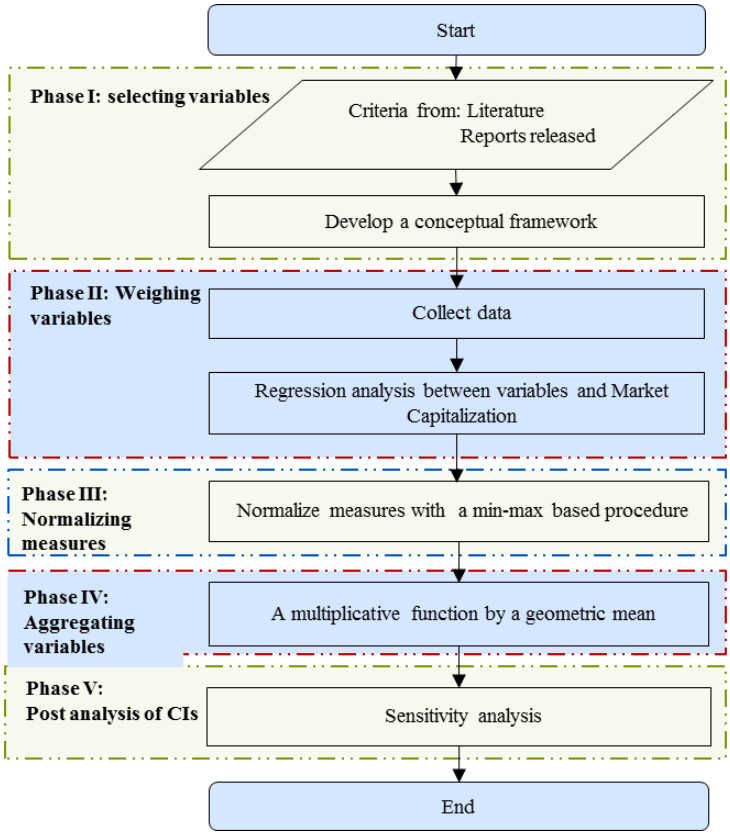


Figure 5.1: The development of the index I_{MVM}

As a statistical-based technique, regression models can tell us something about the 'linkages' between large numbers of indicators and a single output measure that represents the objective to be attained. A multiple regression model is estimated to retrieve the relative weights of the indicators (Competence Centre on Composite Indicators and Scoreboards, 2019). To elicit the weights, multiple linear regression analysis is conducted in this research with market capitalization as an endogenous variable. The importance levels (w) of the variables are generated upon the coefficients between the eight measures and the measure "market capitalization". The normalized value of the standardized coefficients works as the importance level set w= (w_{V1}, w_{V2}, w_{V3}, w_{V5}, w_{V5}, w_{V6}, w_{V7}, w_{V8}), where $\sum w_{Vi}=1$.

5.3.2 Phase III - Normalizing measures

Before aggregating those measures into a single index, a normalization phase needs to be done to transfer measures with different measurement units into dimensionless measures. Originally, the min-max algorithm transforms the data set into the range [0, 1] by equation (5.2). In this research, the equation (5.2) is modified into equation (5.3) due to Consideration 1 and Consideration 2. There are measures that have negative values. In order to be able to adopt potential aggregations in the following phase, the equation (5.3) is developed. As a result, the value out of equation (5.3) can be qualified as a base number in power functions.

As presented in Section 4.3 , for all measures with the impact "+", the higher value a manufacturer gets, the better performance the manufacturer. for all measures with the impact "-", the lower value a manufacturer gets, the better performance the manufacturer. However, after the normalization in equation (5.3), for all the measures, the higher normalized value a manufacturer gets, the better performance the manufacturer has in terms of the measure. For instance, the measure CO_2 emissions consumption per vehicle produced belongs to the impact

"-". Its value needs to be normalized by the second function in equation (5.3). Afterward, the higher it's normalized value a manufacturer gets, the better the performance in terms of CO_2 emissions reduction the company has.

$$x^* = \frac{x - \min x}{\max x - \min x} \tag{5.2}$$

$$x^{*t}_{ij} = \begin{cases} \dfrac{x^t_{ij}}{\max\limits_i x^t_{ij}} + 2, \text{for meaure with impact "+"} \\ \dfrac{\min\limits_i x^t_{ij}}{x^t_{ij}} + 2, \text{for meaure with impact "-"} \end{cases} \tag{5.3}$$

Where:

t: The fiscal year, t=0,1,...,T.

i: The MVMs, i=1,2,…,n.

j: The individual measures, j=1, 2,…,m.

x^t_{ij}: The value of the measure j for the manufacturer i in fiscal year t.

$\max\limits_i x^t_{ij}$: Within manufacturer i, the maximum value of measure j in t.

$\max\limits_i x^t_{ij}$: Within manufacturer i, the minimum value of measure j in t.

x^{*t}_{ij}: The normalized value of x^t_{ij}, and $x^{*t}_{ij} \in [1,2]$.

5.3.3 Phase IV - Aggregating measures

Following the phases of weighing measures and normalizing measures, an aggregation phase needs to be conducted to integrate those individual measures into a single index. Weighted geometric aggregation is a commonly used aggregation method that entails partial compensability. Here, compensability can be understood in this way: weighted geometric mean can better reflect a situation when a shortage in one measure limits the result and cannot be compensated by other measures. For example, in this chapter, despite the huge profit of some manufacturers, if the normalized value for energy consumption is very low, the final I_{MVM} index probably will get very low as well. Its function is in equation (5.4), where x_i is the value of the measure i, w_i is the weight of measure i, $\sum w_i$ is the sum of the weights w_1, w_2, ⋯, w_n.

$$\bar{x} = \left(\prod_{i=1}^{n} x_i^{wi}\right)^{\frac{1}{\sum_{i=1}^{n} wi}} = \exp\left(\frac{\sum_{i=1}^{n} wi \ln x_i}{\sum_{i=1}^{n} wi}\right) \tag{5.4}$$

An aggregation function based on the weighted geometric mean is developed in equation (5.5) due to Consideration 3. For instance, we disagree that high cash flows from operating activities can compensate for a loss of available water. In equation (5.5), $x^{*}_{ij}{}^{t}$ works as the unfixed base of a power function while w_{ij} works as an exponent. There are three steps for calculating this multiplicative function: 1) denote $x^{*}_{ij}{}^{t}$ as the unfixed base of a power function,

2) denote the weights w_{ij} as an exponent to the measure j in manufacturer i, and 3) multiply these values raising from power functions.

$$I_{MVM_i}^{t} = f\left[x_{ij}^{*t}, w_{ij}\right] = \prod_{j=1}^{m} x_{ij}^{*t\,w_{ij}} \tag{5.5}$$

Where:

I_{MVMi}^{t}: The company performance index for MVM i in the fiscal year t.

w_{ij}: The weight of measure j for MVM i, $w_{ij} \in (0,1)$ and $\sum w_i = 1$.

5.3.4 Conducting the post-analysis on the index I_{MVM}

A sensitivity analysis is an integral part of model development and involves an analytical examination of input parameters to aid in model validation (Hamby, 1995). Here, a sensitivity analysis is performed in order to gauge the robustness and increasing the transparency of the I_{MVM}. With this phase, it can be determined how the variation in the I_{MVM} is connected quantitatively to different sources of variation. Normally the impacts of measures weights are used for sensitivity analysis (Li & Zhao, 2016). However, the variation in the I_{MVM} stays the same in terms of the impact on measures' weights due to the nature of the multiplicative function in equation (5.5).

With methods for weighing and normalizing measures unchanged, we analyze how the different aggregation methods affect the final value. Simple additive weighing (SAW) is widely used in practice due to its ease of understanding for non-experts (Zhou, Ang, & Poh, 2006). In this dissertation, SAW is used during the post-analysis phase.

5.4 Implementing the development for I_{MVM}

5.4.1 Case sampling

According to the scope of MVMs as well as the five requirements in Section 4.2.2, manufacturers are sampled by three requirements as follows.

- Including manufacturers that rank the top 15 by motor vehicle production volume.
- Excluding non- listed manufacturers.
- Excluding manufacturers that do not provide the required data for measures V_1-V_8 with a ten-year time span.

As stated in chapter 2, this dissertation selects the top 15 MVMs by production volume from OICA. When writing this dissertation, the production statistics by manufacturer in FY2019 and in FY2018 were not released, the production statistics in FY2016 and FY2017 are referred in order to identify the top 15 MVMs. The information in terms of the three requirements is shown in Table 5.1. The sampling process results in twelve eligible MVMs, including Toyota, Audi, Hyundai, GM, Ford, Nissan, Honda, FCA, Renault, PSA, Daimler, and BMW. Audi AG was used for the Volkswagen Group. Suzuki is not included as a case study manufacturer due to insufficient information in terms of energy-related sources. Similarly, SAIC and Geely are excluded due to insufficient information out of the limited published reports of their environmental performance.

Table 5.1: Sample manufacturers

Rank	Manufacturer (Abbreviation)	Production in FY2016	Production in FY2017	Data availability
		SUM 94,771,814	SUM 96,922,080	
1	Toyota Motor Corporation (Toyota)	10,213,486	10,466,051	YES
2	Volkswagen Group Subsidiary Audi AG (Audi)	10,126,281	10,382,334	YES
3	Hyundai Motor Company (Hyundai)	7,889,538	7,218,391	YES
4	General Motors (GM)	7,793,066	6,856,880	YES
5	Ford Motor Company (Ford)	6,429,485	6,386,818	YES
6	Nissan Motor Company (Nissan)	5,556,241	5,769,277	YES
7	Honda Motor Company (Honda)	4,999,266	5,236,842	YES
8	Fiat Chrysler Automobiles N.V. (FCA)	4,681,457	4,600,847	YES
9	Group Renault (Renault)	3,373,278	4,153,589	YES
10	Group PSA (PSA)	3,152,787	3,649,742	YES
11	Suzuki Motor Corporation (Suzuki)	2,945,295	3,302,336	NO
12	SAIC Motor Corporation Limited (SAIC)	2,566,793	2,866,913	NO
13	Daimler AG	2,526,450	2,549,142	YES
14	Bayerische Motoren Werke AG (BMW)	2,359,756	2,505,741	YES
15	Geely Auto Group (Geely)	1,266,456	1,950,382	NO

5.4.2 Data collection

No existing dataset is available for all eight measures over ten or more than ten FYs. In this chapter, data is collected from multiple sources: 1) annual reports from MVMs including financial reports, sustainability reports, environmental reports and corporate social responsibility reports and 2) professional websites for stock market information. The time span is a ten-year period from FY2008 to FY2017. In order to make the data comparative, the currency is all adjusted to US dollars. The units of the three environmental measures have been unified as follows that are in line with the units in equation (4.6), equation (4.7) and equation (4.8).

- The unit of water consumption has been unified into cubic meters (m^3). Fourteen out of fifteen manufacturers report data in m^3 while Hyundai in ton. 1.0 ton of water = 1.0160469 metric ton of water = 1.0160469 $m^3$of water.

- The unit of energy consumption has been unified into megawatt hour (MWh). Ten manufacturers report data in megawatt hour while Daimler in gigawatt hour, Ford in kilowatt hour, Honda in Terajoule, FCA and Toyota in Gigajoule. 1.0 Kilowatt hour= 1.0×10^{-6} Gigawatt hours= 1.0×10^{-3} Megawatt hours. 1.0 Terajoule = 1.0×10^{3} Gigajoules = 277.7778 Megawatt hours.

- The unit of CO_2 emissions has been unified into metric ton (t). Thirteen out of fifteen manufacturers report data in metric ton while FCA and Toyota in ton. 1.0 ton of CO_2 emissions = 1.0 × 1.0160469 metric ton of CO_2 emissions.

5.4.3 Data analysis

Phase II - Weigh the measures. A dataset with non-missing values from twelve manufacturers over ten FYs (2008-2017) is built, including the measures V_1, V_2, V_3, V_4, V_5, V_6, V_7, V_8 and market capitalization. This chapter intends to include all eight measures for constructing the I_{MVM}. Multiple linear regression analysis is used with the "Enter" method. The confidence interval is set up as 95%. The value from standardized coefficients is used. An example is presented using the data from Toyota by four steps.

1) Perform a regression analysis in order to get the standardized coefficients in Table 5.2.
2) Get the absolute value as (0.152, 0.293, 0.178, 0.03, 0.398, 0.484, 0.297, and 0.056).
3) Sum up the value as 0.152+0.293+0.178+0.03+0.398+0.484+0.297+0.056 = 1.888.
4) Get a normalized set as (0.152/1.888, 0.293/1.888,0.178/1.888,0.03/1.888, 0.398/1.888, 0.484/1.888,0.297/1.888, 0.056/1.888) = (0.08, 0.155, 0.094, 0.016, 0.211, 0.256, 0.157, 0.03).

Table 5.2: Coefficients summary and importance levels for Toyota

Coefficients[a]					
Model		Unstandardized Coefficients		Standardized Coefficients	Importance level (w)
		B	Std. Error	Beta	
1	(Constant)	757627.482	358657.448		
	V_1	-575036.949	753897.287	-0.152	0.080
	V_2	185753.499	183545.411	0.293	0.155
	V_3	0.182	0.463	0.178	0.094
	V_4	-0.582	6.176	-0.030	0.016
	V_5	12000.682	7842.252	0.398	0.211
	V_6	-28219.560	15474.354	-0.484	0.256
	V_7	-111274.883	108095.606	-0.297	0.157
	V_8	-29504.894	227525.446	-0.056	0.030
a. Dependent Variable: Market Capitalization					

This new set was used as the importance levels (w) of the eight measures for Toyota, namely, w= (w_{V1}, w_{V2}, w_{V3}, w_{V5}, w_{V6}, w_{V7}, w_{V8}) = (0.08, 0.155, 0.094, 0.016, 0.211, 0.256, 0.157, and 0.03). Therefore, the multiplicative function of company performance for Toyota is generated as follows.

$$I_{MVM}{}^{t}_{Toyota} = f\left[x_j^{*t}, w_j\right] = \prod_{j=1}^{8} x^{*t}_{j}{}^{w_j} = x^{*t}_{V1}{}^{0.08} * x^{*t}_{V2}{}^{0.155} * x^{*t}_{V3}{}^{0.094} * x^{*t}_{V4}{}^{0.016} * x^{*t}_{V5}{}^{0.211} * x^{*t}_{V6}{}^{0.256} * x^{*t}_{V7}{}^{0.157} * x^{*t}_{V8}{}^{0.03}$$

Similar calculations have been applied to the other eleven MVMs, and the importance levels are listed in Table 5.3.

Phase III and Phase IV - Normalize and aggregate the measures. The normalized value for the eight measures is calculated with equation (5.3). Accordingly, the value of the index I_{MVM} can be calculated with equation (5.5). The normalized value of measures and the I_{MVM} value in FY2008 are shown in Table 5.4.

Table 5.3: Importance levels of measures for eleven manufacturers

Manufacturer	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8
Audi	0.060	0.154	0.056	0.279	0.002	0.230	0.055	0.163
Hyundai	0.062	0.101	0.268	0.194	0.021	0.004	0.123	0.227
GM	0.018	0.189	0.304	0.107	0.125	0.004	0.078	0.176
Ford	0.120	0.015	0.127	0.089	0.047	0.037	0.266	0.299
Nissan	0.035	0.029	0.124	0.128	0.052	0.131	0.366	0.135
Honda	0.062	0.101	0.268	0.194	0.021	0.004	0.123	0.227
FCA	0.082	0.228	0.099	0.069	0.288	0.101	0.023	0.109
Renault	0.119	0.113	0.105	0.037	0.266	0.145	0.033	0.182
PSA	0.154	0.079	0.235	0.104	0.169	0.097	0.087	0.074
Daimler	0.026	0.016	0.118	0.102	0.015	0.217	0.349	0.157
BMW	0.087	0.184	0.199	0.031	0.010	0.241	0.214	0.033

Table 5.4: The normalized value (x) of measures and the I_{MVM} value in FY2008*

MVM	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	I_{MVM}^{2008}
Toyota	3.000	2.377	1.810	2.546	2.743	2.316	2.277	2.152	2.396
Audi	2.111	2.621	3.000	3.000	2.584	2.426	2.313	2.629	2.640
Hyundai	2.301	2.000	2.406	2.425	2.247	2.196	2.175	2.187	2.275
GM	2.897	1.604	0.414	2.634	2.767	2.234	2.278	2.112	1.310
Ford	2.585	1.578	1.401	2.691	3.000	2.215	2.200	2.112	2.151
Nissan	2.368	2.517	1.883	2.568	2.569	2.164	2.313	2.194	2.269
Honda	2.424	2.188	2.138	2.600	2.404	3.000	3.000	3.000	2.535
FCA	2.478	2.032	2.201	2.268	2.293	2.186	2.129	2.215	2.209
Renault	2.252	1.942	2.030	2.385	2.382	2.236	2.318	2.530	2.276
PSA	2.360	2.002	2.050	2.271	2.393	2.317	2.399	2.426	2.252
Daimler	2.235	2.082	2.182	2.435	2.231	2.171	2.142	2.070	2.172
BMW	2.156	3.000	2.064	2.756	2.439	2.470	2.254	2.149	2.388

Similar calculations have been applied to the data in other FYs. Finally, I_{MVM} values over ten FYs are obtained in Table 5.5.

Phase V - Sensitivity analysis. With methods for weighing and normalizing measures unchanged, how the different aggregation methods affect the final value is analyzed. A set of values is calculated with methods including the regression analysis, the linear normalization procedure in equation (5.3) and the SAW approach. This set of values is shown in Table 5.6.

Table 5.5: The I_{MVM} value for twelve manufacturers over FY2009 to FY2017

MVM	I_{MVM} 2009	I_{MVM} 2010	I_{MVM} 2011	I_{MVM} 2012	I_{MVM} 2013	I_{MVM} 2014	I_{MVM} 2015	I_{MVM} 2016	I_{MVM} 2017
Toyota	2.505	2.646	2.489	2.545	2.659	2.637	2.663	2.591	2.583
Audi	2.646	2.902	2.893	2.868	2.837	2.868	2.746	3.003	2.626

Hyundai	2.462	2.588	2.481	2.449	2.510	2.457	2.505	2.410	2.403
GM	2.021	2.406	2.406	2.434	2.459	2.401	2.562	2.630	2.636
Ford	2.220	2.447	2.450	2.442	2.421	2.385	2.532	2.485	2.447
Nissan	2.365	2.534	2.523	2.604	2.611	2.517	2.716	2.647	2.462
Honda	2.668	2.428	2.311	2.362	2.338	2.317	2.356	2.413	2.463
FCA	2.275	2.396	2.379	2.402	2.396	2.407	2.413	2.414	2.542
Renault	2.341	2.377	2.379	2.378	2.379	2.401	2.457	2.468	2.555
PSA	2.280	2.375	2.333	2.262	2.263	2.271	2.386	2.465	2.500
Daimler	2.131	2.320	2.303	2.289	2.254	2.231	2.315	2.389	2.296
BMW	2.416	2.642	2.684	2.649	2.599	2.557	2.585	2.558	2.558

Table 5.6: Values of company performance with the SAW approach as an aggregation method

Manufacturer	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Toyota	2416	4.541	4.879	4.739	4.695	4.763	4.791	4.661	4.609	4.692
Audi	4.752	4.784	5.392	5.351	5.193	5.109	5.228	4.856	6.066	4.795
Hyundai	4.471	4.757	5.030	4.927	4.815	4.856	4.844	4.893	5.156	5.054
GM	3.897	4.321	4.912	4.891	4.809	4.813	4.805	4.942	5.564	5.087
Ford	4.361	4.452	4.901	4.886	4.812	4.748	4.748	4.886	5.286	4.751
Nissan	4.290	4.458	4.683	4.686	5.358	5.369	5.265	5.470	5.742	5.586
Honda	5.553	5.675	4.685	4.534	4.571	4.517	4.533	4.559	4.937	5.443
FCA	4.278	4.385	4.733	4.688	4.750	4.704	4.774	4.762	4.326	5.429
Renault	4.340	4.446	4.737	4.666	4.548	4.522	4.594	4.630	4.794	5.267
PSA	4.446	4.522	4.848	4.817	4.511	4.489	4.533	4.645	5.145	5.035
Daimler	4.091	4.050	4.369	4.343	4.268	4.176	4.188	4.274	4.681	5.467
BMW	4.477	4.545	5.124	5.161	4.951	4.832	4.848	4.834	4.797	5.141

To gauge the robustness of the company performance index I_{MVM}, Pearson's correlation test (2-tailed) was used to compare the set of I_{MVM} values with the set of values from the methods including SAW. The test indicates whether there is a correlation between the two sets of values calculated from different aggregation methods (with other methods unchanged). Therefore, the null hypothesis and the alternative hypothesis are as follows.

H_0 There is no correlation between the values calculated from different aggregation methods.
H_1 There is a positive correlation between the values calculated from different aggregation methods.

As shown in Table 5.7, for manufacturers Toyota, Audi, GM, Ford, Nissan, Honda, FCA, Renault, PSA and BMW, the correlation coefficients were all close to 1.0. Besides, the P values of these tests were all smaller than 0.05 at the 0.05 level (2-tailed) or smaller than 0.01 at the 0.01 level (2-tailed). For the ten manufacturers, the values calculated from I_{MVM} have a high positive correlation with the values from the method with the SAW technique. Despite that there were weak correlations in Hyundai and Daimler, the average correlation coefficient of the twelve manufacturers was 0.892 (close to 1.0) and the average P-value was 0.001. Therefore, the null hypothesis H_0 was rejected at the significance level $\alpha = 0.05$ for the tests which indicates a high positive correlation between the two sets of values.

Table 5.7: The summary of Pearson correlation coefficient

MVM	Correlation coefficient R	Sig.	Significant (YES/NO)	MVM	Correlation coefficient R	Sig.	Significant (YES/NO)
Toyota	0.742*	0.140	YES	Honda	0.919**	0.000	YES
Audi	0.919**	0.000	YES	FCA	0.835**	0.003	YES
Hyundai	0.516	0.127	NO	Renault	0.902**	0.000	YES
GM	0.912**	0.000	YES	PSA	0.930**	0.000	YES
Ford	0.847**	0.002	YES	Daimler	0.494	0.147	NO
Nissan	0.760*	0.011	YES	BMW	0.866**	0.001	YES
Average of the twelve manufacturers					0.892**	0.001	YES
* Correlation is significant at the 0.05 level (2-tailed) ** Correlation is significant at the 0.01 level (2-tailed)							

5.5 Benchmark the indices

Besides the existing indices of company performance in academia, there are several indices or methodologies for rating companies in industry. In this section, in order to test how the index I_{MVM} performs in practice, a benchmark will be done on the methodology for constructing the index I_{MVM}. In this research, three methodologies are chosen from the industry, including 1) Dow Jones Sustainability Indices World, 2) Newsweek Green Rankings and 3) the Automobile Manufacturer Industry Scorecard. The reasons why the three methodologies have been chosen are as follows.

- The index I_{MVM} distinguishes itself from the majority of the indices with an environmental perspective. In other words, the index I_{MVM} has focused on not just delivering financial performance but also performance of sustainability issues. Therefore, it is necessary to benchmark this index with well-accepted sustainability indices. Dow Jones Sustainability Indices World has been chose since it is "the first global indices tracking the financial performance of leading sustainability-driven companies worldwide" (Finch, 2005, pp.20). Newsweek's Green Rankings has been chose since it has "gained prominence for assessing the performance of the 500 largest publicly-traded companies by market capitalisation" globally (Eco-Business, 2016). Both Dow Jones Sustainability Indices World and Newsweek's Green Rankings provide the most recognized environmental performance assessments of the world's largest companies.

- The index I_{MVM} distinguishes itself from the majority of the indices with a focus on motor vehicle manufacturers. It is necessary to benchmark this index with well-accepted indices that are especially for MVMs in practice. In this section, a rating methodology by Moody's Investors Service has been chosen considering it is one of the methodologies that are especially for the automobile manufacturer industry. This methodology includes a scorecard that is a relatively simple reference tool that can be used to form "the factors that are generally most important in assigning ratings to issuers in the automobile manufacturer industry" (Moody's Investors Service, 2017, pp.2)

Prior to the benchmark, an introduction is provided about the methodologies of Dow Jones Sustainability Indices World in Section 5.5.1, Newsweek Green Rankings in Section 5.5.2 and

the Automobile Manufacturer Industry Scorecard in Section 5.5.3. The introduction consists of two parts, namely, what the factors are and how their weights are assigned.

5.5.1 Dow Jones Sustainability Indices World

The World Index, or the Dow Jones Sustainability Indices (DJSI) World, comprises global sustainability leaders as identified by RobecoSAM. The DJSI World indexes identify "the top 10% of the companies in the Dow Jones Global Index that lead the field in terms of corporate sustainability" (DJSI 2003, pp. 6). The factors and their weights for automobile companies are listed in Table 5.8. There are three dimensions totally with 24 criteria from economic,

Table 5.8: The Dow Jones Sustainability World Methodology for automobile companies (Source: RobecoSAM Corporate Sustainability Assessment 2018)

Industry Group	Dimension	Factors	Weight (%)
Automobiles & Components	Economic Dimension	Corporate Governance	9
		Codes of Business Conduct	6
		Supply Chain Management	4
		Innovation Management	4
		Risk & Crisis Management	3
		Materiality	3
		Brand Management	2
		Customer Relationship Management	2
		Product Quality and Recall Management	2
		Tax Strategy	1
		Policy Influence	1
	Environmental Dimension	Operational Eco-Efficiency	8
		Low Carbon Strategy	6
		Environmental Reporting	6
		Climate Strategy	5
		Product Stewardship	3
		Environmental Policy & Management Systems	3
	Social Dimension	Occupational Health and Safety	6
		Talent Attraction & Retention	6
		Human Capital Development	6
		Social Reporting	5
		Corporate Citizenship and Philanthropy	3
		Labor Practice Indicators	3
		Human Rights	3

environmental and social developments. The environmental factors include operational eco-efficiency, low carbon strategy, environmental reporting, climate strategy, product stewardship and environmental policy & management systems (Dow Jones Indexes, 2013). The weights of the 24 criteria have been provided by RobecoSAM.

5.5.2 Newsweek Green Rankings

Green Rankings 2017 is one of the most recognized environmental performance assessments of the world's largest publicly-traded companies (Newsweek, 2018). This ranking was produced by the magazine Newsweek in partnership with Corporate Knights. The Global 500 from Green Rankings consists of an assessment of the 500 largest publicly-traded companies in the world by revenue. The environmental metrics have been obtained based on the data from Bloomberg, FactSet, Thomson Reuters and the Carbon Disclosure Project. Nineteen motor vehicle companies were included in GLOBAL 500, with the ranking range from 16_{th} to 366_{th}. The environmental metrics and their weights are listed in Table 5.9.

Table 5.9: Factors and weights from Green Rankings Global 500 (source Newsweek Green Rankings)

Factor	Weight (%)	Factor	Weight (%)
Combined energy productivity	15	Green revenue percent range	20
Combined GHG productivity	15	Sustainability pay link	10
Combined water productivity	15	Sustainability board committee	5
Combined waste productivity	15	Audited environmental metric	5

5.5.3 Automobile Manufacturer Industry Scorecard

In 2017, Moody's Investors Service developed a scorecard (Moody's Investors Service, 2017) as the methodology for rating companies that are primarily engaged in the design and manufacture of passenger vehicles. The factors and their corresponding weights are listed in Table 5.10. Its methodology includes a scorecard that is a relatively simple reference tool that can be used in most cases to explain the factors that are generally most important in assigning ratings to issuers in the motor vehicle manufacture sector. All factors are financial measures except the "trend in Global Unit Share over Three Years". However, this forward-looking measure brings a shortcoming. Key rating assumptions related to unanticipated changes such as general financial market conditions and industry competition can cause the rating to be incorrect.

5.5.4 Benchmark against seven items

In line with the five requirements in Section 4.2.2, the methodologies can be broken down into seven aspects as benchmark items.

- Considering that, this research has a focus an environmental perspective, one benchmark item has been developed as 1) whether the factors take into account environmental concerns.
- Considering that this research has a focus on motor vehicle manufacturers, one aspect has been developed as 2) whether the measurement is developed for MVMs.
- Considering that this research aims to construct the index rigorously, three aspects have been developed as 3) when the measurement involves experts 'scoring as measures' weighing method, it tackles the uncertainty and subjectivity inherent in weighing measures, 4) whether the factors are assigned by proper importance levels.

Table 5.10: Automobile Manufacturer Industry Scorecard (source Moody's Investors Service)

Rating Factors	Weight (%)	Sub-factors	Weight (%)
Business Profile	40	Trend in Global Unit Share Over Three Years	10
		Market Position and Product Breadth/Strength	30
Profitability and Efficiency	20	EBITA Margin	20
Leverage and Coverage	30	Debt / EBITDA	10
		(Cash + Marketable Securities) / Debt	5
		RCF / Debt	5
		FCF / Debt	5
		EBITA / Interest Expense	5
Financial Policy	10	Financial Policy	10

- Considering that this research aims to construct the index transparently, three aspects have been developed as 5) whether all of the measures in the methodology can be measurable based on publicly available data, 6) whether the index is constructed with clear methods for normalizing measures and aggregating measures, 7) whether the index is transparent with a post-analysis phase.

Table 5.11 shows the benchmark results on the methodology for constructing the index I_{MVM} against methodologies for the DJSI World, Newsweek Green Rankings and the Automobile Manufacturer Industry Scorecard by Moody's Corporation.

As shown in Table 5.11, despite those methodologies for the DJSI World, Newsweek Green Rankings and the Automobile Manufacturer Industry Scorecard are well accepted, however, there are several shortcomings as follows.

1) The Automobile Manufacturer Industry Scorecard by Moody's Corporation does not consider environmental measures.

2) The Global 500 from Newsweek Green Rankings is based on the same methodology (with the same criteria) for multiple industry sectors.

3) Methodologies for the DJSI World and the Automobile Manufacturer Industry Scorecard involve questionnaires to get weights. However, a step of handling the subjectivity of respondents is missing.

4) The three methodologies keep the importance levels/weights of factors/measures approximated, fixed or totally the same for all companies. This is not applicable in reality because actual importance levels/weights of measures may vary substantially. Besides, companies in different application sectors may value the measures differently.

5) The three methodologies do not provide a post-analysis phase on the indices with different methodologies. This missing step makes the indices short of robustness. This missing phase makes the indices short of robustness.

6) The three methodologies are not constructed with clear methods for normalizing measures and aggregating measures.

The development of the index I_{MVM} does not involve subjective scoring methods, as shown in Table 5.11, so the third benchmark item is not applicable to I_{MVM}. In conclusion, the index I_{MVM} satisfies all six applicable benchmark items while the three indices are incapable to satisfy their applicable benchmark items.

Table 5.11: A benchmark against three other methodologies

Benchmark Item	A	B	C	I_{MVM}
1) The index takes into account environmental concerns.	√	√	×	√
2) The index is developed for MVMs	√	×	√	√
3) The index tackles the uncertainty and subjectivity inherent in weighing measures if the experts' scoring method is used as the weighing method.	×	N.A.	×	N.A.
4) The index makes the measures' weights adjustable for different manufacturers rather than fix the weights of measures the same for all manufacturers.	×	√	×	√
5) All of the measures in the index can be measurable based on publicly available data.	×	√	×	√
6) The index is constructed with clear methods for normalizing measures and aggregating measures.	√	√	√	√
7) The index is transparent with a post-analysis phase.	×	×	×	√
Note: A represents Dow Jones Sustainability World Index, B represents Newsweek Green Rankings, C represents Automobile Manufacturer Industry Scorecard; "√" means the index satisfies the item, "×" means the index dissatisfies the item and "N.A." means the item is not applicable for this index.				

5.6 Discussion

5.6.1 Motivation to compare the ranking R with the $R_{exc.env}$.

Currently, there are several rankings by manufacturer without environmental concerns. For instance, OICA refers to the production volume as the only criterion to rank "the 15 largest manufacturers". Hyundai ranked 3_{rd} based on the OICA ranking in FY2016 while this manufacturer ranked 11_{th} based on the I_{MVM} value in Table 5.5. One reason for the big ranking difference is that the index I_{MVM} takes into account environmental concerns while other rankings such as the one from OICA do not. Manufacturers have to pay attention to sustainable development rather than exclusively focusing on profitability. They have to be aware of CO_2 emissions during vehicles' production. In order to introduce the environmental impact on rankings, the next section makes a comparison on the ranking R by manufacturer with environmental concerns with the ranking $R_{exc.env}$ by manufacturer excluding environmental measures.

5.6.2 The ranking R by manufacturer based on I_{MVM} value over FY2008-FY2017

Based on the index I_{MVM}, it is possible to generate a ranking R by manufacturer with environmental concerns. The ranking R by manufacturer during FY2008 to FY2017 is presented in Table 5.12. The rankings varied over the ten FYs. Generally, Audi ranks the top among the twelve manufacturers, except in FY2009 and FY2017 it ranked the second. Toyota ranked either the second or the third, except in FY2011, FY2012 and FY2016 it ranked 4_{th}. BMW usually ranked the third, 4_{th} or 5_{th}, except in FY2011 and FY2012 it ranked the second. FCA usually ranked either 8_{th} or 9_{th}, except in FY2014 and FY2017 it ranked 6_{th}. Daimler usually ranked the last among the twelve manufacturers, except in FY2008, FY2009 and FY2012, it ranked 10_{th}, 11_{th} and 11_{th} respectively.

Table 5.12: The ranking R by manufacturer with environmental concerns

FY / Manufacturer	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Toyota	3	3	2	4	4	2	2	3	4	3
Audi	1	2	1	1	1	1	1	1	1	2
Hyundai	6	4	4	5	5	5	5	7	11	11
GM	12	12	8	7	7	6	7	5	3	1
Ford	11	10	6	6	6	7	9	6	6	10
Nissan	7	6	5	3	3	3	4	2	2	9
Honda	2	1	7	11	10	10	10	11	10	8
FCA	9	9	9	8	8	8	6	9	9	6
Renault	5	7	10	9	10	9	8	8	7	5
PSA	8	8	11	10	12	11	11	10	8	7
Daimler	10	11	12	12	11	12	12	12	12	12
BMW	4	5	3	2	2	4	3	4	5	4

5.6.3 The ranking $R_{exc.env}$ by manufacturer

This section presents the final value of company performance excluding the three environmental measures, namely V_6, V_7 and V_8. The five measures (V_1-V_5) are weighted with regression analysis, normalized the five measures with equation (5.3) and aggregated the five measures with equation (5.5). Based on final values of company performance, Table 5.13 lists the ranking $R_{exc.env}$ for each manufacturer during FY2008 to FY2017.

Generally, FCA ranked the top among the twelve manufacturers, except in FY2013, FY2015, FY2016 and FY2017, it ranked the second respectively. GM ranked either the first or the second among the twelve manufacturers, except in FY2008 and FY2009 it ranked the last and 8_{th} respectively. PSA usually ranked either the third or 4_{th}, except in FY2008 and FY2012 it ranked the second and 5_{th} respectively. In contrast, Daimler usually ranked the last among the twelve manufacturers, except in FY2008 it ranked 11_{th}. Similar situations happened to Nissan which usually ranked 11_{th} among the twelve manufacturers, except in FY2008 and FY2009 it ranked 9_{th} and 10_{th} respectively. Ford ranked 10_{th} among the twelve manufacturers, except for in FY2009 it ranked 11_{th}. BMW usually ranked 9_{th} among all manufacturers, except in both FY2008 and FY2011 it ranked 8_{th}.

5.6.4 Comparison between the ranking $R_{exc.env}$ and the ranking R in FY2017

$R_{exc.env}$ stands for the ranking based on the company performance value excluding environmental measures. R stands for the ranking based on the I_{MVM} value that considers environmental concerns. As shown in Table 5.15, there are three ranking trends from $R_{exc.env}$ to R. Hyundai, Honda, FCA and PSA were with a decrease in rankings. GM, Ford, Renault and Daimler had unchanged rankings no matter based on the ranking $R_{exc.env}$ and the ranking R.

Table 5.13: The ranking $R_{exc.env}$ by manufacturer excluding environmental measures

FY / MVM	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Toyota	7	7	7	9	8	6	7	5	7	6
Audi	3	5	6	5	4	4	4	6	6	7
Hyundai	4	2	3	3	3	5	5	7	8	8
GM	12	8	2	2	2	1	2	1	1	1
Ford	10	11	10	10	10	10	10	10	10	10
Nissan	9	10	11	11	11	11	11	11	11	11
Honda	5	4	5	6	6	7	8	8	4	4
FCA	1	1	1	1	1	2	1	2	2	2
Renault	6	6	8	7	7	8	6	4	5	5
PSA	2	3	4	4	5	3	3	3	3	3
Daimler	11	12	12	12	12	12	12	12	12	12
BMW	8	9	9	8	9	9	9	9	9	9

Table 5.14: Differences between the two rankings in FY2017

Ranking / MVM	$R_{exc.env}$	R	Trend	Ranking / MVM	$R_{exc.env}$	R	Trend
Toyota	6	3	↑	Honda	4	8	↓
Audi	7	2	↑	FCA	2	6	↓
Hyundai	8	11	↓	Renault	5	5	--
GM	1	1	--	PSA	3	7	↓
Ford	10	10	--	Daimler	12	12	--
Nissan	11	9	↓	BMW	9	4	↑

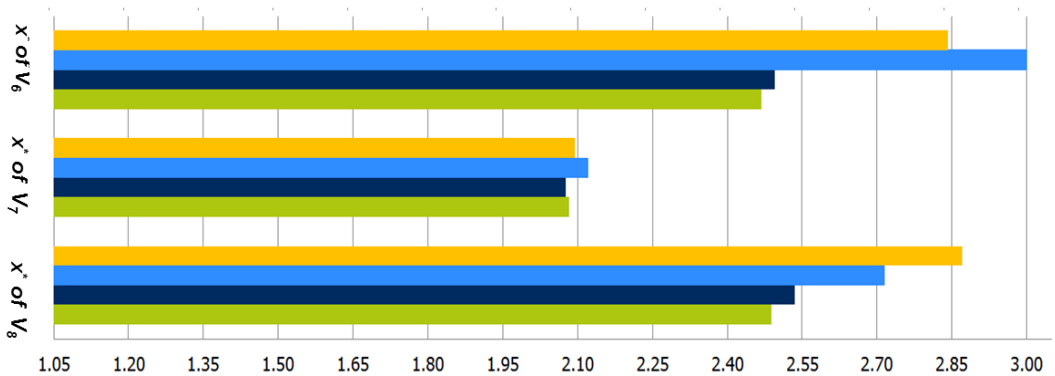
Note: The trend "↑" denotes the manufacturer that has an improved ranking from $R_{exc.env}$ to R. The trend "↓" denotes the manufacturer that has a drop-in rankings from $R_{exc.env}$ to R. The trend "--" denotes the manufacturer that keeps an unchanged ranking.

As shown in Table 5.14, Audi ranked 7_{th} without environmental concerns. Once the three environmental measures were taken into account, Audi improved its ranking to 2_{nd}. For Toyota, the ranking improved from 6_{th} to 3_{rd}. For BMW, the ranking improved from 9_{th} to 4_{th}, and for Nissan, the ranking improved from 11_{th} to 9_{th}. All four manufacturers had an increase in rankings due to the contribution of their environmental performance.

5.6.5 The environmental performance of manufacturers with the trend ↑

As introduced above, this section focuses on the environmental performance of the manufacturers that had improved rankings from $R_{exc.env}$ to R in FY2017. There are four manufacturers including Toyota, Audi, Nissan and BMW. According to the multiplicative function (5.5), the environmental performance is up to the normalized value (x^*) and the weights (w) of the measures V_6, V_7 and V_8. The x^* was obtained with the linear method in equation (5.3). The weight w was obtained by the regression analysis in Section 5.2.1, which was the normalized value of the standardized coefficients between the measures V_6, V_7 and V_8 and the measure "market capitalization". Both the x^* value and the w value were based on the raw value of measure V_6, V_7 and V_8.

However, it is not practical to put all their raw data into one figure. For instance, the raw data for V_3 Profit per employee can be over 1,000,000 while the raw data for V_8 CO_2 emissions per vehicle produced can be less than 5.0. Instead of the absolute values of the measures V_6, V_7 and V_8, their normalized values are used. The normalized value (x*) of measures V_6, V_7 and V_8 for the four manufacturers is presented in Figure 5.2. As presented in Section 5.3.2 , the higher normalized value of the measures V_6, V_7 or V_8, the better performance the company has in terms of water conservation, energy conservation or CO_2 emissions reduction.



	Normalized value (x*) of V6 Water consumption per vehicle produced	Normalized value (x*) of V7 Energy consumption per vehicle produced	Normalized value (x*) of V8 CO2 emissions per vehicle produced
BMW	2.842	2.094	2.871
Nissan	3.000	2.121	2.714
Audi	2.495	2.077	2.535
Toyota	2.468	2.083	2.488

Figure 5.2: Normalized values (x) of environmental measures for manufacturers with an increase in rankings*

The environmental performance in terms of water consumption. As seen in Figure 5.2, Nissan had the highest x* of V_6 as 3.000. In FY2017, Nissan reduced water consumed per vehicle produced by 16.2% compared to the level of FY2010. The x* of V_6 was 2.842 for BMW. BMW reduced water consumed per vehicle produced by 1.3% to 2.22 (m^3/#) in FY2017 compared to the level of FY2016. BMW targets to achieve a reduction of 45% by FY2020 compared to the level of FY2006.

The x* of V_6 was 2.495 for Audi. Audi has set up a membrane bioreactor that could turn wastewater into hygienically safe industrial water by three stages. This will help Audi realize its target of a one-third reduction for water required in production. The x* of V_6 was 2.468 for Toyota. Toyota's approach to water conservation consists of "a comprehensive reduction in

the amount of water used, and water purification and returning it to the earth". Toyota has implemented "rainwater collection and filtering to increase the recycling rate".

The environmental performance in terms of energy consumption. As seen in Figure 5.2, the x* of V_7 was 2.121 for Nissan. Nissan engages in a variety of energy-saving activities in the manufacturing process. The total energy consumption of Nissan's global production sites accounted for 8.462 million MWh in FY2017, a reduction of 6.4% compared to the level of FY2016. The x* of V_7 was 2.094 for BMW. In 2017, BMW launched a digitalization project in the area of energy consumption. Energy consumption per vehicle produced was 2.17 (MWh /#) in FY2017. Compared to the level of FY 2006, BMW has achieved a reduction of 36.5%. This manufacturer targets to achieve a reduction of 45% by FY2020. The x* of V_7 was 2.077 for Audi. Audi concentrates on generating energy from renewable sources. Energy consumption amounted to 2,924,694 MWh in FY2017 compared to 2,867,015MWh in FY2016. This is mainly due to the operation of the new plant in Mexico and lower production output by the European production sites.

The environmental performance in terms of CO_2 Emissions. The x* of V_8 was 2.871 for BMW. BMW has the plan to move towards carbon-free production. As a key driver of electric mobility, BMW increased the share of electric vehicles in its product portfolio and delivered 103,080 electric vehicles FY2017. In Europe, BMW sources its electricity free of CO_2. The x* of V_8 was 2.714 for Nissan. Nissan aims to achieve zero-emission production. From FY2010 to FY2017, Nissan globally sold more than 320,000 units of the Nissan LEAF, a zero-emission vehicle. In FY2017, Nissan had a reduction of 31% on CO_2 emissions per vehicle produced compared to the level of FY2005. Nissan targets to reduce CO_2 emissions from new vehicles by 90% based on FY2000 levels by FY2050.

The x* of V_8 was 2.525 for Audi. Audi aims to be a leader in electric cars that can reduce carbon footprint. In April 2017, Audi's new all-electric concept vehicle, the e-tron Sportback, made its debut. Audi sets a target that one in three Audi cars sold by 2025 can be an electric model. The x* of V_8 was 2.488 for Toyota. In its New Vehicle Zero CO_2 Emissions Challenge, Toyota has set the target of a 90% CO_2 emissions reduction in new vehicles by FY2050 compared to the level of FY2010.

5.7 Summary

Chapter 5 constructed an index of company performance during the fiscal year 2008 to 2017. The construction of this index integrates the eight measures that have been developed in Chapter 4. In Section 5.2, three considerations were proposed based on the background of MVMs. In Section 5.3, techniques were identified for constructing the I_{MVM}. Data was collected from fifteen MVMs over the recent ten fiscal years (FYs), that is, from FY2008 to FY2017. A sensitivity analysis with the simple additive weighing method was performed to analyze how different aggregation methods affect the final value. Section 5.4 demonstrated how to implement the method to develop the index. Section 5.5 assessed the index I_{MVM} through a benchmark against seven benchmark items. Section 5.6 presents a discussion on MVMs' environmental performance in terms of water consumption, energy consumption and CO_2 emissions in FY2017.

5.8 Conclusion

The third sub research question in this dissertation is: what methods are used to construct the composite indicator, for generating the historical performance data for MVMs. In order to

answer this sub research question, this chapter has constructed an index I_{MVM} as the performance of MVMs from economic and environmental perspectives. The development of this index has integrated the eight measures that have been developed in Chapter 4. This index has been constructed with the five requirements in Section 4.2.2. With three considerations in Section 5.2, the index $I_{MVM}{}_i^t = f\left[x_{ij}^{*t}, w_{ij}\right] = \prod_{j=1}^{n} x_{ij}^{*t}{}^{w_{ij}}$ has been constructed.

The development of the index I_{MVM} involves techniques including regression analysis for weighing measures, a linear procedure based on min-max normalization for normalizing measures, and a geometric aggregation for aggregating individual measures into a multiplicative index. A sensitivity analysis has been used to analyze the robustness of I_{MVM}. In general, the sensitivity analysis indicates the outcome from the I_{MVM} has a strong correlation with the outcome with the simple additive weighing as an aggregation method. The simple additive weighing technique is widely used in practice because of its ease of understanding for users. However, it asks for an assumption of preference independence that exists if and only if measures are mutually preferentially independent (Podvezko, 2011). Here arises the advantage of the rigorous development of the I_{MVM}, that is, it does not involve that idealistic assumption. This chapter has answered the third sub research question by constructing the index I_{MVM}.

5.9 Reflection

The index I_{MVM} has been assessed through a benchmark against seven items. The construction of the I_{MVM} satisfies all of its six applicable benchmark items while the other three indices do not. The results have indicated that the new measurement is feasible and effective for MVMs to measure their company performance from economic and environmental perspectives.

A discussion has been conducted on MVMs' environmental performance in terms of water consumption, energy consumption and CO_2 emissions in FY2017 as well as their targets in the near future. MVMs have to raise awareness of CO_2 emissions in vehicles' production. For MVMs, it is essential to create a bigger market share of zero-emission or low emission vehicles. Manufacturers have to get aware of the potential risks such as the bills due to excessive carbon emissions and carbon tax. Manufacturers with a decrease in rankings such as Honda and FCA need take it seriously considering their normalized values of CO_2 emission were below the average level. Manufacturers with an increase in rankings need to raise awareness as well even though they had improved rankings. For instance, the normalized value of CO_2 emissions for Audi and Toyota was 2.525 and 2.488 respectively. The value was below average level (2.638), which suggests that Audi and Toyota need to make an effort on reducing their CO_2 emissions. Audi aims to develop its roster of electrified vehicles to include over 20 models, so that the manufacturer can reach a target of 800,000 annual sales of electrified vehicles by 2025. This indicates Audi may have better performance regarding its environmental protection with less CO_2 emissions. Toyota aims to achieve zero CO_2 emissions at all plants by 2050 and has introduced low-CO_2 production technologies into vehicle manufacturing processes. This indicates that Toyota may have more competitive environmental performance in the future.

The historical data (FY2008-FY2017) can be generated by the index I_{MVM}. In order to get the company performance measurement data for the following fiscal years, an approach needs developing to generate the trend I_{MVM} data. Therefore, the next chapter will focus on measuring MVMs future performance from economic and environmental perspectives.

Chapter 6

Measurement of Future Performance for MVMs

6.1 Introduction

As presented in the previous chapter, the historical data (FY2008-FY2017) can be generated by the index I_{MVM}. Nevertheless, this index is insufficient for trend analysis with forecasts in future I_{MVM} data. In order to answer the fourth sub research question, this chapter aims at developing an approach to generating the trend I_{MVM} data in the following FYs.

This chapter is organized as follows. Section 6.2 presents a general introduction of time series trend analysis methods. Section 6.3 introduces the autoregressive integrated moving average (ARIMA) models. Section 6.4 develops a trend analysis approach by ARIMA models. Section 6.5 implements the approach to identify ARIMA models with data of fifteen MVMs. Future I_{MVM} data in FY2018, FY2019 and FY2020 are generated by ARIMA models of the best fit. In Section 6.6, the data out of the models contribute to benchmarking company performance (during FY2008-FY2017) of MVMs. Section 6.7 conducts the trend analysis with I_{MVM} values from the period FY2008-FY2017 verse the values in FY2018. Section 6.8 and Section 6.9 summaries and concludes this chapter respectively. Section 10 presents the reflection on this chapter.

Section 6.2, Section 6.3, Section 6.4, Section 6.5, Section 6.6 and Section 6.7 are from the work:

Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C. and Lodewijks, G. (2019), Benchmarking company performance from economic and environmental perspectives: Time series analysis for motor vehicle manufacturers. *Benchmarking: An International Journal*, *27* (3), 1127-1158.

Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C. and Lodewijks, G. (2019), An integrated framework of company performance trend analysis for motor vehicle manufacturers. On the 26th International Annual European Operations Management Association Conference, Helsinki, Finland.

6.2 Time series trend analysis

Much concentration is on the historical performance and on the things that have already happened (Unahabhokha et al., 2007). Manufacturers perform trend analysis of their

performance mainly relying on experts' judgment and some financial data for decision-making. In other words, current efforts in the field of performance measurement and management have not provided sufficient quantitative trend analysis with environmental concerns for MVMs. This section aims to develop an approach for company performance trend analysis.

Historical data of a measure collected at regular intervals in time sequence is called a time series. Time series analysis can be used in business applications for forecasting a quantity into the future and explaining its historical patterns. Time series trend analysis can aid decision-makers to plan by understanding how changes in inputs affect outcomes. This method generates trend data based on underlying patterns that are obtained from the historical data. As one of trend analysis methods, the autoregressive integrated moving average models can represent different types of time series such as pure autoregressive models, pure moving average models and mixed autoregressive and moving average processes (Ramos et al., 2015).

6.3 Autoregressive integrated moving average models

The autoregressive integrated moving average (ARIMA) model is one of the most traditional methods of non-stationary time series analysis. In contrast to the regression models, the ARIMA model allows time series to be explained by its past or lagged values and stochastic error terms. ARIMA models use a combination of autoregressive, the process of differencing to produce the forecast and moving average operations discussed by Box et al. (2015).

6.3.1 Box-Jenkins procedures

In time series analysis, the Box–Jenkins method (Box et al., 2015) applies ARIMA models to find the best fit of a time-series model to past values of a time series. Autoregressive (AR) is a weighted-average calculating process of estimating time series value using previous observations; moving average (MA) represents the process of estimating time series value based on the weight-average of estimation error residuals of previous observations. An ARIMA model can be denoted as ARIMA (p, d, q) where:

- *p* represents the order of the autoregressive process. Each AR term corresponds to the use of a lagged value of the residual in the forecasting equation for the unconditional residual. An autoregressive model of order p, AR (p) has the form as in equation (6.1).

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + ... + \alpha_p X_{t-p} + \varepsilon_t \tag{6.1}$$

- *q* represents the order of the moving average process. A moving average model uses lagged values of the forecast error to improve the current forecast. A first-order moving average term uses the most recent forecast error; a second-order term uses the forecast error from the two most recent periods, and so on. An MA (q) has the form as in equation (6.2).

$$X_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} \tag{6.2}$$

- *d* is the number of times that the raw observations are differenced, also called the degree of differencing.

Compared with other time series analysis techniques, Box-Jenkins procedure tends to fit more models that are accurate by taking into consideration estimation error residuals and lagged

dependent variables (Box et al., 2015). The steps in order to define an ARIMA model as stated by Box and Jenkins (2015) include identifying a model, estimating the parameters of the model, and diagnostic checking. A three-step procedure (Bowerman et al., 2005) is demonstrated for ARIMA model fitting, namely, model identification, parameter estimation, and model validation.

6.3.2 Criteria for trend analysis accuracy

It is important to evaluate trend analysis accuracy using genuine forecasts. The accuracy of trend analysis can only be determined by considering how well a model performs on data that were not used when fitting the model (Hyndman & Athanasopoulos, 2018). Trend analysis accuracy can be evaluated based on the minimum value of selection criteria. There are criteria including Root mean squared error, Mean absolute error, Maximum absolute percentage error, Maximum absolute standard error and Bayesian information criteria (Kumari et al., 2014; Rahman et al., 2013). Percentage errors have the advantage of being scale independent that makes it frequently used to compare trend performance between different data sets. The main percentage errors are the mean percentage error and the mean absolute percentage error.

6.3.3 ARIMA modeling steps

Based on the three-step procedures demonstrated by Bowerman et al. (2005), this dissertation lists seven detailed steps as follows.

1) Examine the data. Plot the data and examine their patterns and irregularities. Clean up outliers and deal with missing values if needed. For certain economic and financial series, a logarithmic transformation process is required to stabilize the volatility of the time series.

2) Decompose the data. Time series decomposition is a mathematical procedure to split a time series into three components including seasonality, trends and random fluctuations. Decomposition is often used to remove the seasonal effect from a time series and provide a cleaner way to understand trends.

3) Check stationarity. If it is unclear to tell stationarity from the data plot, a unit root test can be performed. The augmented Dickey-Fuller (ADF) test is a formal statistical test for stationarity. The null hypothesis assumes that a unit root is present in a series. The alternative hypothesis assumes that the series is stationary. Normally, the non-stationary series can be corrected by difference transformations.

4) Identify the order of AR (Auto-regressive) and/or MA (Moving average) terms. Besides the order of differencing *d*, there are another two parameters for ARIMA models. The autocorrelation function (ACF) plot summarizes the correlation of observations with lag values. The x-axis shows the lag and the y-axis shows the correlation coefficient between -1 and 1 for negative and positive correlation. ACF plots can help in determining the order of the MA (q) model. The partial autocorrelation (PACF) plot summarizes the correlations of observations with lag values that are not accounted for by prior lagged observations. PACF plots are useful when determining the order of the AR (p) model. By examining the ACF and PACF plots, the order of the MA (q) model and the order of the AR (p) model can be tentatively identified.

5) Fit ARIMA models. Models with some extent of non-stationary in the AR part or moving average part should be excluded. Compare model errors and fit criteria. The two widely used criteria are Akaike information criteria (AIC) and Bayesian information criteria (BIC). These criteria are related and can be interpreted as an estimate of how much information would be lost if a given model is chosen. The less the AIC or BIC value is, the better the model fits the time series data. In this dissertation, the criterion AIC is used as the fit criterion considering AIC encourages the goodness of data fitting and tries to avoid overfitting.

6) A diagnostic analysis of the identified model. Check residuals to see if the residual of the resulting model that is with the least AIC value is white noise. The residuals should have no patterns and be normally distributed.

7) Calculate trend values using the identified model. In this dissertation, data in FY2008-FY2016 is used for fitting the ARIMA model. Data in FY2017 and data in FY2018 will be used for testing the errors between the trend value and the real value. The value in FY2018, FY2019 and FY2020 will be forecast by the model.

6.4 Construction of forecasting models for trend analysis

Despite the abundant studies about company performance measures and on business forecasting methods, trend analysis based on ARIMA models from economic and environmental perspectives is not there yet for MVMs. We aim to develop a trend analysis method that is feasible to analyse MVMs from economic and environmental perspectives. A trend analysis method is developed for analyzing company performance for MVMs' performance with five phases. All five phases are shown in Figure 6.1.

6.4.1 Phase I and Phase II

In phase I, the preliminary model of the company performance measurement method in Figure 4.1 is used. In order to transfer measures with different measurement units into dimensionless measures, a normalization phase is done in phase II. Unlike the function (5.3) in Chapter 5, a new linear method based on the min-max algorithm is used by equation (6.3). This is because values calculated by this function are narrower than the ones by function (5.3), which contributes to more precise results. As presented in Section 4.3 , for all measures with the impact "+", the higher value a manufacturer gets, the better performance the manufacturer. for all measures with the impact "-", the lower value a manufacturer gets, the better performance the manufacturer. However, after the normalization in equation (6.3), for all the measures, the higher normalized value a manufacturer gets, the better performance the manufacturer has in terms of the measure.

$$x'^{t}_{ij} = \begin{cases} 1 + \dfrac{x^{t}_{ij} - \min x^{t}_{j}}{\max x^{t}_{j} - \min x^{t}_{j}}, \text{for meaure with impact "+"} \\ 1 + \dfrac{\max x^{t}_{j} - x^{t}_{ij}}{\max x^{t}_{j} - \min x^{t}_{j}}, \text{for meaure with impact "-"} \end{cases} \tag{6.3}$$

Where:

j: The individual measures, j=1, 2,…,m

x^t_{ij}: The value of the measure *j* for the manufacturer *i* in fiscal year *t*.

$minx^t_j$: The minimum value of the measure *j* for manufacturer *i* in fiscal year *t*.

$maxx^t_j$: The maximum value of the measure *j* for manufacturer *i* in fiscal year *t*.

x'^t_{ij}: The normalized value of x^t_{ij}, and $x'^t_{ij} \in [1,2]$.

6.4.2 Phase III - Weighing based on the Shannon entropy

Different from the method used in Chapter 5, Shannon entropy is used in this chapter. The entropy concept is a measure of uncertainty in information formulated in terms of probability theory (Shannon, 1948). Shannon's concept is capable of being deployed as a weighing calculation method (Shemshadi et al., 2011) as follows:

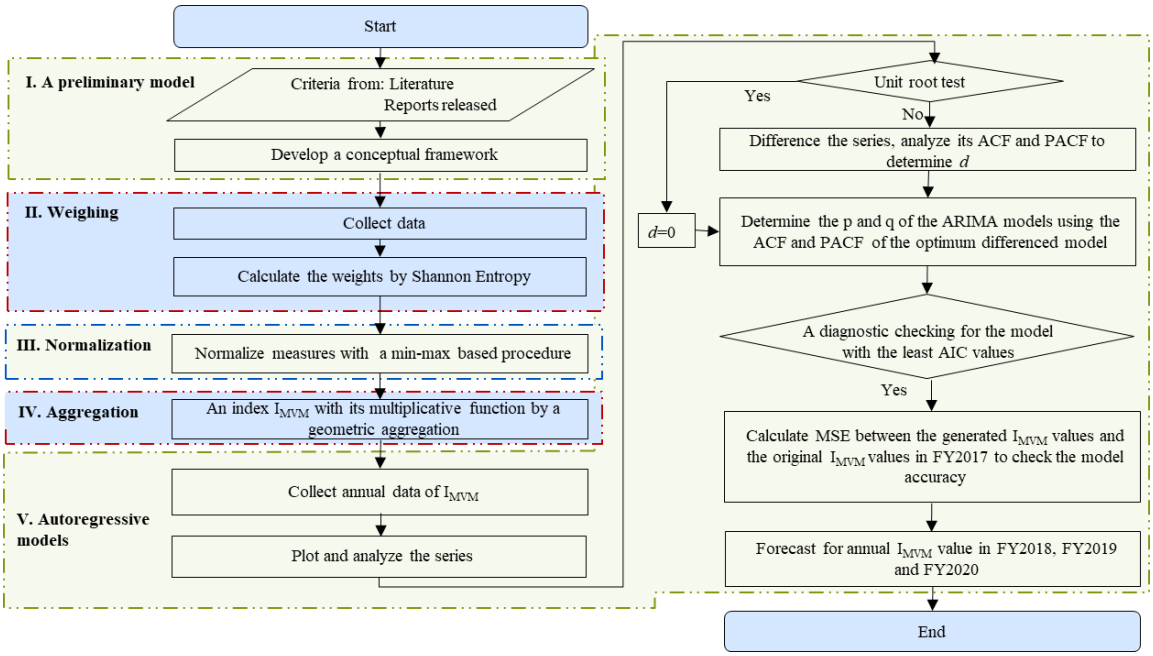


Figure 6.1: An approach to performing a trend analysis of company performance from economic and environmental perspectives for MVMs

- Normalize the evaluation index:

$$P_{ij} = \frac{x_{ij}}{\sum_j x_{ij}} \tag{6.4}$$

- Calculate the entropy index:

$$e_j = -k\sum_{j=1}^{n} p_{ij}\ln(p_{ij}), \text{where } k = \left(\ln(n)\right)^{-1} > 0, e_j \geq 0 \tag{6.5}$$

- Define the divergence through:

$$d_j = 1 - e_j \tag{6.6}$$

- Obtain the normalized weights of indexes as:

$$W_j = \frac{d_j}{\sum_j d_j} \tag{6.7}$$

Where:

p_{ij}: The relative frequency of x_{ij}.

d_j: The degree of diversification.

w_j: The weight of the measure j for the manufacturer i, $w_j \in (0,1)$ and $\sum w_j=1$.

Shannon's concept is capable of being deployed as a weighing calculation method in this dissertation. Conduct the data transformation in equation (6.3) for measures with negative values or not satisfied for logarithm application. Calculate the entropy value of measure j as equation (6.5) and get weights for each measure as equation (6.7).

6.4.3 Phase IV – Aggregating into a single index

The method in Phase IV is a geometric aggregation for aggregating individual measures into the single index I_{MVM}. Construct a multiplicative function in equation (6.6) to quantitatively generate the historical data of the I_{MVM}. I_i^t is the overall performance index for the manufacturer i in the fiscal year t, w_j stands for the final weights of measure j. The historical data of I_{MVM} can be generated with measures as inputs based on equation (6.8).

$$I_{MVM}{}_i^t = f\left[x_{ij}'^t, w_j\right] = \prod_{j=1}^{8} x_{ij}'^t{}^{w_j} \tag{6.8}$$

6.4.4 Phase V – Generating the trend of the index

In phase V, the seven steps as listed in Section 6.3.3 to generate the trend of the I_{MVM} build ARIMA models. The minimum AIC value is used to identify the model of the best fit. The trend analysis accuracy of the ARIMA models is tested by the mean absolute percentage error. The I_{MVM} values from the FY2018 to FY2020 can be calculated by the identified models.

6.5 Implementation of the ARIMA trend analysis models

6.5.1 Sampling cases and data collection

As stated in Chapter 2, this dissertation refers to the top 50 MVMs listed in OICA. This dissertation filters the MVMs that are without publicly available data for measures V_1 to V_8 during the FY2008-FY2017. The sampling processes result in fifteen MVMs, including Toyota, Audi, Hyundai, GM, Ford, Nissan, Honda, FCA, Renault, PSA, Daimler, BMW, Mazda, Mitsubishi and Tata. The other 35 cases are not included as a case study manufacturer due to insufficient information in terms of their environmental performance. A data set that consists of available data for all the eight measures from the fifteen MVMs is built.

6.5.2 Normalizing measures based on a Min-Max method

Get the normalized values of eight measures, that is, V_1' - V_8', by equation (6.3) for each MVM. Take the data in FY2017 as an example. As shown in Table 6.1, the normalized values

range from 1.0 to 2.0. The higher the normalized value an MVM gets, the better the performance the MVM has.

Table 6.1: The normalized values in FY2017

MVM	V_1'	V_2'	V_3'	V_4'	V_5'	V_6'	V_7'	V_8'
Toyota	2.000	2.000	1.199	1.524	1.286	1.721	1.582	1.539
Audi	1.072	1.530	1.185	2.000	1.210	1.750	1.547	1.618
Hyundai	1.911	1.446	1.219	1.835	1.281	1.694	1.675	1.602
GM	1.911	1.446	1.219	1.835	1.281	1.694	1.675	1.602
Ford	1.587	1.000	1.090	1.813	1.429	1.760	1.650	1.615
Nissan	1.491	1.379	1.199	1.524	1.000	2.000	1.726	1.824
Honda	1.407	1.181	1.199	1.524	1.256	1.297	1.533	1.098
FCA	1.348	1.425	1.045	1.095	1.239	1.836	1.000	1.931
Renault	1.228	1.464	1.018	1.349	1.244	1.708	1.733	2.000
PSA	1.210	1.278	1.029	1.255	1.291	1.788	2.000	1.939
Daimler	1.142	1.184	1.173	1.732	1.157	1.519	1.206	1.000
BMW	1.160	1.034	1.337	1.949	1.201	1.954	1.636	1.935
Mazda	1.042	1.033	1.029	1.491	1.206	1.480	1.622	1.879
Mitsubishi	1.005	1.477	2.000	1.628	1.020	1.488	1.645	1.916
Tata	1.000	1.276	1.000	1.000	2.000	1.000	1.548	1.566

6.5.3 Weighing measures by Shannon entropy

Weights vary from year to year. The value of the entropy is calculated for each of the eight measures in each year by equation (6.6). Accordingly, the weights of the eight measures are calculated by equation (6.7) and listed in Table 6.2.

6.5.4 Aggregating measures into I_{MVM} and generating its historical data

Aggregate the eight measures into one single index, namely, the company performance index I_{MVM} by equation (6.8). As shown in Table 6.3, the data represents the values of the company performance index for each MVM during FY2008 to FY2017. The I_{MVM} value in FY2018 is generated while the data of measures are only available for Audi, GM, Ford, Honda, FCA, Renault, PSA, Daimler and BMW.

6.5.5 Checking stationarity of historical data during FY2008 - FY2016

To demonstrate how to develop the autoregressive model, data from Toyota is used as an example. The data consists of nine observations. As shown in the left part Figure 6.2, this data from Toyota has no missing values, no outliers or seasonality. Basically there is an increasing trend in this data. It is unclear to test the stationarity from the plot. As shown in the right part Figure 6.2, the same conclusion can be obtained for data in first order difference data. Therefore, an ADF test is performed with the null hypothesis as: a unit root is present in a time series. The null hypothesis will be rejected if the p-value is less than 0.05.

Table 6.2: The weights by Shonna entropy during FY2008 - FY2017

FY	Weight	V_1'	V_2'	V_3'	V_4'	V_5'	V_6'	V_7'	V_8'
2008	e_j	0.992	0.993	0.995	0.993	0.992	0.994	0.988	0.994
	W_j	0.138	0.116	0.087	0.126	0.130	0.102	0.203	0.098
2009	e_j	0.992	0.990	0.993	0.993	0.993	0.995	0.996	0.990
	W_j	0.141	0.167	0.125	0.121	0.118	0.086	0.074	0.168
2010	e_j	0.992	0.993	0.992	0.994	0.993	0.993	0.993	0.994
	W_j	0.148	0.119	0.147	0.110	0.120	0.121	0.133	0.101
2011	e_j	0.990	0.992	0.992	0.993	0.994	0.991	0.995	0.994
	W_j	0.168	0.141	0.133	0.114	0.108	0.157	0.085	0.094
2012	e_j	0.990	0.994	0.990	0.993	0.995	0.993	0.995	0.995
	W_j	0.181	0.113	0.187	0.123	0.089	0.125	0.094	0.088
2013	e_j	0.990	0.993	0.992	0.994	0.994	0.993	0.994	0.996
	W_j	0.184	0.131	0.146	0.118	0.104	0.121	0.118	0.077
2014	e_j	0.992	0.992	0.993	0.994	0.995	0.993	0.994	0.996
	W_j	0.156	0.153	0.133	0.118	0.099	0.144	0.112	0.084
2015	e_j	0.992	0.990	0.992	0.993	0.995	0.995	0.992	0.995
	W_j	0.151	0.174	0.146	0.123	0.090	0.089	0.144	0.083
2016	e_j	0.991	0.993	0.993	0.993	0.994	0.995	0.995	0.994
	W_j	0.170	0.144	0.138	0.137	0.110	0.099	0.090	0.111
2017	e_j	0.989	0.993	0.993	0.993	0.994	0.995	0.995	0.993
	W_j	0.206	0.122	0.128	0.135	0.105	0.096	0.084	0.124

Table 6.3 – The values of I_{MVM} for each case during FY2008 - FY2017

MVM	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
Toyota	-	1.613	1.594	1.764	1.712	1.607	1.610	1.397	1.570	1.546	1.578
Audi	1.5310	1.421	1.526	1.649	1.698	1.552	1.719	1.504	1.614	1.511	1.557
Hyundai	-	1.590	1.354	1.469	1.500	1.457	1.537	1.488	1.492	1.373	1.326
GM	1.8277	1.590	1.595	1.647	1.457	1.549	1.610	1.518	1.530	1.338	1.427
Ford	1.6819	1.462	1.509	1.595	1.539	1.498	1.535	1.456	1.499	1.379	1.408
Nissan	-	1.475	1.567	1.610	1.553	1.425	1.516	1.500	1.453	1.465	1.484
Honda	1.4772	1.306	1.366	1.383	1.406	1.341	1.402	1.415	1.397	1.540	1.573
FCA	1.3664	1.330	1.329	1.272	1.387	1.292	1.346	1.315	1.295	1.300	1.277
Renault	1.4529	1.402	1.436	1.525	1.473	1.359	1.405	1.365	1.394	1.441	1.421
PSA	1.4370	1.386	1.431	1.429	1.368	1.318	1.329	1.295	1.409	1.413	1.460
Daimler	1.2503	1.238	1.296	1.186	1.173	1.170	1.237	1.223	1.252	1.142	1.206
BMW	1.6853	1.446	1.433	1.484	1.514	1.467	1.584	1.380	1.469	1.446	1.481
Mazda	-	1.279	1.317	1.436	1.304	1.371	1.258	1.316	1.270	1.265	1.316
Mitsubishi	-	1.443	1.476	1.410	1.487	1.378	1.475	1.416	1.253	1.111	1.102
Tata	-	1.215	1.288	1.252	1.251	1.168	1.217	1.433	1.374	1.613	1.387

Figure 6.2 The plot of data from Toyota

As shown in Table 6.4, the p-value is 0.6023 with the ADF result from the original data. This indicates that the null hypothesis will be accepted. In this case, differential processing is needed. Generally, the differencing process starts with the order of *d* =1. The augmented Dickey-Fuller test on first order difference (diff1) data accepts the null hypothesis of non-stationarity. This suggests that diff1 is insufficient and needs excluding in the model. In the second order difference data, the p-value is 0.01 which is below the value 0.05. Therefore, the null hypothesis is rejected which means the second order difference data can be considered to be stationary.

Table 6.4 – Augmented Dickey-Fuller Test results for Toyota during FY 2008- FY2016

Data	Dickey-Fuller	Lag order	p-value	Significant (YES/NO)
Original	-1.9215	2	0.6023	NO
Data(diff1)	-0.99007	1	0.922	NO
Data(diff2)	-5.0366	1	0.01	YES

The same test is performed to data of the other fourteen MVMs. The test results are listed in Table 6.5. The data of FCA, PSA, Mitsubishi and Tata are non-stationary, no matter by their original data, first order difference data, second order difference data or logarithm data. This kind of sequence data is relatively rare in economic finance. One explanation can be that the sequence data size is too small. This data is insufficient to reflect regularities. Therefore, the four MVMs are excluded from the following data analysis.

6.5.6 Choosing the order of ARIMA models

Besides the order of differencing *d*, the order of the MA (q) model and the order of the AR (p) model need to be tentatively identified. Take the data from Toyota as an example. The second order differentiation data can be considered stationary, namely, d=2. As seen in Figure 6.3, the order of MA term q is 1. Similarly, the order of AR term is p=1. So, the parameters (p=1, d=2, q=1) is used to fit models.

6.5.7 Fitting ARIMA models and identifying the model with the least AIC value

For fitted ARIMA models, AR orders (1 through 2) are run against MA orders (1 through 2). The differentiating order is identified as 1 or 2. Therefore, a total of 7 models can be fitted for each MVM. The AIC values are calculated for each potential fitted model in Table 6.6. The AIC with "N.A." indicates that there is some extent of non-stationary in the auto-regressive

Table 6.5 – Augmented Dickey-Fuller Test results for 15 cases during FY2008 - FY2016

MVM	p-value from original data	Significant (YES/NO)	p-value from Data(diff1) or Data(diff2) or Data Ln()	Significant (YES/NO)
Toyota	0.6023	NO	diff2-0.01	YES
Audi AG	0.99	NO	diff2-0.01	YES
Hyundai	0.9221	NO	diff2-0.045	YES
GM	0.691	NO	diff2-0.011	YES
Ford	0.702	NO	diff2-0.011	YES
Nissan	0.99	NO	diff1-0.02561	YES
Honda	0.01	YES	diff1-0.01	YES
FCA	0.99	NO	diff2- 0.4154	NO
Renault	0.99	NO	Ln(diff2)- 0.0412	YES
PSA	0.7909	NO	diff1- 0.1662, diff2- 0.6325, Ln(diff2)- 0.1662	NO
Daimler	0.99	NO	diff2- 0.02741	YES
BMW	0.9491	NO	Ln(diff2)- 0.03001	YES
Mazda	0.9505	NO	diff1- 0.04479	YES
Mitsubishi	0.6334	NO	diff1- 0.6334, diff2- 0.5933, Ln(Diff1)- 0.6416	NO
Tata	0.953	NO	diff1- 0.7951, diff2- 0.8651, Ln(diff1)- 0.8027, Ln(diff1)- 0.8464	NO

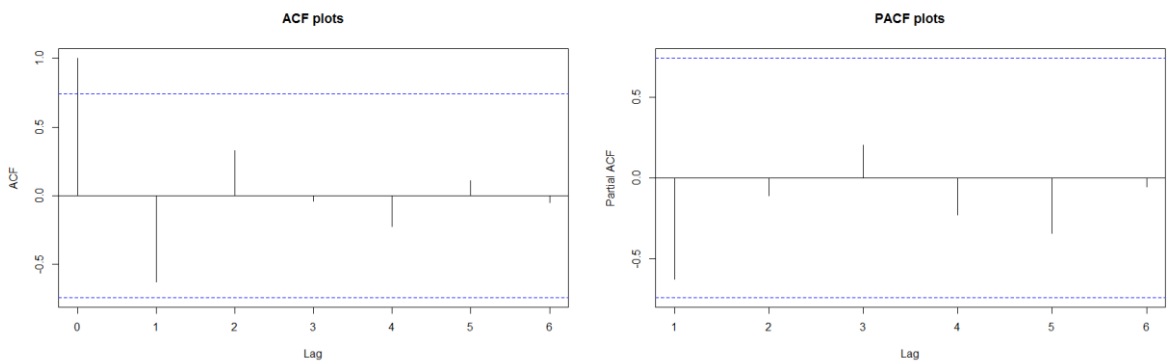


Figure 6.3: The ACF and PACF plots from the second order differentiation data of Toyota

part of the model. These models are excluded despite the AIC values are the least. The minimum value of AIC is used to identify the model of the best fit for eleven MVMs. The models of the best fit are highlighted in bold. Take Toyota as an example. The model ARIMA (2, 2, 0), which incorporates second order difference data and an autoregressive model of order 2, has been identified as the ARIMA model of the best fit. The model can be written as equation (6.9) where "E" stands for error.

$$\hat{Y}_t = 1.0083\hat{Y}_{t-1} - 0.4323\hat{Y}_{t-2} + E \tag{6.9}$$

Table 10: AIC values for eleven cases during FY2008- FY2016

MVM	ARIMA models						
Toyota	ARIMA (1,2,1)	ARIMA (1,2,0)	ARIMA (0,2,1)	**ARIMA (2,2,0)**	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	9.8554	9.5936	11.4782	6.5011	10.4035	10.4484	10.2594
Audi	ARIMA (1,2,1)	ARIMA (1,2,0)	ARIMA (0,2,1)	ARIMA (2,2,0)	ARIMA (0,2,2)	ARIMA (1,2,2)	**ARIMA (2,2,1)**
AIC	9.4583	9.4606	14.4914	N.A.	12.6915	12.6915	5.0678
Hyundai	ARIMA (1,2,1)	**ARIMA (1,2,0)**	ARIMA (0,2,1)	ARIMA (2,2,0)	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	1.2380	-0.2600	3.8988	N.A.	2.9941	3.1908	3.2376
GM	**ARIMA (1,2,1)**	ARIMA (1,2,0)	ARIMA (0,2,1)	ARIMA (2,2,0)	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	10.5333	10.8904	10.4147	1.7116	10.7439	11.7233	N.A.
Ford	ARIMA (1,2,1)	ARIMA (1,2,0)	ARIMA (0,2,1)	ARIMA (2,2,0)	ARIMA (0,2,2)	ARIMA (1,2,2)	**ARIMA (2,2,1)**
AIC	3.5397	3.5552	5.6987	N.A.	5.1134	4.5248	-3.2409
Nissan	ARIMA (1,1,1)	ARIMA (1,1,0)	**ARIMA (0,1,1)**	ARIMA (2,1,0)	ARIMA (0,1,2)	ARIMA (1,1,2)	ARIMA (2,1,1)
AIC	-1.4362	-0.8296	-3.0179	N.A.	-3.0731	-1.1269	N.A.
Honda	ARIMA (1,1,1)	ARIMA (1,1,0)	ARIMA (0,1,1)	**ARIMA (2,1,0)**	ARIMA (0,1,2)	ARIMA (1,1,2)	ARIMA (2,1,1)
AIC	-4.4397	-2.9865	-4.1863	-15.4561	-5.3659	-4.4734	-13.3862
Renault	ARIMA (1,2,1)	ARIMA (1,2,0)	ARIMA (0,2,1)	**ARIMA (2,2,0)**	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	-0.0451	-0.9895	-0.9509	-15.4561	N.A.	0.8986	-1.4914
Daimler	ARIMA (1,2,1)	**ARIMA (1,2,0)**	ARIMA (0,2,1)	ARIMA (2,2,0)	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	-0.1456	-1.9034	3.3447	-0.3844	3.1949	1.3630	N.A.
BMW	ARIMA (1,2,1)	ARIMA (1,2,0)	ARIMA (0,2,1)	**ARIMA (2,2,0)**	ARIMA (0,2,2)	ARIMA (1,2,2)	ARIMA (2,2,1)
AIC	8.0654	8.6389	11.2107	4.8758	9.5154	8.1798	6.9831
Mazda	ARIMA (1,1,1)	ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (2,1,0)	ARIMA (0,1,2)	ARIMA (1,1,2)	**ARIMA (2,1,1)**
AIC	8.0654	8.6389	1.9076	4.8758	-0.0242	8.1798	-4.8845

6.5.8 A diagnostic analysis of the identified model

For Toyota, the model ARIMA (2, 2, 0) has been identified with the least AIC value. To test its effectiveness, the model residuals need examining by ACF plots. Its ACF residual plot is shown in Figure 6.4. Since lag=1, all the residuals are located within a 95% confidence interval. This fitted model AMRMA (2, 2, 0) is validated as stationary. In other words, this

model can be used to do trend analysis on future I_{MVM} values in FY2018. Do diagnostic analysis to other sampled cases and get the validated models for each MVM in Table 6.6.

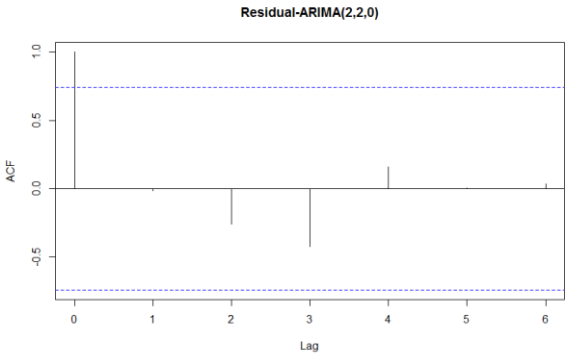


Figure 6.4 The ACF plot from ARIMA (2,2,0) of Toyota

6.5.9 The trend I_{MVM} value during FY2017 to FY2020

The forecast horizon *h* ahead for predictions is set as *h*=4, that is, in FY2017, FY2018, FY2019 and in FY2020. The data during FY2008 to FY2016 are used to build the training data set, while the data in FY2017 are used for the validation data set. The trend analysis accuracy by ARIMA models in FY2017 is tested by the mean absolute percentage error (MAPE). MAPE is calculated as in equation (6.10). The trend values $\hat{y}_t$ from the models are compared and shown as a percentage of the actual value y_t. Both over and underestimations were considered of the same relevance, which means that only the absolute value of the errors is considered. The identified model is used to generate the trend I_{MVM} value during FY2018 to FY2020.

Table 6.6 – Validated models for eleven cases

Case	ARIMA models	Case	ARIMA models
Toyota	ARIMA (2,2,0)	Honda	ARIMA (2,1,0)
Audi AG	ARIMA (2,2,1)	Renault	ARIMA (1,2,0)
Hyundai	ARIMA (1,2,0)	Daimler	ARIMA (1,2,0)
GM	ARIMA (1,2,1)	BMW	ARIMA (1,2,0)
Ford	ARIMA (2,2,1)	Mazda	ARIMA (2,1,1)
Nissan	ARIMA (0,1,1)		

$$MAPE_i = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \tag{6.10}$$

Where:

$MAPE_i$: The mean absolute percentage error between the historical I_{MVM} value and the trend I_{MVM} value for the MVM *i*.

n: the sample size.

y_t: The historical or actual I_{MVM} value.

$\hat{y}_t$: The trend I_{MVM} value.

So far, the publicly available data in FY2018 are only available for nine MVMs including Audi, GM, Ford, Honda, FCA, Renault, PSA, Daimler, and BMW. Because PSA and FCA have been excluded for building ARIMA models, seven MVMs are with available I_{MVM} data in FY2018. As shown in Table 6.7, the MAPE value for Toyota in FY2017 was 3.58%. As shown in Figure 6.5, the blue area shows the fit provided by the model ARIMA (2,2,0) for Toyota. The light blue area and dark blue area cover the trends with confidence intervals of 95% and 80% respectively.

Table 6.7 – The trend I_{MVM} value in FY2017 and FY2018 of Toyota

FY	y_t	$\hat{y}_t$	Lo 80	Hi 80	Lo 95	Hi 95	MAPE
2017	1.613	1.6707	1.4954	1.8461	1.4026	1.9389	3.58%
2018	N.A.	1.5947	1.3478	1.8416	1.2171	1.9723	-
2019	N.A.	1.5660	1.1966	1.9355	1.0010	2.1310	-
2020	N.A.	1.5556	1.0474	2.0638	0.7784	2.3328	

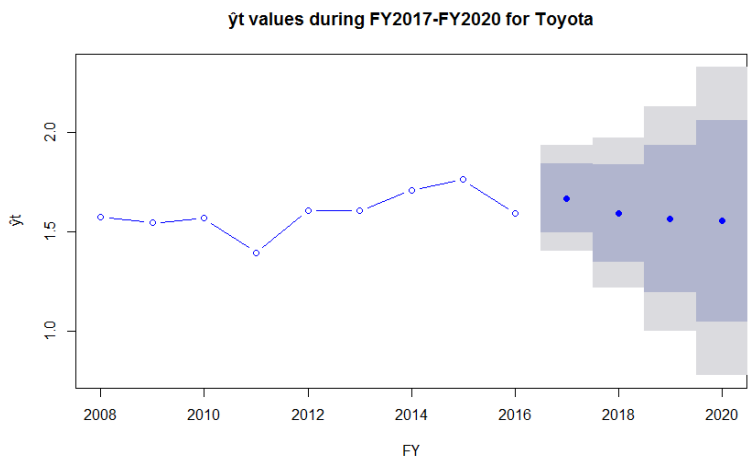


Figure 6.5 The ACF plot from ARIMA (2, 2, 0) of Toyota

Calculate MAPE values in FY2017 and/ or in FY2018 for each MVM. Calculate trend I_{MVM} values during FY2019 and FY2020 for each MVM. As shown in Table 6.8, the average MAPE values in FY2017 is 8.31%. Audi, Hyundai, Ford and Mazda are with MAPE over 10%. The average MAPE values in FY2018 is 10.02%. Ford, Daimler and BMW are with MAPE over 10%. In this dissertation, 10% is set up as an error threshold for MAPE. MAPE over 10% indicates that the trend analysis is not accurate for the MVMs. The reason behind the relative higher MAPE may be specific activities taking place in the MVMs that have influenced the actual I_{MVM} value. For instance, BMW blotted its copybook in FY2018 when the automotive business only managed a 7.2% return on sales, with trade tensions, rising raw material costs, and Brexit uncertainty as a heavy burden (Bloomberg Opinion, 2019). The consequences by the burdens have influenced the actual I_{MVM} value in FY2018, which is with relatively high MAPE with the trend value generated by ARIMA models developed in this dissertation.

6.6 Discussions in terms of the historical company performance

This dissertation develops an approach to measuring the performance of MVMs from economic and environmental perspectives. An index I_{MVM} is constructed as the performance

from economic and environmental perspectives. Its historical data during FY2008 to FY2017 is generated by equation (6.6). In addition, its future data in FY2018 is generated by ARIMA models of the best fit. Benchmarking has been recognised as one of the most widely known improvement techniques or tools in the world (Al Nuseirat et al., 2019). The data out of this dissertation can contribute to benchmarking the company performance (during FY2008 - FY2017) of MVMs as well as the performance in FY2018.

Table 6.8 – Trend I_{MVM} values during FY2017 to FY2020

MVM	y_{2017}	$\hat{y}_{2017}$	MAPE(%)	y_{2018}	$\hat{y}_{2018}$	MAPE(%)	$\hat{y}_{2019}$	$\hat{y}_{2020}$
Toyota	1.6130	1.6707	3.58	-	1.5947	-	1.5660	1.5556
Audi	1.4210	1.6707	17.57	1.5310	1.5947	4.16	1.5660	1.5556
Hyundai	1.5900	1.2926	18.71	-	1.1970	-	1.1232	1.0355
GM	1.5900	1.6687	4.95	1.8277	1.6749	8.36	1.7173	1.7403
Ford	1.4620	1.6945	15.90	1.6819	1.4790	12.06	1.7939	1.4490
Nissan	1.4750	1.5670	6.24	-	1.5670	-	1.5670	1.5670
Honda	1.3060	1.3690	4.82	1.4772	1.3698	7.27	1.3696	1.3695
Renault	1.4020	1.4040	0.14	1.4529	1.3490	7.15	1.3032	1.2537
Daimler	1.2380	1.3274	7.22	1.2503	1.4225	13.77	1.4659	1.5512
BMW	1.4460	1.4469	0.06	1.6853	1.3926	17.37	1.3880	1.3578
Mazda	1.2790	1.4359	12.27	-	1.3349	-	1.4321	1.3471
Average	1.4384	1.5043	8.31		1.4524	10.02	1.4811	1.4348

6.6.1 Benchmark the environmental performance of MVMs during FY2008 to FY2017

Benchmarking performance involves a comparison of metrics while best practice benchmarking involves "studying the practices of those organisations that are higher performers and adapting their 'better practices' to another organisation" (Adebanjo & Mann, 2008). This section constructs an environmental performance index. Based on the outcome, the best performer and the worst performer from an environmental perspective are identified. A benchmark is performed regarding their environmental performance.

An environmental performance index I_{ENVI} is constructed as follow. The normalized values of the three measures (V_6- V_8) are the same as the ones when constructing the I_{MVM}. However, the weights of the three measures are different from the ones when constructing the I_{MVM}. Calculate the weights of the three measures in equation (6.6) and equation (6.7). Finally, aggregate the three environmental measures into a single index $I_{ENVI.}$ as in equation (6.11).

$$I_{ENVI.i}^{t} = f\left[x_{ij}^{'t}, w_j\right] = \prod_{j=6}^{8} x_{ij}^{'t\,w_j} = x_{i6}^{'t\,w_{V_6}} \times x_{i7}^{'t\,w_{V_7}} \times x_{i8}^{'t\,w_{V_8}} \tag{6.11}$$

The weights of the three measures and the aggregated $I_{ENVI.}$ values are listed in Table 6.9 and Table 6.10 respectively.

6.6.2 The best performer and the worst performer

The purpose of benchmarking is to systematically measure and compare performance with the best-in-class to determine what needs be improved for achieving superior performance

(Anand & Kodali, 2008; Motwani et al., 2006). As is seen in Table 6.10, Audi was the best performer in terms of its environmental performance. During FY2008 to FY2017, its average

Table 6.9 – The weights by Shanna entropy during FY 2008 - FY 2017 for three environmental measures

FY / Weight	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
V_6	0.312	0.330	0.281	0.424	0.333	0.407	0.467	0.341	0.264	0.252
V_7	0.287	0.301	0.456	0.330	0.333	0.307	0.253	0.374	0.225	0.505
V_8	0.402	0.369	0.263	0.247	0.334	0.286	0.280	0.284	0.511	0.243

Table 6.10 – The values of the $I_{ENVI.}$ for each case during FY2008- FY2017

FY / Case	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Toyota	1.623	1.678	1.743	1.406	1.770	1.754	1.766	1.630	1.580	1.607	1.656
Audi	1.759	1.878	1.911	1.463	1.973	1.941	1.955	1.784	1.807	1.638	1.811
Hyundai	1.437	1.702	1.673	1.520	1.714	1.831	1.808	1.840	1.751	1.652	1.693
GM	1.555	1.584	1.696	1.469	1.691	1.724	1.708	1.701	1.608	1.652	1.639
Ford	1.442	1.547	1.632	1.467	1.697	1.693	1.695	1.683	1.637	1.670	1.616
Nissan	1.611	1.706	1.648	1.668	1.858	1.850	1.858	1.802	1.763	1.849	1.761
Honda	1.967	1.961	1.439	1.580	1.427	1.464	1.436	1.428	1.331	1.273	1.531
FCA	1.262	1.447	1.370	1.309	1.478	1.469	1.471	1.244	1.466	1.575	1.409
Renault	1.714	1.757	1.811	1.555	1.788	1.780	1.774	1.774	1.756	1.829	1.754
PSA	1.781	1.863	1.821	1.499	1.774	1.764	1.756	1.732	1.756	1.908	1.765
Daimler	1.157	1.080	1.271	1.329	1.280	1.117	1.178	1.108	1.231	1.202	1.195
BMW	1.618	1.650	1.748	1.332	1.809	1.791	1.802	1.748	1.736	1.851	1.709
Mazda	1.384	1.413	1.454	1.809	1.438	1.503	1.356	1.632	1.622	1.673	1.528
Mitsubishi	1.004	1.201	1.317	1.572	1.749	1.743	1.706	1.711	1.678	1.696	1.538
Tata	1.389	1.725	1.458	1.791	1.328	1.380	1.333	1.347	1.326	1.357	1.443

value of the environmental performance index was the highest among all the fifteen MVMs. Audi aims to be a leader in electric cars which can reduce carbon footprint. In April 2017, Audi's new all-electric concept vehicle, the e-tron Sportback, made its debut. Audi aims that one in three Audi cars sold by 2025 is to be an electric model. This indicates that Audi might have even better performance regarding environment protection with less CO_2 emissions and energy consumption.

In terms of the average environmental performance, Daimler was identified as the worst performer during FY2008 to FY2017. Compared with car manufacturing, truck manufacturing and bus manufacturing consume more energy, more water and generate more pollutants. Daimler is one of the biggest suppliers of premium cars and commercial vehicles with a global reach. Its industrial divisions include Mercedes-Benz Cars, Daimler Trucks, Mercedes-Benz Vans and Daimler Buses. In FY2017, Daimler spent 8.7 billion euros on activities including researching and developing the EQ electric brand in Mercedes-Benz Cars, emission standards and fuel efficiency in Daimler Trucks, the fulfillment of future emissions standards and measures to further reduce fuel consumption in Daimler Buses. The Mercedes-

Benz Citaro is further reducing its fuel consumption with its new electro-hydraulic steering system. The demand for clean and economical transport is growing all over the world. That might boost the development of Daimler Trucks and Daimler Buses. Considering the high level of research and development expenditure on fuel-efficient and environmentally friendly drive systems, Daimler Group will probably have higher normalized values of the three environmental measures in the following years.

6.6.3 Economic performance and environmental performance during FY2008 - FY2017

An economic performance index $I_{ECON.}$ can be constructed with the same methods in Section 6.4. The weights of the five measures (V_1- V_5) are calculated and listed in Table 6.11. The aggregated value of the index $I_{ECON.}$ is listed in Table 6.12.

$I_{ENVI.}$ performance versus $I_{ECON.}$ performance. The average $I_{ENVI.}$ values and $I_{ECON.}$ Values of the fifteen MVMs are pitched in Figure 6.6. As shown, it is visible that the $I_{ECON.}$ values had a downward trend since FY2008 which can be explained by the economic crisis between FY2008 and FY2009. In FY2010 most MVMs revived and the economic performance increases due to the rapid economic recovery. Nevertheless, it remains unstable until FY2013 when there was a continuously increasing trend.

In terms of environmental performance, generally, the average values increase. It is obvious that data at several points showing a contraction between $I_{ECON.}$values and I_{ENVI} values. For example, in FY2010 there was a peak of the $I_{ENVI.}$ value, while there was a valley of the $I_{ECON.}$ value. Similar phenomena showed up in FY2011, FY2012, FY2015, FY2016 and FY2017. This may be reasoned by the fact that a struggling economy leads to a decline in vehicles' production volume which results in less resource consumption and less CO_2 emissions.

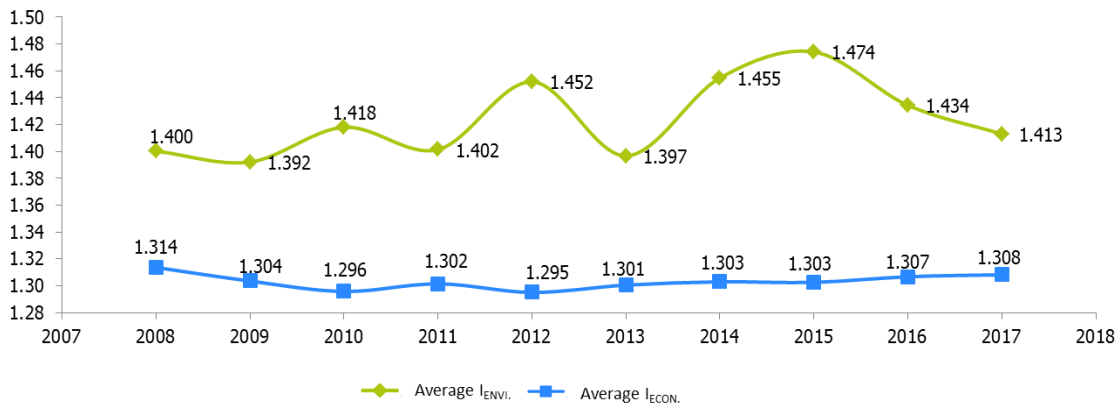


Figure 6.6: Average values of the $I_{ECON.}$ and the $I_{ENVI.}$ during FY2008 - FY2017

6.6.4 Performance matrix on the $I_{ENVI.}$ versus the I_{MVM}

The generated I_{MVM} values and the values of the environmental performance index are combined in a matrix. The I_{MVM} values are presented for each MVM on the horizontal axes. The values of the environmental performance index ($I_{ENVI.}$) are presented on the vertical axes. A common practice is to compare with average (Deming, 1986). The average levels by the average score on I_{MVM} values (1.424) and by the average score on the $I_{ENVI.}$ values (1.603) are added. The combined result is presented in Figure 6.7. MVMs are distributed in four quadrants that are formed by two average levels. MVMs located in Quadrant I are with high $I_{ENVI.}$ values and high I_{MVM} values. On the contrary, MVMs located in Quadrant III are with

low $I_{ENVI.}$ values and low I_{MVM} values. MVMs located in Quadrant II are with high $I_{ENVI.}$ values but low I_{MVM} values. MVMs located in Quadrant IV are with high I_{MVM} values but low $I_{ENVI.}$ values.

Table 6.11 – Weights of the five economic measures during FY2008 - FY2017

Measure	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
V_1	0.270	0.243	0.221	0.237	0.270	0.262	0.253	0.230	0.210	0.231
V_2	0.159	0.206	0.254	0.232	0.191	0.163	0.213	0.185	0.248	0.194
V_3	0.203	0.198	0.214	0.202	0.213	0.270	0.200	0.229	0.187	0.145
V_4	0.207	0.196	0.180	0.179	0.173	0.177	0.172	0.171	0.180	0.212
V_5	0.161	0.158	0.132	0.151	0.153	0.128	0.163	0.186	0.176	0.218

Table 6.12 – Values of the index $I_{ECON.}$ For each case during FY2008 - FY2017

Case	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Toyota	1.592	1.602	1.564	1.604	1.569	1.599	1.607	1.611	1.599	1.587	1.593
Audi	1.365	1.363	1.333	1.339	1.323	1.330	1.352	1.363	1.355	1.343	1.347
Hyundai	1.207	1.180	1.190	1.190	1.192	1.195	1.184	1.175	1.194	1.208	1.192
GM	1.541	1.517	1.510	1.532	1.526	1.538	1.529	1.523	1.538	1.552	1.531
Ford	1.381	1.327	1.342	1.342	1.344	1.351	1.333	1.316	1.353	1.381	1.347
Nissan	1.310	1.314	1.303	1.321	1.324	1.324	1.325	1.329	1.325	1.327	1.320
Honda	1.318	1.300	1.304	1.307	1.309	1.310	1.304	1.300	1.312	1.322	1.309
FCA	1.234	1.237	1.220	1.234	1.211	1.229	1.234	1.233	1.228	1.220	1.228
Renault	1.265	1.263	1.238	1.251	1.223	1.243	1.255	1.257	1.252	1.242	1.249
PSA	1.221	1.211	1.199	1.205	1.186	1.200	1.205	1.203	1.206	1.202	1.204
Daimler	1.265	1.251	1.245	1.246	1.248	1.245	1.250	1.252	1.258	1.261	1.252
BMW	1.302	1.279	1.290	1.280	1.303	1.286	1.282	1.281	1.297	1.312	1.291
Mazda	1.156	1.135	1.133	1.130	1.126	1.129	1.131	1.128	1.139	1.144	1.135
Mitsubishi	1.330	1.375	1.376	1.363	1.406	1.365	1.379	1.403	1.373	1.361	1.373
Tata	1.219	1.200	1.190	1.179	1.137	1.165	1.175	1.165	1.173	1.162	1.176

MVMs located in Quadrant III. MVMs located in this quadrant are Audi, Toyota, GM, Nissan, Ford, BMW and Hyundai. They came up high both in $I_{ENVI.}$ values and in I_{MVM} values. As shown in Figure 6.7, Audi had the highest $I_{ENVI.}$ value (1.811) and Toyota had the highest I_{MVM} value (1.599). Toyota's approach to water conservation is the two-measure plan that consists of "a comprehensive reduction in the amount of water used, and water purification and returning it to the earth". Toyota is famous for its lean production system, which makes Toyota outstanding decreasing the waste generated from vehicles' production. Toyota comes up with innovative vehicles that reduce the overall carbon footprint. One of the most outstanding cars is the Prius model that is also celebrated as the world's first mass-market hybrid vehicle. This allows Toyota to have better environmental performance.

MVMs located in Quadrant I. Opposite to the MVMs located in Quadrant III, MVMs located in Quadrant I failed to perform well in neither environmental performance nor company performance. There are six MVMs in this quadrant, including Daimler, FCA, Tata, Mazda, Mitsubishi and Honda. Daimler had both the lowest $I_{ENVI.}$ value (1.195) and the lowest I_{MVM} value (1.212). FCA remains dedicated to a culture of sustainability aimed at

balancing its environmental responsibilities, including making its contribution by supporting the United Nations Sustainable Development Goals. More than two billion cubic meters of water were saved at FCA plants in FY2017. Besides, FCA implemented about 5,000 environment projects at their plants around the world, reducing its carbon footprint and leading to about 68 million euros in savings. Globally, plants of FCA reduced CO_2 emissions by 2.2 percent in FY2017. Its Verrone transmission plant earned the prestigious international "Lean and Green Management Award" based on its optimum integration of environmental and energy issues and innovative manufacturing solutions. Despite these efforts, FCA had the second least $I_{ENVI.}$ value (1.409).

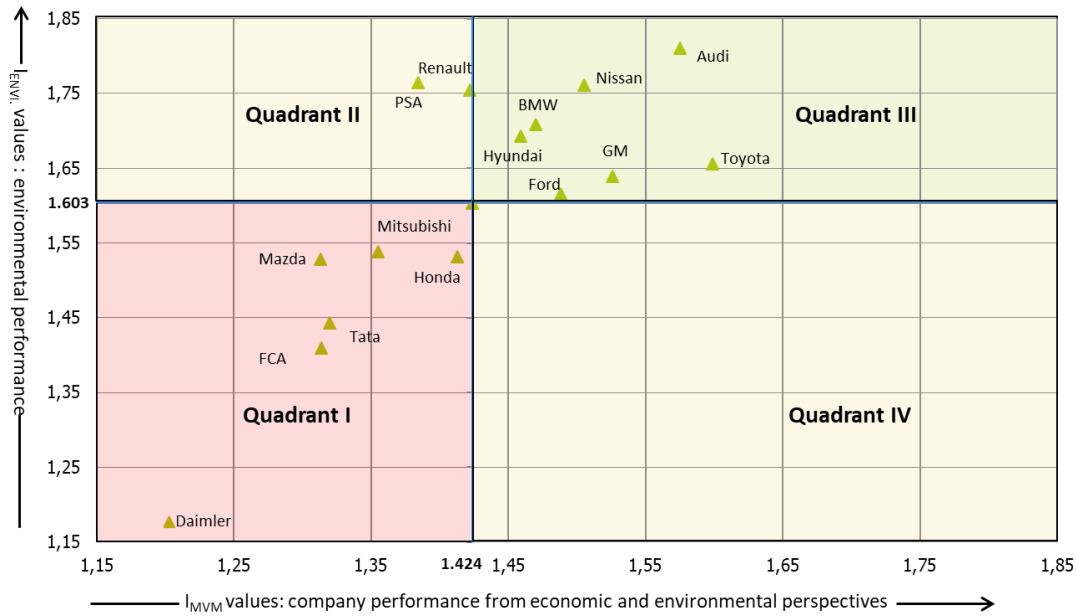


Figure 6.7: Performance matrix on environmental performance index versus company performance index (FY2008-FY2017)

MVMs located in Quadrant II or in Quadrant IV. In Figure 6.7, two MVMs including PSA and Renault are with high $I_{ENVI.}$ values but low I_{MVM} values. This indicates that PSA and Renault had both better environmental performance (1.765 and 1.754 respectively), but neither of them had better company performance (1.384 and 1.422 respectively) compared with the average level among the fifteen MVMs. It is obvious that Renault had the highest normalized value of CO_2 Emissions per vehicle produced (2.0) among all the fifteen MVMs. As a pioneer in Europe, Renault is building on nine years of expertise in the design, production, and sale of electric vehicles. In FY2015, Renault was the best performing brand in Europe in terms of electric vehicle sales, with a market share of 23.6%. In FY2017, Renault set a new record of roughly 36,300 units' all-electric car sales. Today, almost one electric vehicle in every four sold in Europe is a Renault. By 2022, Renault will have a range of eight electric vehicles and twelve electrified vehicles, as part of the Group's strategic "Drive the Future" plan.

6.7 Trend analysis: I_{MVM} values from the period FY2008-FY2017 verse I_{MVM} values in FY2018

In this section, the trend of I_{MVM} values from the period FY2008 to FY2017 with FY2018 is analysed. As shown in Figure 6.8, the average I_{MVM} values from the period FY2008 to

FY2017 for the eleven MVMs are placed along the horizontal axis. The average level (x=1.451) for the eleven MVMs is marked in blue. The trend I_{MVM} values in FY2018 for the eleven MVMs are placed on the vertical axis. The average level (y=1.452) for the eleven MVMVs is marked in orange. During FY2008 to FY2017, there are seven MVMs including Toyota, GM, Nissan, Ford, BMW, Audi and Hyundai that had better performance than the average level. However, in FY2018, BMW, Audi and Hyundai will drop below the average level. The slight increase in the average level from 1.451 to 1.452 indicates a better company performance for the eleven MVMs in FY2018.

MVMs that are located in the diagonal line (y=x) in red means that the average I_{MVM} values from the period FY2008 to FY2017 is equal to the trend I_{MVM} values in FY2018. It means that MVMs located above the diagonal line will improve their company performance in FY2018. On the contrary, MVMs that are located below the diagonal line means they will have a drop in their company performance in FY2018. Five MVMs including GM, Nissan, Renault, Mazda and Daimler will have better company performance in FY2018. A big improvement is clearly observed in Daimler. Despite the lowest I_{MVM} value (1.212) in the past, its trend value in FY2018 moves to 1.422.

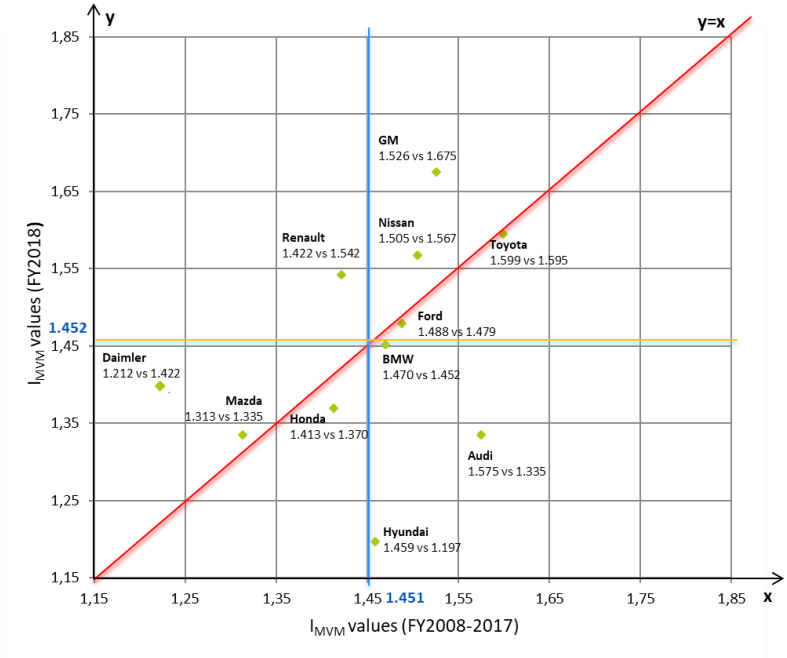


Figure 6.8: I_{MVM} values during FY2008-2017 to I_{MVM} values in FY2018

Five MVMs including Ford, BMW, Audi, Honda and Hyundai will move backward regarding their company performance. As shown in Figure 6.8, Hyundai has the biggest drop from 1.459 in the past to 1.197 in FY2018. However, as seen in Table 6.8, for Hyundai, the MAPE between the actual I_{MVM} value in FY2017 (1.59) with the trend I_{MVM} value in FY2017 (1.29) is 18.71% which is higher than the average MAPE (7.356%). This large MAPE makes the trend I_{MVM} value in FY2018 less convincing. The company performance of Audi will move forward from 1.575 to 1.335. As seen in Table 6.8, the MAPE in FY2017 is 1.04% that makes the trend I_{MVM} value in FY2018 reliable. Audi needs to look into its specific performance measures and benchmark with better performers.

6.8 Summary

This chapter aimed at developing an approach to generating the trend I_{MVM} data in the following FYs. A general introduction of time series trend analysis methods was presented in Section 6.2. Section 6.3 introduced the autoregressive integrated moving average (ARIMA) models. A quantitative trend analysis approach by ARIMA models was developed in Section 6.4. Section 6.5 implemented the approach to identify ARIMA models with data of fifteen MVMs. Future I_{MVM} data in FY2018, FY2019 and FY2020 were generated by ARIMA models of the best fit. In Section 6.6, the data out of the models contributed to benchmarking company performance (during FY2008-FY2017) of MVMs relative to their competitors. A trend analysis was conducted with the I_{MVM} values from the period FY2008-FY2017 verse the values in FY2018.

6.9 Conclusion

The fourth sub research question in this dissertation is: given the information of an MVM's historical performance, what methods can be used to generate its future performance data for the following fiscal years. In order to answer this sub research question, this chapter has developed an approach to analysing the trend of MVMs' performance from economic and environmental perspectives. Autoregressive integrated moving average models of the best fit have been built to generate the time series data of this performance for MVMs during the fiscal years 2018 to 2020. The minimum Akaike information criteria value has been used to identify the model of the best fit as an error criterion. The effectiveness of the approach has been shown with its trend accuracy based on forecasts with the mean absolute percentage error as an error criterion. Future I_{MVM} data in FY2018, FY2019 and FY2020 have been generated by ARIMA models of the best fit. This chapter has answered the fourth sub research question by generating future company performance data with ARIMA models for eligiable case study MVMs.

6.10 Reflection

The data out of the models contribute to a discussion on benchmarking the forecast performance in the FY2018. Please feel free to contact the author to get the R Script for generating the trend values by using the method from Section 6.4.

Based on the I_{MVM} trend value in FY2018, a ranking by manufacturer is determined from the best to the worst MVMs. As shown in Table 6.8, six MVMs have better performance than the average level (1.470), including GM, Toyota, Nissan, Renault, Audi and Ford. There are four MVMs that have worse performance than the average level, including Daimler, Honda, Mazda and Hyundai. GM has the highest I_{MVM} trend value (1.674856). This indicates that GM will be assigned as the best performing MVM in FY2018 in terms of heading towards company performance from economic and environmental perspectives. On the contrary, Hyundai will be assigned as the worst performing MVM in FY2018 due to its lowest I_{MVM} trend value (1.196974).

Benchmarking provides the reason for good performance and explanation for poor performance for remedial action (Tseng et al., 2014). The ARIMA models developed in this chapter enable the identification of the best performer GM and the worst performer Hyundai in terms of their trend performance in FY2018. The biggest difference between Hyundai and GM is in the measure Market Share that reaches a gap of 0.554. Despite a wider plan by GM to slash car production in North America and halt production of several low-selling brands in

November 2018, GM is still the largest American automobile manufacturer based on production volume. The market has been a source of frustration for Hyundai since the South Korean automaker was slow to respond to a consumer shift toward sports utility vehicles. Hyundai was forced to cut production at its factory in the U.S. and export fewer vehicles to the U.S. to reduce inventories of less-favoured sedans.

It is interesting to see that Hyundai excels at energy consumption performance. Hyundai becomes the first company in the world to mass-produce hybrid, plug-in hybrid and all-electric vehicles with a single dedicated eco-car platform. The Hyundai ix35 is the world's first mass-produced hydrogen fuel cell electric vehicle. By FY2017, more than 700 units of Hyundai ix35 were sold in 17 countries. In September 2017, Hyundai first unveiled the Nexo, a second-generation fuel cell electric vehicle that has reduced charging time to just five minutes. The Nexo is powered by electric energy produced by a reaction between hydrogen and oxygen. It does not discharge exhaust gases or other substances that could pollute the environment. The normalized trend value of this measure in Hyundai was 0.164. The same happens to CO_2 emissions performance where Hyundai excels GM by 0.126. In terms of the environmental perspective, GM did not perform well in FY2017. In October 2017, GM publicly announced that its vehicle lineup would feature 20 electric car models by the year 2023. It indicates that GM might have higher normalized values of energy consumption and CO_2 emissions in the following years, which could enhance their principles regarding the environment. In order to present the generated data and enable users to gain insights, the next chapter will focus on the development of an online tool for company performance measurement.

Chapter 7

A Measurement Tool

7.1 Introduction

Chapter 5 and chapter 6 developed approaches to measuring historical I_{MVM} values and future I_{MVM} values respectively. In order to answer the fifth sub research question, this chapter aims to visualize the generated values. This chapter does not focus on providing original scientific value. Instead, this chapter provides a package via a website developed in JavaScript and Hypertext Preprocessor for the society to use. An online calculator is set up with eleven measures as inputs in section 7.3. Data on company performance from economic and environmental perspectives are as outputs. The outputs are compared with the fifteen sampled MVMs in the case study. A ranking by manufacturer is generated based on the outputs. The weaknesses of MVMs can be pointed out through real-time graphs. Section 7.4 and Section 7.5 summaries and concludes this chapter respectively.

7.2 Performance measurement tools

Performance benchmarking involves a comparison of measures (Adebanjo & Mann, 2008). Current benchmarking tools focus more on individual benchmarking of certain individual measures from their previous performance. A comprehensive picture of MVMs' performance from economic and environmental perspectives is missing. Benchmarking in the automobile industry sometimes involves a third party who can collect the data, make the comparison and provide feedback but on a confidential basis (Managing Innovation, 2019). For instance, the program 'the future of the automobile' organized by MIT (Womack et al., 1990) explored a variety of aspects of the industry including product design and innovation, service delivery, retailing and supply chain management.

Currently, several tools are being adopted to rank or rate companies. The majority are only accessible with commercial products, which means that users have to pay for use. In addition, the tools only target at top companies that means that not every MVM is qualified to be included. For instance, Green Rankings 2017 is one of the most recognized environmental performance assessments of the world's largest publicly traded companies (Newsweek, 2018). The magazine Newsweek in partnership with Corporate Knights produced this ranking. The Global 500 from Green Rankings consists of an assessment of the 500 largest publicly traded companies in the world by revenue. Consequently, only nineteen motor vehicle companies were included in GLOBAL 500 2017, with the ranking ranging from 16_{th} to $366_{th.}$

This chapter aims to develop a tool to measure their company performance from economic and environmental perspectives. This tool can be accessible to any potential MVM as long as the raw data for the eight measures are available.

7.3 Development of the online measurement tool

The online tool comprises a set of programs and databases developed by JavaScript and Preprocessor Hypertext. Preprocessor Hypertext (PHP) is a server-side web programming language used for web development. PHP is particularly useful because it allows for advanced programming, easy to integrate with web pages, and is with open source (Gosselin, 2006).

7.3.1 User register page

In order to implement and test the measurement tool, a web page named "Company Performance Index for MVMs" has been created on the local host (https://cpi.mvm.tudelft.nl). As shown in Figure 7.1, companies can register themselves as users of the site by providing unique login names and passwords for authentication purposes in the register page.

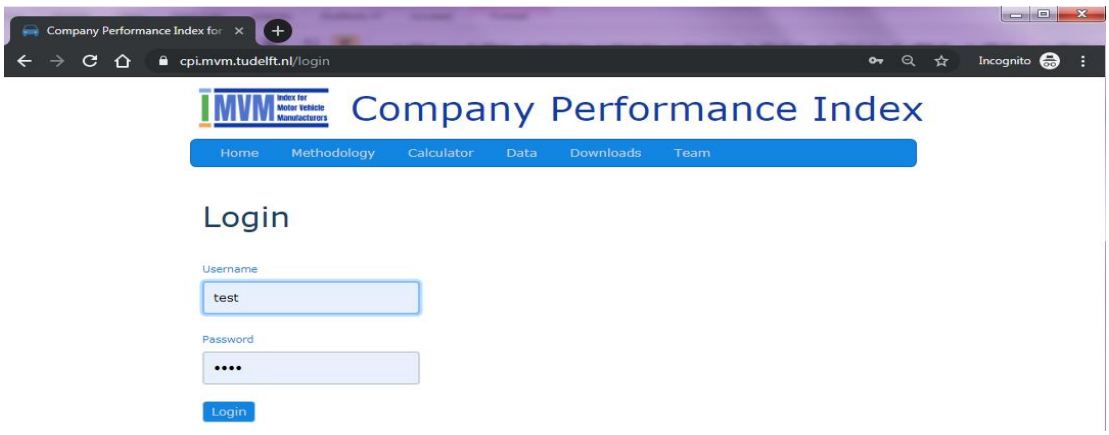
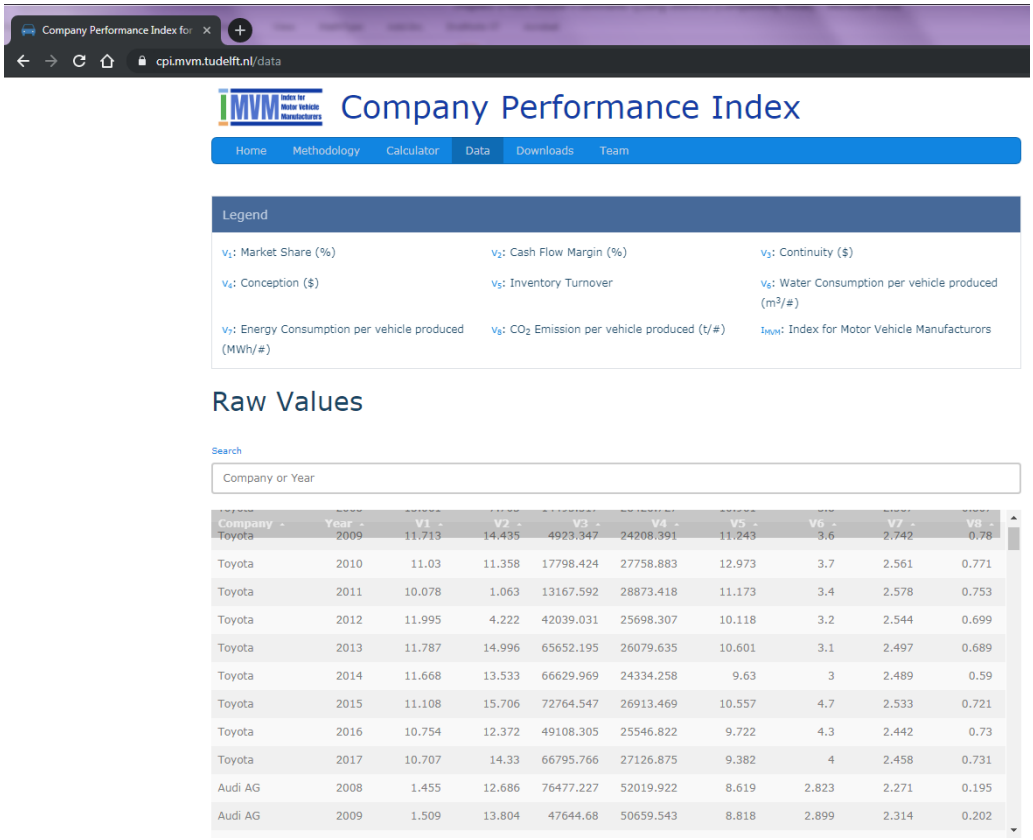


Figure 7.1: User login page

7.3.2 Dataset page

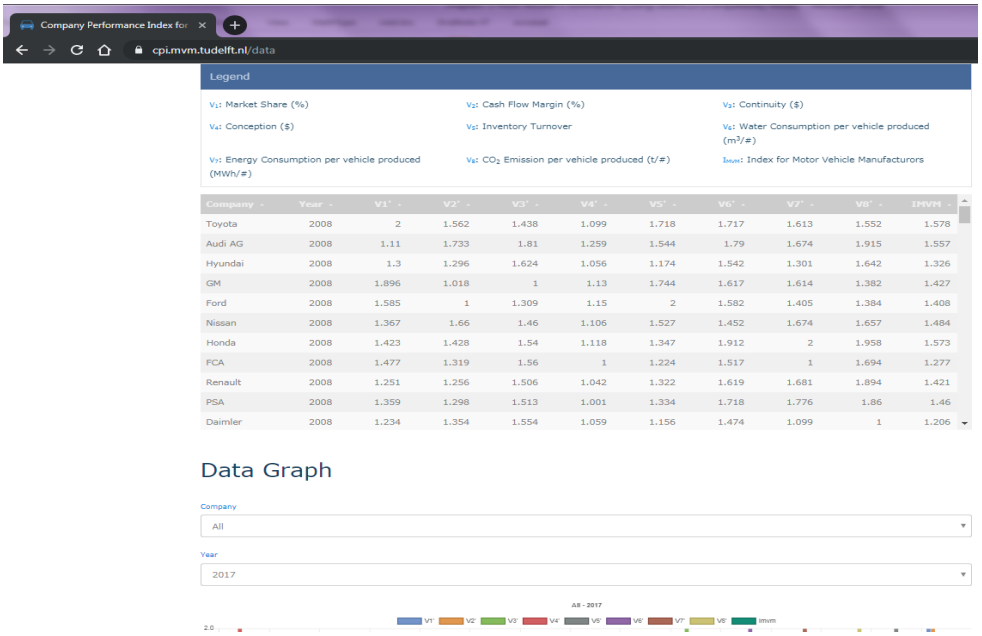
As shown in Figure 7.2, the dataset page contains a dataset of eight measures. It contains raw data of fifteen MVMs including Toyota, Audi, Hyundai, GM, Ford, Nissan, Honda, FCA, Renault, PSA, Daimler, BMW, Mazda, Mitsubishi and Tata. Users can index by the name of the MVMs or by the fiscal year that they want to look into.



Company	Year	V1	V2	V3	V4	V5	V6	V7	V8
Toyota	2009	11.713	14.435	4923.347	24208.391	11.243	3.6	2.742	0.78
Toyota	2010	11.03	11.358	17798.424	27758.883	12.973	3.7	2.561	0.771
Toyota	2011	10.078	1.063	13167.592	28873.418	11.173	3.4	2.578	0.753
Toyota	2012	11.995	4.222	42039.031	25698.307	10.118	3.2	2.544	0.699
Toyota	2013	11.787	14.996	65652.195	26079.635	10.601	3.1	2.497	0.689
Toyota	2014	11.668	13.533	66629.969	24334.258	9.63	3	2.489	0.59
Toyota	2015	11.108	15.706	72764.547	26913.469	10.557	4.7	2.533	0.721
Toyota	2016	10.754	12.372	49108.305	25546.822	9.722	4.3	2.442	0.73
Toyota	2017	10.707	14.33	66795.766	27126.875	9.382	4	2.458	0.731
Audi AG	2008	1.455	12.686	76477.227	52019.922	8.619	2.823	2.271	0.195
Audi AG	2009	1.509	13.804	47644.68	50659.543	8.818	2.899	2.314	0.202

Figure 7.2: The dataset of eight measures for fifteen MVMs

Below the raw value dataset, another zone shows up. As shown in Figure 7.3, this zone contains the normalized values of the eight measures, namely, V_1-V_8. Besides, the I_{MVM} values have been calculted and listed.



Company	Year	V1'	V2'	V3'	V4'	V5'	V6'	V7'	V8'	IMVM
Toyota	2008	2	1.562	1.438	1.099	1.718	1.717	1.613	1.552	1.578
Audi AG	2008	1.11	1.733	1.81	1.259	1.544	1.79	1.674	1.915	1.557
Hyundai	2008	1.3	1.296	1.624	1.056	1.174	1.542	1.301	1.642	1.326
GM	2008	1.896	1.018	1	1.13	1.744	1.617	1.614	1.382	1.427
Ford	2008	1.585	1	1.309	1.15	2	1.582	1.405	1.384	1.408
Nissan	2008	1.367	1.66	1.46	1.106	1.527	1.452	1.674	1.657	1.484
Honda	2008	1.423	1.428	1.54	1.118	1.347	1.912	2	1.958	1.573
FCA	2008	1.477	1.319	1.56	1	1.224	1.517	1	1.694	1.277
Renault	2008	1.251	1.256	1.506	1.042	1.322	1.619	1.681	1.894	1.421
PSA	2008	1.359	1.298	1.513	1.001	1.334	1.718	1.776	1.86	1.46
Daimler	2008	1.234	1.354	1.554	1.059	1.156	1.474	1.099	1	1.206

Figure 7.3: The dataset of eight measures for fifteen MVMs

Based on the normalized values of the eight measures and the I_{MVM} values, a graph is generated which shows the comparison of different performances in terms of each measure for individual MVMs. Users can select to have an overview of all the 15 MVMs with all of the eight measures. In addition, users can select and compare specific MVM's specific measures with another MVM. In other words, this graph can show the different performances in terms of each individual measure as well as the overall performance of the MVM(s). For instance, our research team is interested in a picture showing the CO_2 emissions performance and the overall performance for all 15 MVMs. Firstly we select All companies. Then we choose to skip the information of V_1' to V_7' because the default is to show all the information about V_1' to V_8'. As shown in Figure 7.4, the graph which contains the information of V_8' and I_{MVM} is listed for all the 15 MVMs.

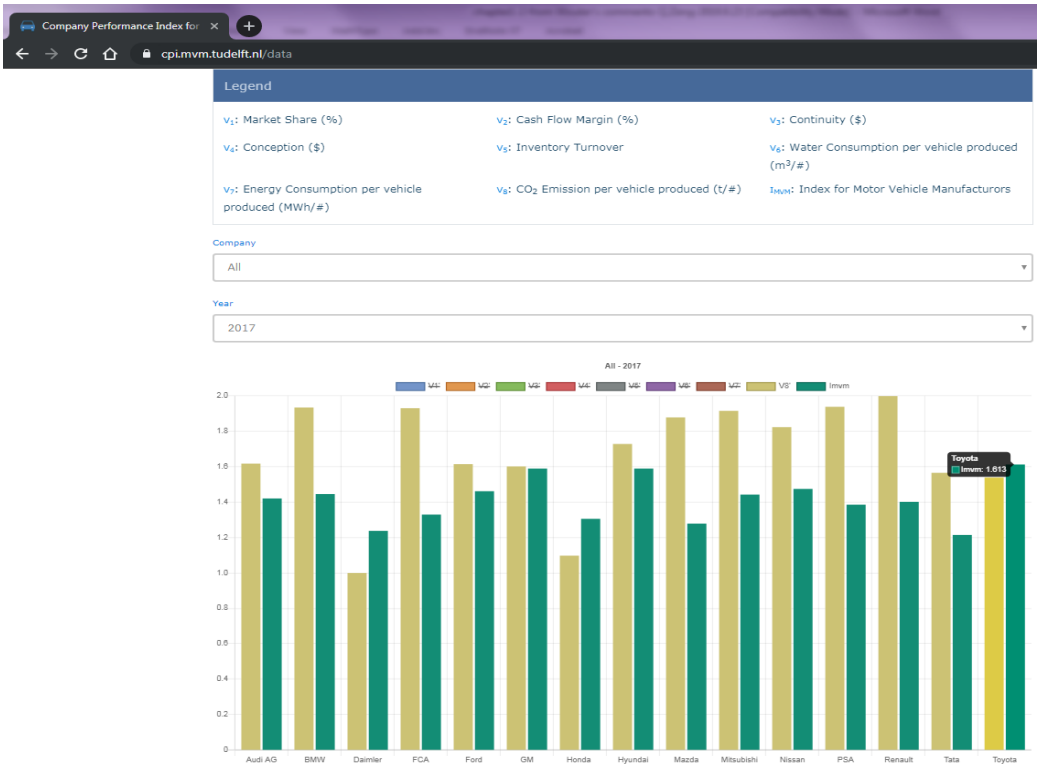


Figure 7.4: The graph to show the environmental performance for fifteen MVMs

7.3.3 Calculator page

Input values of measures and select the fiscal year. The next page is shown in Figure 7.5. Users need to input the values of measures. In addition, the fiscal year needs to be selected because the calculation of the eight measures may vary in different fiscal years.

Raw values and normalized values of measures. The normalized values of the measures can be calculated and generated in the boxes shown in Figure 7.6. Details about measures' calculations have been discussed in Section 4.4. The results consist of the values of individual measures.

7.3.4 Test the calculator

In order to test the accessibility and the operability of the calculator, a user is required to input random values of the measures as inputs. In this case, our research team had a try out as a user. We chose the FY2017 as it was the recent fiscal year when writing this dissertation. We filled

the eleven boxes with random values. As shown in Figure 7.7, with the inputs filled, the raw values of the measures as well as their normalized values are generated immediately.

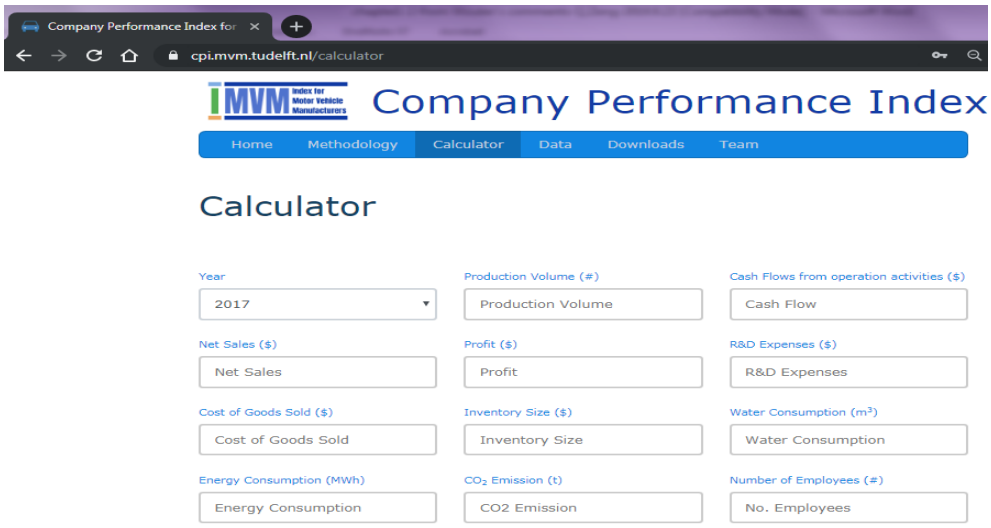


Figure 7.5: Input raw values of the measures

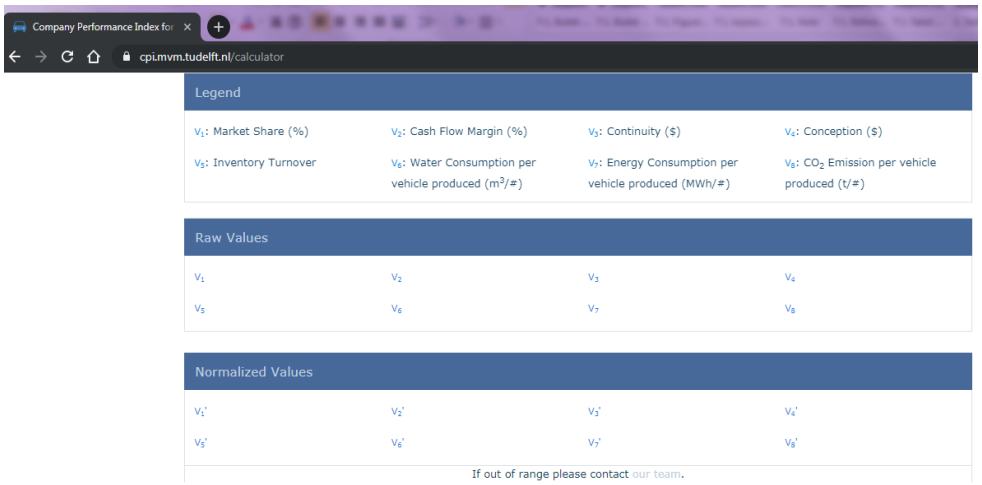


Figure 7.6: The normalized value of the measures

Based on the values that the user randomly inputs, a comparison between the user and other MVMs can be generated. The result can be used as basic data to conduct company performance benchmarking. Users can conduct this benchmarking against one or multiple MVMs. For instance, if the user intends to benchmark its performance in the FY2017 against the best performer, the user needs to 1) firstly, identify which MVM is the best performer. As presented in Section 6.5.4, Toyota has been identified as the best with the highest I_{MVM} value in FY2017. 2) Secondly, the user needs to choose Toyota as the benchmark MVM. To achieve this, the user only needs the data from Mydata and the data from Toyota. However, the default option is including all the 15 MVMs as well as the user. Therefore, the user needs to strikethrough the other 14 MVMs. As shown in Figure 7.8, a graph is formed, comparing the user and Toyota in terms of their performances of the eight measures.

From this comparison, the user can know its relative strengths and weaknesses in terms of the individual aspects. Strengths have to be sustained, while weaknesses have to be converted into strengths. The value-based comparison gives information to indicate that more efforts can be

made to conquer the weaknesses from the performance of V_1, V_2, V_3, V_4, V_5, V_6, and V_8. Especially for V_3 and V_8, considering there are bigger gaps between the user's performance and Toyota's performance.

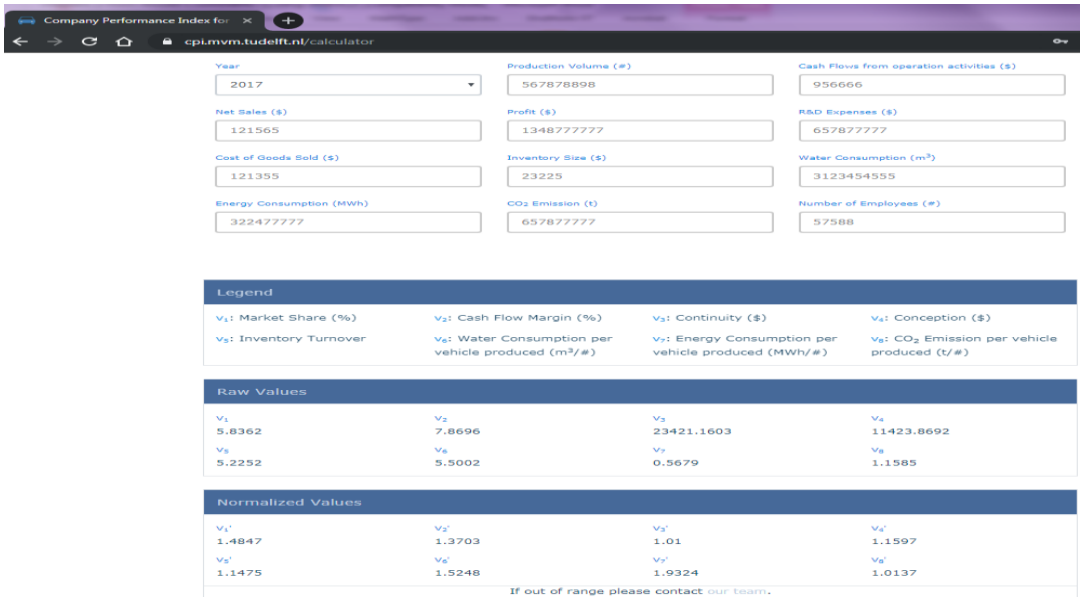


Figure 7.7: Test the calculator with random input values

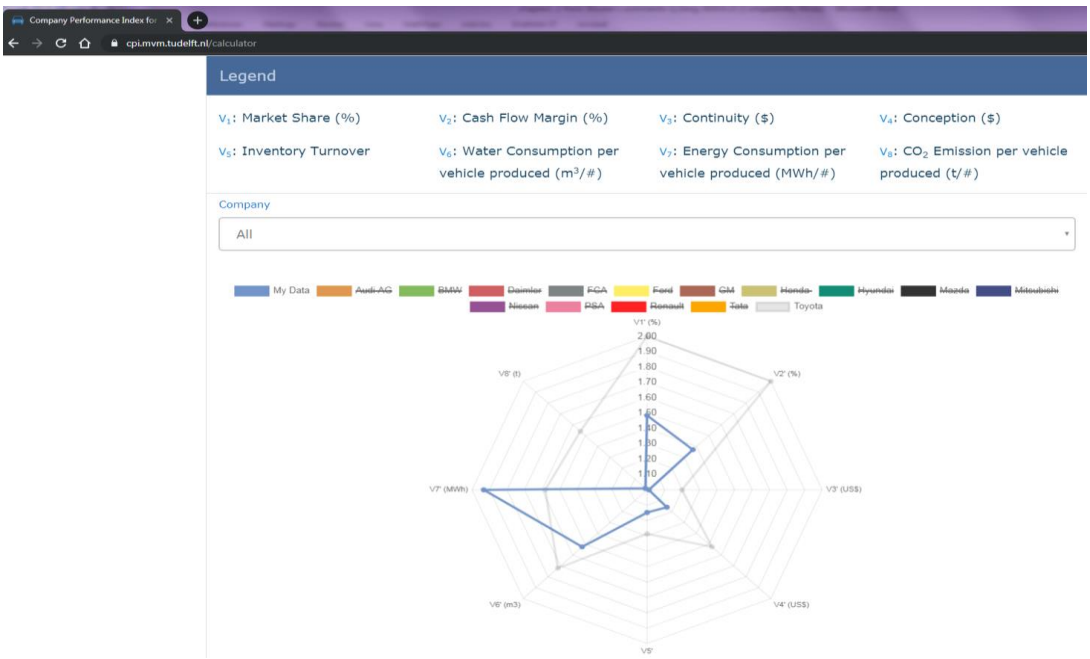


Figure 7.8: Benchmark the performance of the MVMs

7.4 Conclusion

The fifth sub research question in this dissertation is how to realize the visualization of company performance data of MVMs. In order to answer this sub research question, this chapter has developed a website on the local hos https://cpi.mvm.tudelft.nl, entitled "Company Performance Index for MVMs". This website works as a measurement tool in JavaScript and Hypertext Preprocessor. An online calculator has been set up with eleven

measures as inputs. Data on company performance from economic and environmental perspectives were generated as outputs. The accessibility and the operability of the calculator have been tested by a set of random input values. The generated raw value of the eight measures as well as their normalized values has indicated that the online calculator is feasible for any MVM to measure its performance. The outcome data has been compared with the fifteen sampled MVMs. The weaknesses of MVMs can be pointed out clearly through real-time graphs. This chapter has answered the fifth sub research question by developing the online company performance measurement tool.

7.5 Reflection

This measurement tool enables the user to understand its existing level and the performance gap with the best performer (among the user and the fifteen MVMs). Competitive advantages and disadvantages can be identified to indicate the direction of improvement. It also provides managers to select the best practice that can be learned from the best performer in this sector. The decision will be a suitable option selected to improve the existing problem and for continuous improvement. The tool was subsequently developed for computerization purposes. The use of the tool has been tested with random inputs by authors, which proves the measurement tool an accessible and feasible tool for any MVM to measure and benchmark its performance.

Chapter 8

Conclusion

In Section 1.2, based on the Problem Statement analysis, a research gap has been identified as follows: a method to measure the historical as well as the future company performance, with consistent measures and rigorous techniques, for MVMs is missing. To narrow down this research gap, this dissertation has presented a method to measure the company performance for MVMs from both an economic perspective and an environmental perspective. The method has been proposed using literature review, a case study, techniques of regression analysis, Shannon entropy, a linear procedure based on min-max normalization, a geometric aggregation for aggregating individual measures into a multiplicative index, a sensitivity analysis and autoregressive integrated moving average models to generate the future data in FY2018, FY2019 and FY2020. The new method in this dissertation has been assessed through a benchmark against seven benchmark items. The results indicate that the new measurement is feasible and effective for MVMs to measure their company performance from economic and environmental perspectives. This also indicates that this dissertation has achieved its research objective.

This chapter is organized as follows. Section 8.1 presents the answer to the main research question. Section 8.2 discusses the contributions of the research to the existing knowledge. Section 8.3 presents reflections on the sampled MVMs' performance. Section 8.4 provides recommendations for the future direction of research.

8.1 Answers to the research question

The objective of this dissertation is to develop a new company performance measurement method for MVMs to measure their historical performance as well as the future performance from economic and environmental perspectives. In order to achieve this research objective, the main research question arises as

Main research question: *How to measure company performance with CIs from economic and environmental perspectives for MVMs*?

The main research question has been addressed by the approaches including four steps. Step one is to identify company performance measures by conducting a state-of-art literature review. Its outcome is a preliminary model of company performance measurement for MVMs

from economic and environmental perspectives. Step two is to measure historical company performance by proposing specific techniques based on three considerations from MVMs. The outcome is a composite index, namely, the I_{MVM}. Step three is to perform a trend analysis of company performance by building ARIMA models for MVMs that are with stationary time series data. The outcome is the trend I_{MVM} value with a forecast horizon as four years. The final step is to benchmark MVMs' I_{MVM} values. This dissertation has answered how to measure company performance with CIs from economic and environmental perspectives for MVMs.

More specifically, the sub research questions have been answered as follows.

Question on the state-of-the-art:

SRQ_1: What is the state-of-art in current CIs of company performance for MVMs?

Answer to SRQ_1:

Chapter 3 has conducted a literature review on current CIs of company performance. Totally, this chapter identified 51 state-of-art CIs that have been utilized in industry. Twenty-nine specific individual techniques for constructing CIs have been analyzed. CIs are utilized in 17 specific sectors. Based on the analysis, two current problems during the development of CIs in the motor vehicle manufacturing sector have been identified, namely, 1) there is a lack of company performance measures with environmental concerns, and 2) there is a lack of rigorous quantitative methods for measuring this performance. In Section 3.8, a call arose for the next generation of the company performance measurement method with three recommendations. Chapter 3 has answered this sub research question by analyzing the 51 state-of-art CIs that utilized in industry. In order to fulfil the first recommendation, Chapter 4 focused on identifying consistent company performance measures, from both an economic perspective and an environmental perspective.

Question on the company performance measures:

SRQ_2: What company performance measures can be applied to construct CIs of MVMs' performance from economic and environmental perspectives?

Answer to SRQ_2:

In chapter 4, analysis has been conducted to identify measures from an economic perspective and from an environmental perspective. This chapter has referred to four sources including stakeholder theory, literature in the automotive industry, documents released from industry and documents about MVMs by organizations. Accordingly, a preliminary framework with eight measures has been built from economic and environmental perspectives. As shown in Figure 4.1, five measures are from an economic perspective, including profit per employee, research and development expenditure per employee, cash flow margin, market share and inventory turnover. Three measures are from an environmental perspective, including water consumption per vehicle produced, energy consumption per vehicle produced and CO_2 emissions per vehicle produced.

Measures from an economic perspective are identified by taking into account concerns from customers, employees, business partners and owners, while measures from an environmental perspective are identified by taking into account concerns from business partners, financial organizations and governments, NGOs or NPOs. All eight measures are with publicly

available data. Chapter 4 has answered this sub research question by proposing the preliminary model of company performance measurement.

Question on the methodology:

SRQ_3: What techniques are used to construct the composite indicator, for generating the historical performance data for MVMs?

Answer to SRQ_3:

Chapter 5 has constructed an index of company performance during the fiscal year 2008 to 2017. The construction of this index integrates the eight measures that have been identified in Chapter 4. Three considerations have been proposed as follows.

- There are two different categories of impact for the eight measures. One category "+" contains measures that satisfy "the larger its value is, the better the result gets" while the other category "-" contains measures that satisfy "the smaller its value is, the better the result gets".
- There are measures that have negative values. In order to adopt potential aggregations, the values need to be qualified as a base number in power functions.
- A complete compensability between the eight measures is not desirable (Joint Research Centre-European Commission, 2008, pp. 19).

The development of the index I_{MVM} involves techniques including regression analysis for weighing measures, a linear procedure based on min-max normalization for normalizing measures, and a geometric mean for aggregating individual measures into a multiplicative index. A sensitivity analysis is used to analyze the robustness of I_{MVM}. The index has been assessed through a benchmark against seven benchmark items. The results indicate that the new measurement is feasible and effective for MVMs to measure their company performance from economic and environmental perspectives. Chapter 5 has answered this sub research question by constructing the index I_{MVM}.

Question on the methodology:

SRQ_4: Given the information of MVMs' historical performance, what methods can be used to generate their future performance data for the following fiscal years?

Answer to SRQ_4:

Chapter 6 has built autoregressive integrated moving average models to generate future performance data for the following fiscal years. The minimum Akaike information criteria value is used to identify the model of the best fit as an error criterion in FY2017. Trend analysis accuracy of the models has been tested by the mean absolute percentage error. Future I_{MVM} data in FY2018, FY2019 and FY2020 are generated by ARIMA models of the best fit. The data out of the models contribute to a discussion on benchmarking the trend performance in the FY2018. Chapter 6 has answered this sub research question by generating future company performance data with ARIMA models for eligiable sampled MVMs.

Question on the application:

SRQ_5: How to realize the visualization of company performance data of MVMs in order to enable users to gain insights?

Answer to SRQ_5:

In order to present the generated data and enable users to gain insights, Chapter 6 has developed a website on the local host https://cpi.mvm.tudelft.nl, entitled "Company Performance Index for MVMs". A measurement tool based on JavaScript and Preprocessor Hypertext has been developed with eleven measures as inputs. The accessibility and the operability of the calculator have been tested by a set of random input values of the measures. The generated raw value of the eight measures as well as their normalized values has indicated that the measurement tool is an effective feasible tool for any MVM to measure and benchmark its performance. The outcome data are compared with the fifteen MVMs in the case study. The weaknesses of MVMs can be pointed out through real-time graphs. This chapter has answered this sub research question by developing the online company performance measurement tool. Contact the author if you want to get the JavaScript codes.

8.2 Contributions

8.2.1 Scientific contributions

Most studies on company performance measurement focus on accessing the economic aspect with financial indicators, or rating the sustainability performance including qualitative indicators. In terms of the data analysis techniques, most studies adopt techniques such as AHP that relies on experts' scoring. As discussed in Section 3.7, a call arises for the next generation of the company performance measurement method. As a response, this dissertation analyzed measures and techniques to improve the existing company performance measurement methods for MVMs. The result of this research is the basis for the fourth generation of company performance measurement that is a step ahead of the previous generations of company performance measurement methods.

This research distinguishes itself 1) with new company performance measures for MVMs from economic and environmental perspectives, 2) with applicable techniques to construct a new composite indicator to measure the company performance, 3) with the trend analysis for the following fiscal years, and 4) with clear and transparent data analysis techniques during the construction of the I_{MVM}. In Section 3.5.2, two current problems have been identified during the development of CIs in the motor vehicle manufacturing sector. Through the development, this research has solved the two problems. In other words, this research has developed a standard set of company performance measures from economic and environmental perspectives. Besides, this research has developed rigorous quantitative methods for measuring this company performance.

In Section 3.3.3, 51 indices have been identified. As shown in Table 3.8 in Section 3.5, there are seven indices that have been utilized in the motor vehicle manufacturing sector. In Section 3.5.2, a benchmark has been conducted against eight benchmark items for the seven references from the literature. Now the research in this dissertation can be added to the references, and a new benchmark result is shown in Table 8.1. The result indicates that the index developed in this dissertation satisfies all the benchmark items that are applicable.

8.2.2 Societal contributions

To make the research more practical to society, an online measurement tool has been developed for any MVM to measure its performance. The detailed societal contributions are presented as follows.

Table 8.1: Benchmark studies on constructing CIs for MVMs

Items / Reference	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
Amrina and Yusof (2010)	×	×	×	×	×	×	√	×
Singh et al. (2010)	×	×	×	×	√	×	√	×
Chahid et al. (2014)	×	×	×	×	×	×	√	×
Gopal and Thakkar (2015)	√	√	√	×	√	√	√	×
Salvado et al. (2015)	√	√	√	×	×	×	×	×
Ayağ and Samanlioglu (2016)	×	×	×	√	√	×	√	×
Beelaerts van Blokland et al. (2019)	×	×	×	×	-	√	√	×
Zeng (2020)	√	√	√	-	-	√	√	√

Note: √ means the reference satisfies the benchmark item; × means the reference dissatisfies the benchmark item; - means it is unnecessary to satisfy that benchmark item in the context of the reference.

I_1: with an environmental perspective; I_2: with concerns about different categories of measures; I_3: with specific normalization technique(s); I_4: with concerns about preference independence between measures; I_5: with fuzzy logic or grey theory to tackle inherent subjectivity; I_6: with objective weighing techniques; I_7: with clear aggregation procedure; I_8: with a post-analysis phase. The detailed meanings of the eight items and the reasons why they are included have been presented in Section 3.5.2.

1) **From the perspective of data analysts.** The investigation of current problems during CIs' construction has a practical impact on providing a state-of-the-art in CIs to data analysts in both academia and industry. In order to construct effective CIs, data analysts have to adopt rigorous techniques taking into account restrictions from the specific utilized industry. The approach developed for delivering an index I_{MVM} is relevant to setting up restrictions for MVMs. A comparison on the I_{MVM} and the DJSI World, Newsweek Green Rankings and the Automobile Manufacturer Industry Scorecard by Moody's Corporation is presented in Table 4.13. It turns out that the index I_{MVM} satisfies all six applicable benchmark items while the three indices are incapable to satisfy their applicable benchmark items.

2) **From the perspective of motor vehicle manufacturers.** As a global response to climate change, organizations such as the European Environmental Agency have been launched. Accordingly, several plans with specific target have been made. In April 2018, the revised EU emissions trading system Directive entered into force. As an ambitious reform during its fourth trading period (2021-2030), EU ETS aims to facilitate a 43% GHG emissions reduction from EU ETS sectors by 2030 (European Commission, 2018). This target is in line with its commitments under the Paris Agreement. For new lorries, in November 2018, the European Parliament set a target with 35% GHG emissions reduction by 2030 (European Parliament, 2018). Although European automakers have raised objections, they have to follow the plans with aggressive targets.

   For MVMs, it is essential to create a bigger market share of zero-emission or low emission vehicles. According to the "cap and trade" principle of EU ETS, holders will be rewarded if they actively reduce carbon emissions to certain amounts during their production. They will be fined if they generated excessive carbon emissions. "The entry price of € 10 per tonne from 2021 is much too low … the price will stabilize on the market and can then rise to €120 to 130 per ton, which many people demand." says the German economist Jens Südekum (FD, 2019). Therefore, manufacturers have to

get aware of the potential risks such as the bills due to excessive carbon emissions and carbon tax.

The developed approach for measuring the environmental performance is practically relevant concerning reducing energy consumption, water consumption and CO_2 emissions during vehicles' production. Better environmental performances are beneficial for MVMs with lower production costs and a higher reputation for sustainable development.

3) **From the perspective of statistics organizations.** The case study in 15 MVMs has practical relevance about providing available and reliable statistics to organizations such as the International Organization of Motor Vehicle Manufacturers and the European Environment Agency. Statistics generated in this dissertation can be integrated as a modular into the statistic network in the organization. The historical data generated by the index I_{MVM} over the fiscal year 2008 to 2017 is useful for historical analysis of MVMs. The forecast data generated by ARIMA models over the fiscal year 2018 to 2020 can aid policymakers to better make decisions to avoid unexpected consequences.

4) **From the perspective of investors.** Data generated in this dissertation has practical relevance, which helps the stakeholders in the investment world, such as asset management organizations, identify MVMs with positive environmental policies for sustainability-themed investments. As to the investment world, there has been a change in thinking from avoiding companies that have a negative impact on the environment to investing in companies that have positive environmental policies. As one of the first international asset management companies, Robeco together with RobecoSAM published "The Big Book of SI" in 2018, which indicates investors take environmental protection to a high level in sustainability investing activities.

5) **From the perspective of benchmarking analysts.** The approach developed for aggregating individual measures into a composite indicator is relevant to benchmarking analysis. Current benchmarking tools focus more on individual benchmarking of certain individual measures from their previous performance. A comprehensive picture of MVMs' performance from economic and environmental perspectives is missing. Benchmarking in the automobile industry sometimes involves a third party who can collect the data, make the comparison and provide feedback but on a confidential basis (Managing Innovation, 2019). Currently, several tools have been adopted to rank or rate companies. The majorities are commercial products, or are only applicable to top companies.

   The development of the measurement tool in this dissertation makes users accessible to benchmark their company performance. This benchmarking from economic and environmental perspectives provides valuable insights that are not obvious to observe from the raw data for MVMs to improve their performance. Data out of the approach developed in Chapter 5 and Chapter 6 helps benchmarking analysts identify competitive advantage and disadvantage that indicates the direction of improvement.

8.3 Reflections on the MVMs' performance

The OICA refers to the production volume as the only criterion to rank "the 15 largest manufacturers". Hyundai ranked 3rd based on the OICA ranking in FY2016 while this

manufacturer ranked 11th based on the I_{MVM} value in this dissertation. One reason for the big ranking difference is that the method developed in this dissertation takes into account environmental concerns while other rankings such as the one from OICA do not. Manufacturers have to pay attention to sustainable development rather than exclusively focusing on profitability.

Through benchmarking environmental performance during FY2008 to FY2017, Audi was identified as the best performer while Daimler as the worst performer. When it comes to the company performance from both an economic perspective and an environmental perspective, MVMs including Toyota, GM, Nissan, Ford, BMW, Audi and Hyundai had better performance than the average level. However, the trend I_{MVM} values showed that company performance in FY2018 for BMW, Audi, and Hyundai would drop below the average level.

As forecasted in FY2018, better performances are expected for MVMs including GM, Nissan, Renault, Mazda, and Daimler. Despite the lowest I_{MVM} value during FY2008 to FY2017, Daimler will make a big improvement in FY2018. Benchmark CO_2 emissions in FY2017 suggests that MVMs including Hyundai, Honda, FCA, and PSA need to raise awareness of CO_2 emissions during their production since their normalized values of CO_2 emission were below the average level.

8.4 Recommendations

8.4.1 Recommendations from a theoretical perspective

1) Extensive data is required for better trend analysis. This can be done by extending the sampling process with more MVMs or collecting data not only on a yearly basis but also in shorter periods. During the data pre-processing, several concerns need to be taken into accounts, such as missing data or inconsistent data. In this dissertation, a step of cleaning extreme values is not included. The maximum or minimum value of the measures is not removed due to the small sample size. Considering each available data is valuable for generating a time series data, this dissertation does not clean extreme values.

2) In terms of testing forecasting capability, different trend analysis methods can be used such as exponential smoothing methods, recurrent neural network methods and support vector regression methods. In terms of testing trend analysis accuracy, more error criteria such as the root mean square error can be referred to. This might contribute to less error in Table 6.8, which represents a more reliable trend analysis. In terms of the sensitivity analysis, methods such as the z-score can be used to analyze how different normalization methods affect the final value.

3) This dissertation focuses on company performance from both an economic perspective and an environmental perspective. This dissertation has not studied the relation between the two perspectives, or the interrelation among the measures. Data on the economic and environmental perspectives during FY2008-FY2017 have been generated. As shown in Figure 6.6 at section 6.6.3, it is obvious that data at several points showed a contraction between economic performance and environmental performance. This may be reasoned by the fact that a struggling economy leads to a decline in vehicles' production volume, which results in less resource consumption and less CO_2 emissions. In order to understand the statistical phenomenon, further research

can be done on conducting a hypothesis as: companies that are with better environmental performance have better economic performance.

4) In terms of the primary type of business, the automobile and light-duty motor vehicle manufacturing sector can be characterized as in the Business-to-Customer market segment. The heavy-duty truck-manufacturing sector can be characterized as in the Business-to-Business market segment. There may be a certain correlation between the performances in the two sectors. In addition, the production of electric vehicles or hybrid vehicles is getting more attention both in industry and in academia. It can be interesting to conduct correlation analysis between the performances in the two sectors. It is also interesting to conduct correlation analysis between sustainable cars production and the relevant environmental performance.

5) The company performance measurement method developed in this dissertation can be extended to a broader level by researching other unexploited fields. It is crucial to identify eligible measures and use proper techniques to weigh the measures. For instance, in the aviation sector, the water vapor in aircraft engine exhaust is a big player in global environmental issues. Nevertheless, in the motor vehicle sector, the water vapor is mostly not considered as an emission. Therefore, it is necessary for airlines to report the negative impact of the water vapor on the environmental impact while it is merely a concern for MVMs to consider water vapor in their reporting.

8.4.2 Recommendations from a practical perspective

1) For MVMs, it is essential to create a bigger market share of zero-emission or low emission vehicles. This is in line with the principle of EU ETS as well as other environmental policies. In order to avoid potential risks such as the carbon tax bills, MVMs must get aware of their environmental performance. Consistent and transparent data is encouraged to be released on periodic reports by manufacturers. The time-series data of the performance from an economic perceptive and an environmental perspective can be added to manufacturers' reports. With this data as a benchmark metric, manufacturers will feel motivated to achieve a balanced integration between their economic performance and environmental performance.

2) The website has been developed as an online measurement tool to present the generated I_{MVM} data. In order to generate the I_{MVM} data, inputs are required to be filled up. Based on the normalization equation (6.3) in section 6.4.2 that has been developed in this dissertation, the calculations of the normalized value for the eight measures are up to the minimum data and the maximum data in the specific fiscal year. We learn that there might be users that are with inputs lower than the existing minimum values in the dataset or higher value than the existing minimum values in the dataset. This might lead to disruptions during the use of the online measurement tool. In that case, the function for generating normalized values needs modifying, which is the reason there will be the notification "value out of range, please contact the research team". Further web development can be made to program the auto modification of the calculation formulas for users via this website. In addition, more work can be done to expand the calculator with the generation of future data as outputs.

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Summary

Company performance measurement is fundamental for decision-makers to monitor a company's performance and to solve management problems. The evolution of company performance measurement tools started from a pure financial-biased framework. The first generation of company performance measurement tools was achieved through supplementing the traditional financial measures with non-financial measures. The second generation addressed the dynamic of value creation by investigating transformations of resources. Both the first and the second generation showed appropriateness in how they reflect the realities in companies. The third generation emphasized the business-oriented methodology to real free cash flow activities. This dissertation, that will present a fourth generation company performance measurement tool, has a focus on motor vehicle manufacturers (MVMs) due to its economic significance and its environmental impact during vehicles' production.

Currently, there are three problems in the field of company performance measurement for MVMs: 1) there is a lack of consistent company performance measures from economic and environmental perspectives; 2) there is a lack of rigorous quantitative methods for measuring the comprehensive picture of company performance from economic and environmental perspectives; and 3) there is a lack of trend performance analysis for the following fiscal years. Overall, a method to measure the historical, as well as the future company performance, with consistent measures and rigorous techniques is missing.

In order to narrow this research gap, this research aims to develop a new company performance measurement method for MVMs to measure their historical company performance as well as the future company performance from economic and environmental perspectives. This new method is addressed as the basis for the fourth generation of company performance measurement in this research. The new method has been proposed through four steps.

- Step one is to identify company performance measures by conducting a state-of-art literature review. Its outcome is a preliminary model of company performance measurement for MVMs from economic and environmental perspectives. This preliminary model consists of eight measures, including market share, cash flow margin, profit per employee, research and development expenditure per employee, inventory turnover, water consumption per vehicle produced, energy consumption per vehicle produced and CO_2 emissions per vehicle produced. All the eight measures have been defined, with publicly available data and with clear mathematical formulas.
- Step two is to measure the historical company performance (during the fiscal year 2008 to 2017) by proposing specific techniques based on three considerations from MVMs. The outcome is a composite index, namely, the I_{MVM}. The development of the index I_{MVM} involves techniques including regression analysis for weighing measures, a

linear procedure based on min-max for normalizing measures, and a geometric mean for aggregating individual measures into a multiplicative index. A sensitivity analysis is used to analyse the robustness of I_{MVM}. The index has been assessed through a benchmark against seven benchmark items. The results indicate that the new measurement is feasible and effective for MVMs to measure their company performance from economic and environmental perspectives.

- Step three is to perform a trend analysis based upon forecasts of company performance by building ARIMA models for MVMs that are with stationary time series data. The outcome is the trend I_{MVM} value with a forecast horizon as four years. The minimum Akaike information criteria value is used to identify the model of the best fit as an error criterion in FY2017. The trend analysis accuracy of the models has been tested by the mean absolute percentage error. Future I_{MVM} data in FY2018, FY2019 and FY2020 are generated by ARIMA models of the best fit. The data out of the models contribute to a discussion on benchmarking the trend performance in the FY2018.
- The final step is to benchmark MVMs based on their historical I_{MVM} values as well as their trend values. This research has developed a measurement tool on the local host https://cpi.mvm.tudelft.nl, entitled "Company Performance Index for MVMs". The accessibility and the operability of the measurement tool have been tested by a set of random input values of the measures. The generated raw value of the eight measures as well as their normalized values has indicated that the measurement tool is an effective feasible tool for any MVM to measure its performance.

Through solving the three current problems with the four steps, this dissertation has contributed with a basis of the fourth generation of company performance measurement that is a step ahead of the previous generations of company performance measurement methods. This research distinguishes itself from other studies 1) with new company performance measures for MVMs from both an economic perspective and an environmental perspective, 2) with applicable techniques to construct a new composite indicator to measure the company performance, 3) with the trend analysis for the following fiscal years, and 4) with clear and transparent data analysis techniques during the construction of the I_{MVM}. In summary, this dissertation has answered how to measure company performance with composite indicators from economic and environmental perspectives for MVMs.

Samenvatting

Het meten van bedrijfsprestaties is van fundamenteel belang voor besluitvormers om de prestaties te bewaken en managementproblemen op te lossen. De evolutie van de meting van bedrijfsprestaties begon vanuit een zuiver eenzijdig financieel kader. De eerste generatie metingen van bedrijfsprestaties werd bereikt door de traditionele financiële maatregelen aan te vullen met niet-financiële maatregelen. De tweede generatie richtte zich op de dynamiek van waard creatie door onderzoek naar transformaties van natuurlijke hulpbronnen. Zowel de eerste als de tweede generatie bleken geschikt te zijn in hoe ze de realiteit in bedrijven weerspiegelen. De derde generatie benadrukte de bedrijfsgerichte methode voor echte vrije geldstromen. Dit proefschrift, waarin een vierde generatie wordt voorgesteld, richt zich op fabrikanten van motorvoertuigen (FvM's) vanwege de economische betekenis en de milieu-impact tijdens de productie van voertuigen.

Momenteel zijn er drie problemen op het gebied van metingen van bedrijfsprestaties voor FvM's. Deze zijn: 1) er is een gebrek aan standaardisatie en consistentie in metingen voor bedrijfsprestaties vanuit economisch en ecologisch perspectief; 2) er is een gebrek aan kwantitatieve methoden voor het meten van het alomvattende beeld van bedrijfsprestaties vanuit economisch en ecologisch perspectief; en 3) er is een gebrek aan trendanalyses voor de prestaties van de komende boekjaren. Samenvattend, ontbreekt er een methode om de historische en de toekomstige bedrijfsprestaties te meten, met consistente maatregelen en technieken.

Om deze kloof te verkleinen, beoogt dit onderzoek een nieuwe methode voor het meten van bedrijfsprestaties voor FvM's te ontwikkelen. Dit om hun historische bedrijfsprestaties te meten, evenals de toekomstige bedrijfsprestaties vanuit een economisch en ecologisch perspectief. Deze nieuwe methode wordt in dit onderzoek aangepakt als de vierde generatie voor prestatiemetingen van ondernemingen. Deze vierde generatie van prestatiemetingen werd voorgesteld in vier stappen.

- Stap één is het identificeren van bedrijfsprestaties door een literatuuronderzoek uit te voeren. Het resultaat is een voorlopig model voor metingen van bedrijfsprestaties voor FvM's vanuit economisch en ecologisch perspectief. Dit voorlopige model bestaat uit acht maatregelen, waaronder: marktaandeel, geldstroom marge, winst per werknemer, uitgaven voor onderzoek en ontwikkeling per werknemer, inventaris omzet, waterverbruik per geproduceerd voertuig, energieverbruik per geproduceerd voertuig en CO2-uitstoot per geproduceerd voertuig. Alle acht maatregelen zijn gedefinieerd, met beschikbare gegevens uit openbare documenten en met duidelijke wiskundige formules.
- Stap twee is het meten van de historische bedrijfsprestaties (tijdens het boekjaar 2008 tot 2017) door specifieke technieken voor te stellen op basis van drie overwegingen van FvM's. Het resultaat is een samengestelde index, namelijk de I_{FvM}. De

ontwikkeling van de FvM-index omvat technieken zoals regressieanalyse voor wegingsvariabelen, een lineaire procedure op basis van min-max-normalisatie voor het normaliseren van variabelen en een geometrisch gemiddelde voor het aggregeren van individuele variabelen in een multiplicatie index. Een gevoeligheidsanalyse wordt gebruikt om de robuustheid van I_{FvM} te analyseren. De index is beoordeeld via een vergelijkende proef aan de hand van drie verschillende indices. De resultaten geven aan dat de nieuwe meting haalbaar en effectief is voor FvM's om hun bedrijfsprestaties te meten vanuit economisch en ecologisch perspectief.

- Stap drie is het uitvoeren van een trendanalyse op basis van prognoses van bedrijfsprestaties door ARIMA-modellen te bouwen voor FvM's met stationaire tijdreeksgegevens. Het resultaat is de trend I_{FvM}-waarde met een voorspellingshorizon als vier jaar. De minimale Akaike information criteria wordt gebruikt om het best passende model te identificeren als een foutcriterium in het boekjaar 2017. De nauwkeurigheid van de trendanalyse van de modellen is getest door de gemiddelde absolute procentuele fout. Toekomstige I_{FvM}-gegevens in het boekjaar 2018, 2019 en 2020 worden gegenereerd door de best passende ARIMA-modellen. De gegevens uit de modellen dragen bij aan een discussie over het vergelijken van de prestaties in het boekjaar 2018.
- De laatste stap is om FvM's te vergelijken met de beste in hun klasse op basis van hun historische I_{FvM}-waarden en hun trendwaarden. Dit onderzoek heeft een meetinstrument ontwikkeld op een lokale host https://cpi.mvm.tudelft.nl, getiteld "Company Performance Index for MVM's". De toegankelijkheid en de bruikbaarheid van de rekenmachine zijn getest door een reeks willekeurige invoerwaarden van de metingen. De gegenereerde ruwe waarde van de acht metingen en hun genormaliseerde waarden hebben aangegeven dat het meetinstrument een effectief instrument is voor elke FvM om zijn prestaties te meten en te vergelijken met de vijftien FvM's. De uitkomsten worden vergeleken met de vijftien FvM's in de case study. De zwakke punten van FvM's kunnen duidelijk worden aangegeven in real time grafieken.

Door het oplossen van de drie huidige problemen met deze vier stappen, heeft dit proefschrift bijgedragen aan een voorstel voor een vierde generatie van metingen voor bedrijfsprestaties. De vierde generatie kenmerkt zich van de eerste drie generaties 1) met nieuwe prestatiemaatstaven voor bedrijven voor FvM's, zowel vanuit economisch perspectief als vanuit milieuoogpunt, 2) met toepasbare technieken om een nieuwe samengestelde indicator te construeren om de bedrijfsprestaties te meten, 3) met de trendanalyse voor de volgende drie boekjaren, en 4) met duidelijke en transparante technieken voor gegevensanalyse tijdens de bouw van de I_{FvM}. Samenvattend heeft dit proefschrift geantwoord op de vraag hoe de bedrijfsprestaties kunnen worden gemeten met samengestelde indicatoren vanuit een economisch en ecologisch perspectief voor FvM's.

Curriculum Vitae

Qinqin Zeng (曾琴琴) was born in July 1987, Yantai, Shandong Province, China. She obtained her B.Sc. degree in Real Estate Operation and Management at Shandong University of Finance and Economics in 2010. After graduation, she has been employed as a strategic assistant in the real estate department in China Sihai Holdings Co. Ltd. She was mainly focusing on calculating engineering quantity, processing and updating data in Microsoft Excel and MySQL.

She left her job in 2012 as she wants to pursue more knowledge in the automotive industry. She passed the Unified National Graduate Entrance Examination in 2013. Then she was offered a master's program with a full scholarship by Chongqing University. She had a seven-month internship in finished vehicle logistics in ChangAn Automobile, and she was mainly assisting logistics specialists to optimize the inbound logistics by FlexSim. Under the supervision of Prof. Xu Wang and Dr. Lin Ni, she finalized her thesis entitled *Research and Application of Inbound Logistics Selection Model of Domestic Auto Parts*. In 2015, she revived M.Sc degree, which made her the first one who is qualified to graduate half a year in advance in Management Science and Engineering in Chongqing University.

Since March 2016, Qinqin has been sponsored by China Scholarship Council as a Ph.D. candidate at the Transport Engineering and Logistics Section at Delft University of Technology. Under the supervision of Prof. Gabriël Lodewijks, Prof. Sicco C. Santema and Dr. Wouter W.A. Beelaerts van Blokland, she develops a new company performance measurement index for motor vehicle manufacturers to quantify their company performance from economic and environmental perspectives.

Her research interests include multi-criteria decision making, constructing indices, low-carbon manufacturing, automotive manufacture, benchmarking, time series analysis.

List of Publications

Zeng, Q. and Beelaerts van Blokland, W.W.A. (2018), Exploring Company Performance Measurement for Truck Manufacturers. *Journal for the Advancement of Performance Information Value*, *10* (1), 102-124.

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Zeng, Q., Beelaerts van Blokland, W.W.A., Santema, S.C. and Lodewijks, G. (2018), Company performance measurement for automobile companies: A composite indicator from an environmental perspective. On the 5th International Conference on Industrial Engineering and Applications: Singapore, Singapore.

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