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A long-term energy efficiency prediction model for the Brazilian automotive industry

Djan Magalhães Castro

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Supervisor: Prof. Dr. Fernando Silva Parreiras

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Abstract

According to law number 12.715/2012, Brazilian government instituted guidelines for a program named Inovar-Auto. In this context, energy efficiency is a survival requirement for Brazilian automotive industry from September 2016. As proposed by law, energy efficiency is not going to be calculated by models only. It is going to be calculated by the whole universe of new vehicles registered. In this scenario, the composition of vehicles sold in market will be a key factor on profits of each automaker. Energy efficiency and its consequences should be taken into consideration in all of its aspects.

In this scenario, emerges the following question: which is the efficiency curve of one automaker for long term, allowing them to adequate to rules, keep balancing on investment in technologies, increasing energy efficiency without affecting competitiveness of product lineup? Among several variables to be considered, one can highlight the analysis of manufacturing costs, customer value perception and market share, which characterizes this problem as a multi-criteria decision-making. To tackle the energy efficiency problem required by legislation, this paper proposes a framework of multi-criteria decision-making. The proposed framework combines Delphi group and Analytic Hierarchy Process to identify suitable alternatives for automakers to incorporate in main Brazilian vehicle segments. A forecast model based on artificial neural networks was used to estimate vehicle sales demand to validate expected results. This approach is demonstrated with a real case study using public vehicles sales data of Brazilian automakers and public energy efficiency data. According to our results Inovar-Auto targets will be reached in spite of little progress over last four years.

Key-words: Inovar-Auto, Energy Efficiency, Demand Forecast, MCDM - Multi-criteria Decision Making.

Resumo

Através da Lei nº 12.715/2012, o Governo Federal do Brasil instituiu as diretrizes de um programa denominado Inovar-Auto. Neste cenário, a eficiência energética é condição de sobrevivência para a indústria automotiva brasileira a partir de setembro de 2016. Como proposto na lei, a eficiência energética não será calculada para um modelo específico e sim para todo o universo de veículos novos emplacados. Neste cenário, a composição dos veículos comercializados no mercado terá grande influência no resultado final do fabricante. Eficiência energética e suas consequências devem ser consideradas em todos os seus aspectos.

Neste cenário, emerge a seguinte pergunta: Qual é a curva de eficiência de um fabricante com previsão de longo prazo, permitindo a adequação às normas vigentes, e um equilíbrio no investimento em tecnologias que aumentem a eficiência energética sem afetar a competitividade da linha de produtos? A escolha dentre as diversas tecnologias possíveis de serem incorporadas inclui a análise do custo de fabricação, do valor percebido pelo cliente e a participação no mercado, caracterizando um problema de apoio a decisão multicritério.

Para resolver o problema da eficiência energética requerido pela legislação, este trabalho propõe uma solução de decisão multicritério. A solução proposta combina grupos *Delphi* e *Analytic Hierarchy Process* para identificar alternativas adequadas para as montadoras incorporarem nos veículos. Após isso, um modelo de previsão baseado em redes neurais foi utilizado para estimar a demanda de vendas de veículo. Esta abordagem foi demonstrada com um caso de estudo real envolvendo dados públicos de venda das montadoras brasileiras e dados sobre a eficiência energética. De acordo com os nossos resultados os objetivos do Inovar-Auto serão alcançado, apesar de pouco progresso nos últimos quatro anos.

Palavras-chaves: Inovar-Auto, Eficiência Energética, Previsão de demanda. ADM – Apoio à Decisão Multicritério.

List of Figures

List of Tables

List of Abbreviations and Acronyms

ABNT *Associação Brasileira de Normas Técnicas*

AHP Analytic Hierarchy Process

ANFAVEA *Associação Nacional dos Fabricante de Veículos Automotores*

ANN Artificial neural network

ANP *Agência Nacional de Petróleo*

CAFE Corporate Average Fuel Economy

DENATRAN *Departamento Nacional de Trânsito*

EE Energy Efficiency

EPA 75 same as FTP 75

FTP 72 Federal Test Procedure 72

FTP 75 Federal Test Procedure 75

GP Goal Programming

GPL General Public License

GRA Grey Relational Analysis

IPI *Imposto sobre Produtos Industrializados*

LP Linear Programing

MADM Multi-attribute decision making

MCDM Multi-criteria decision making

MJ Megajoules

MLP multi-layer perceptrons

MODM Multi-objective decision making

NBR *Norma Brasileira Regulamentadora*

PBE *Programa Brasileiro de Etiquetagem*

PTFN	Positive Trapezoidal Fuzzy Number
SAW	Simple Additive Weighting
SLR	Systematic Literature Review
SUP	Sport Utility Pickup
SUV	Sport Utility Vehicle
TFN	Triangular Fuzzy Number
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TS	Time Series
TSF	Time Series Forecasting
WTO	World Trade Organization

Contents

1 Introduction

Vehicle energy efficiency has now an important place in the public policy agenda. Objectives could be linked to commercial, industrial competitiveness, energy security benefits and to environmental concern. Brazil, which in 2015 Brazil was seventh largest market worldwide [5], is also engaging this group. According to law number 12.715/2012, Brazilian government instituted guidelines for a program named Inovar-Auto [6]. This program aims to improve the competitiveness of domestic industry encouraging the growth of embedded technologies in vehicles, especially those related to energy efficiency (EE). Similar policies have been adopted and/or adjusted throughout the world. The Corporate Average Fuel Economy (CAFE) US date in 1975, but in 2010 the rules increased the EE requirements of vehicles [7]. European standards for carbon emission reduction also have analogous effect in the European Union [8] as China's Fuel Economy Standards [9]. If compared to Europe or United States, the ratio of person by vehicles remains low in Brazil. The country continue to arouse interest of automakers worldwide. This regulation has the potential to change the market.

One of the measures of the program includes increasing tax rates in 30 p.p, however this increase can be neutralized if Brazilian automakers join the program, as shown in Figure 1. Automakers which joined the program have an equal benefit of reduction, however need to run at least six manufacturing activities in Brazil by 2013 and achieving a minimum energy efficiency of 12 % over EE obtained in 2011. It is planned yet a possible additional reduction of taxes in 1 % for those who increase EE by 15.4 % and to 2 % for those who increase EE to 18,8%.

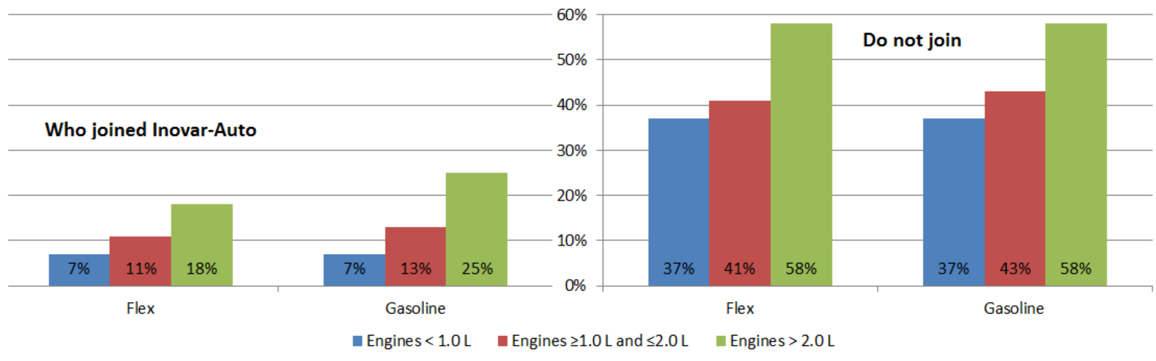

Figure 1 – IPI tax rates options for Brazilian automakers. Font: own author.

The government will carry out a monitoring of EE indexes for all automakers that adopt the program based on license plate data of vehicles sold from September 2016. Automakers that do not meet the provisions will be penalized with a surcharge of 31 %

in taxes. If the EE goals are not met, it is estimated a surcharge around 10 billions of Brazilian currency for each one of the three major manufacturers (Fiat, GM and WV). In this scenario, EE becomes a survival criterion for all automakers in the country which join the program. Of course, due to market competitiveness, automakers which do not join the program also will be out of market.

We propose an approach based on AHP combined with Delphi group to identify the most prioritized factors for improving EE to solve Inovar-Auto challenges. This decision was supported by advantages of the combination of methods which is frequently in automotive industry, since 62,2% of approaches used combined methods. It is note that Delphi group is used to deal with uncertainty which is one drawback of AHP. Among factors that contribute to propose AHP we found popularity, simplicity in interpreting and mainly consistency test to ensure judgments quality. In order to forecast vehicle sales numbers, we use a artificial neural network (ANN). ANN is proposed due to capacity of discover pattern adaptively from the data and handling with nonlinear models. Historical vehicle sales number in Brazil is a public information due to federal law 12.527/2011 [10].

1.1 Problem

Although EE rates are part of new product development, as a result of Inovar-Auto, they will play a key role in business strategy with precedence over virtually any other variables. Inovar-Auto regulations requires predicting EE of models to be launched in five or six years, and their impact on the overall EE of an automaker. In 10 years, the market share for small vehicles segment, up to 1.000cc, dropped from 39.1% of to 24.6%. In segments such as small SUVs it was inexpressive. Small pick-ups segments practically only exist in Brazil. Even new segments can arise such as SUP (sport utility pick-ups). These changes of consumers' preferences directly impacts the estimates. Due to long chain of suppliers, modifications in automotive projects are long term operations. Typically, a vehicle remains in production for 4-5 years before changes are made[11, 12].

Vehicle EE calculation, in design, can be estimated by mathematical models that take into account estimates weight, engine size, performance, among others with a high degree of accuracy. However, with the Inovar-Auto determinations it will be necessary to estimate with considerable accuracy which the efficiency curve of an entire assembly plant, taking in the different vehicles produced accounts, the number of units sold with many years ahead. Technology investment can increase EE, however this embedded technology make products expensive reducing their competitiveness. Similarly, demand increase for low EE products can impact the overall automaker EE curve blocking them to achieve desired EE which could result in surcharge.

In this scenario, emerges the question: **What is a manufacturer efficiency**

curve, with long-term forecast that increase energy efficiency without affecting the competitiveness of product line? Long-term in automotive engineering means to forecast around 4 to 5 years ahead, because this is the time consumed by automakers to launch new vehicles or made significant improvements in existent ones [11, 12]. EE in this context means a physical-thermodynamic indicator which is basically a ratio of useful output of process by energy input into a process [13]. An energy efficiency curve is essentially the EE of a vehicle, automaker or entire marketing over the time. Details about EE concept and Energy efficiency curve will be explored in Section 2.2.3.

1.2 Objectives

Develop a long-term forecasting model, using techniques from analysis by multiple criteria and neural network, allowing achievement of established goals. In the same time, keeping a balance between technologies investment that increase energy efficiency without affecting the competitiveness of product line. Through the analysis of market forecasts for the last 10 years allowing estimates for next year to minimize the investment without compromise the deal.

This combination of factors necessary to forecast Brazilian market coupled with Brazilian peculiarities and obscure effects of Inovar-Auto provide unique characteristics which justify creation of a specific model to guide decision making. The number of alternatives and criteria involved is also determinant to Multi-criteria Decision Making (MCDM) usage in the proposed model.

The specific objectives of this work are:

- **Objective 1:** To identify multi-attribute decision making (MADM) methods frequently used in automotive engineering.
- **Objective 2:** To compare the performance of frequently used methods in EE problem of automakers.
- **Objective 3:** To analyze how technical improvements have been used over last 10 years in Brazil.
- **Objective 4:** To identify key vehicles segments to tackle with EE challenge.
- **Objective 5:** To analyze effects of technology adoption guided by our approach to EE curve in 2017.

1.3 Motivation

Inovar-Auto is an unprecedented change in Brazilian automotive industry. In spite of similar regulations there are in other regions or country such as USA, Europe or China none of them is equal to Brazilian regulations. Since automakers already joined the program, achieve EE is a survival question. The number of automakers has increased over time, because Brazil remains with a low ratio of vehicles per person. This ratio is a signal that number of vehicles could increase over time. Automakers that do not achieve agreed EE will be on the road to bankruptcy. MCDM is a established branch of operational research, however, there is a gap in use of MCDM in EE for automotive industry.

1.4 Adherence to FUMEC's Graduate Program in Information Systems and Knoweldge Management

FUMEC's graduate program in Information Systems and Knoweldge Management is focused on academic knowledge, scientific development and applied research on the Information Systems and Knowledge Management fields. The program is organized into two main streams: Technology and Information Systems and Information and Knowledge Management. Multidisciplinary approach is a key concept on FUMEC's graduate program.

This research proposes the application of MCDM method to aid automotive companies to enhance EE for adequacy to Inovar-Auto. Since Multiple-criteria decision making (MCDM) is a sub-field of operations research [1, 14, 15, 16, 17, 18] that is concerned with designing mathematical and computational tools to support the evaluation of decision making process [19, 20] fits with track related to application of statistical models for decision making assisted by computing. This proposal focus is under the Information Systems field in compliance with FUMEC's graduate program. The multidisciplinary aspect arise from the business application of this study which will help to define corporative strategy whilst uses corporate knowledge.

1.5 Document Structure

The proposal is structured in 3 chapters. Chapter 1 presented the introduction. Chapter 2 presents a Systematic Literature Review (SLR) on MCDM developed during the research project definition. This research implementation, follows methodological procedures described in this chapter. Chapter 3 presents the analyses about Brazilian EE scenario over the last 10 years and also a projection for next year with feasible solutions to be implemented by Industry to reach Inovar-Auto objectives.

2 Systematic Literature Review

2.1 Introduction

Decision process can be defined as a set of actions and methods dynamically organized. This process is triggered by demand for action and ends with specific engagement execution [21]. Decision making is one of the main abilities of human being that differs us from any other creatures. It is perhaps as old as the history of mankind [22]. Corporations have to choose the best option from a number of alternatives by aggregating outcomes of different stakeholders [23]. In spite of a decision-making problem with multiple stakeholders could be constructed as more than one hierarchy with different criteria [24] to be solved, this process is still hard due to some particularities.

- They are non-repetitive, most unprecedented and unique [23].
- They have a long term effect on the success of the company. In an automotive industry, the supply chain is complex and to make the scenario worse is also long [25]. The impact of changes or wrong decision is expressive. Typically, a new launched model remains in production for 4 to 5 years without significant changes [11, 12].
- Criteria may conflict itself, for example, customers want quality but also want something inexpensive. Conflicting criteria make the decision task tough [26, 27].
- Large number of criteria. Human information processing is limited. The results of research in human cognition indicate that human short term memory can store 7 +-2 chunks [28, 29]. Others researches suggests that our memory span is even smaller.
- Many criteria can be objectively measured, commonly named as tangible criteria, such as fuel consumption. However, others cannot, such as flexibility, quality, efficiency or future income, this group is classified as intangible criteria. Intangible criteria cannot be converted into numeric or monetary values [30, 31].
- Even numerical criterias can have incomparable units [15].

As proposed by law[6], energy efficiency (EE) should not be calculated by models only, but by the whole universe of new vehicles registered. Increase EE for just some

This section contains work of the paper “Multi-Criteria Decision-Making on Energy Efficiency in the Automotive Industry: A Systematic Literature Review” submitted to Computers in Industry journal.

models and or versions could not solve the problem. In this scenario, the composition of vehicles sold in the market will have a influence on profits of each automaker. Since additional taxes are going to be applied for those automakers that do not achieve a specified target. Among variables to be considered, one can highlight the analysis of manufacturing costs, customer value perception and market share, which characterizes this problem as a multi-criteria decision-making. Due to the increasing competition, dynamic customer demands and regulatory laws, the scenario requires automakers add energy efficiency items in practically all cars of portfolio. This change is a complex decision and should be assisted by methodologies to achieve the goal.

Starting from the pioneer works published in 1974, this paper overviews relevant research papers until October 2015, that is a period of 42 years of research. Applications of MCDM methods found were categorized according to Behzadian et al.[14]. Allowing the reader to understand main applications of techniques, trends and opportunities for further investigations. This paper identify 30 techniques or combination of techniques self described as MCDM. Despite 339 papers analyzed none of them was focused on defining a vehicles features in other to increase EE.

The purpose of this paper is to review systematically the applications and techniques available to solve the problem of incorporate technologies of EE keeping the balancing of manufacturing costs, customer value perception and market share. However, this work does not intend to help researchers to select the most adequate method. But, to choose one from this variety of methods different questions should be answered, such as which method fits better to decision-making style of organization? Is it compatible with the data that are available? Is it important that results can be explained and understandable? Questions like that can be answered by Hobbs e Horn[32]. This issue of validity should not be ignored because there is ample evidence that choice of method can significantly affect decisions (sometimes making more difference than which person applies the method)[32].

The purpose of this paper is to fill a gap of knowledge. We propose application of MCDM techniques to solve the problem of incorporate EE technologies in automotive industry. In the same time, keeping the balancing of manufacturing costs, customer value perception and market share to allow adequacy to Inovar-Auto. The issue of validity should not be ignored because there is ample evidence that choice of method can significantly affect decisions (sometimes making more difference than which person applies the method)[32]. Despite that a rational approach lead wiser decisions.

To this purpose, we make use of the systematic literature review (SLR) approach. The classification scheme for this review contains 339 papers from 33 journals since 1974, separated by applications areas according to table 6 (see appendix). The SLR involves documenting all the procedures undertaken and hence the reports of systematic reviews.

The present paper attempts to answer the following questions focused on automotive industry: Which methods were most frequently used? How rate of combined approaches instead of single method used? Should we expect more accurate results when applying combined approaches? Or a specific method could be killer for a specific problem. Additionally, common SLR questions were also answered such as which countries, journals, year and authors have published. This study focus on MCDM for automotive engineering. We used this strategy to narrow the results.

This work has been organized as follows: in Section 1, the purpose of this work is detailed. In Section 2 the background of research we explained MCDM and EE. In Section 3, we identify related work. Section 4 describes the details of methodology. Section 5 presents the results. In Section 6, the results are discussed. In Section 7, we conclude this work with suggestions and future researches.

2.2 Background

Multiple-criteria decision making (MCDM) is a sub-field of operations research [1, 14, 15, 16, 17, 18], concerned with designing mathematical and computational tools to support the subjective evaluation of performance criteria by decision [19, 20]. MCDM techniques are divided in two main groups, multiple objective decision making (MODM) and multiple attribute decision making (MADM) approaches [33, 22, 2, 34]. MCDM is a collection of methodologies to compare, select, or rank multiple alternatives that where multiple and conflicting criteria involving both tangible and intangible factors [35, 1]. MCDM have being used to assist decision makers using their own preferences to choose the best one to meet the decision maker's goals, objectives, desires and values [36, 37].

MCDM has been used in the solution of real-world decision making problems [38]. Usage of MCDM goes from autonomous drive [39] to assessment of Mars mission [40]. Of course, most part of applications are related to supplier selection and evaluation [41, 42, 43, 44, 45, 46, 47, 48, 49] and materials selection [50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61]. The application of MCDM methods has become easier for users and decision makers by improvement of computer techniques[62].

2.2.1 Multi-Objective and Multi-Attribute

MCDM can be splited in between Multi-Objective Decision Making (MODM) and Multi-Attribute Decision-Making (MADM) methods [15, 22, 63]. The goal in MADM problems is to design the best alternative considering evaluation the whole set of attributes which are often hard to quantify, incommensurable and incomparable [15, 64]. In MODM, alternatives are not predetermined, but instead a set of objective functions is optimized, subject to a set of constraints, with number of alternatives effectively infinite. The most

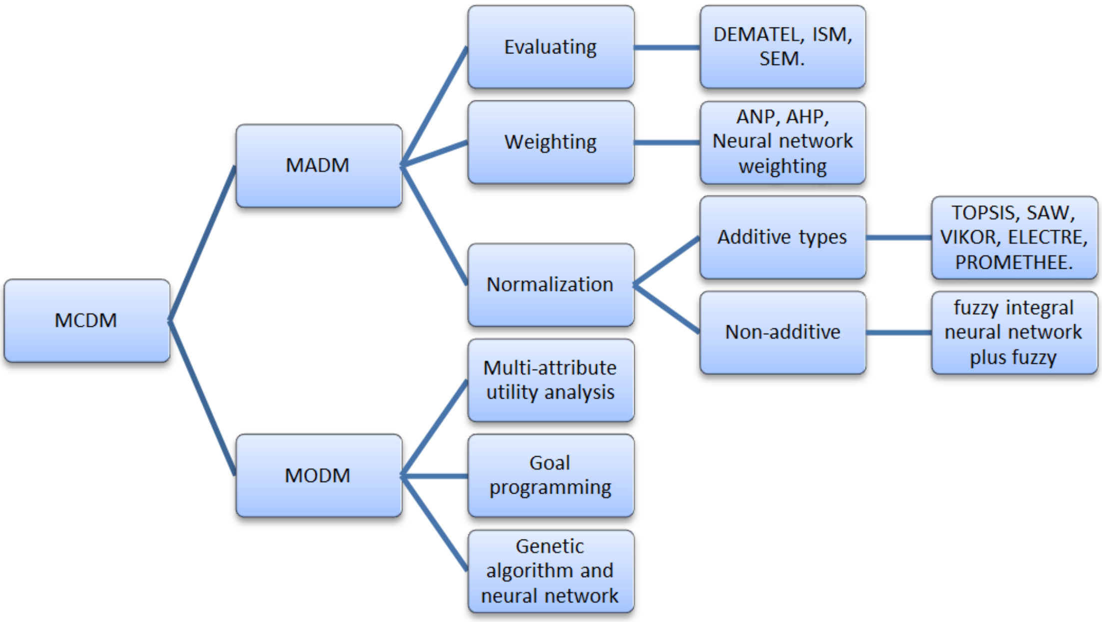

Figure 2 – MCDM classification splited in between MADM [1] and MODM [2]. Font: own author.

satisfactory and efficient solution is the goal, in this solution it is not possible to improve the performance of any objective without degrading the performance of others[15, 65].

From this point on, there are a lot of different proposals among authors for classification of techniques.

Mardani, Jusoh e Zavadskas[1] split MADM into three classes, Jahan et al.[2] proposes a categorization for MODM in three classes. Figure 2 mix this both proposals. Pohekar e Ramachandran[15] offers two possible classifications:

- By method: deterministic, stochastic and fuzzy methods.
- By the type of data employed, methods can also be classified as: quantitative, qualitative or mixed.

Nogués e González-González[66] classify methods in:

- Outranking approaches (ELECTRE, PROMETHEE).
- Additive methods (linear additive model, AHP and the Multi-Attribute Utility Theory).
- Multiple Objective Programming (Multi-Objective Lineal Programming).

Chen[67] classify methods in single or combined. Single models are sub-divided in Mathematics, Single Model and Artificial Intelligence. Mathematics methods includes for example AHP, Linear Programing (LP) and Goal Programming (GP).

2.2.2 Analytic Hierarchy Process

Saaty proposed the Analytic Hierarchy Process(AHP) [24, 68]. AHP is a powerful technique which supports decision making in a multi-attribute environment. It allows the creation of an understandable hierarchical model by the decomposition of complex problems [69]. The idea is that smaller parts of the problem can be easily handled by human information processing capabilities than the entire problem[70]. AHP is based on pairwise comparisons of criteria to establish the weights and alternatives to evaluate performance [71].

Advantages of AHP include:

- Ability to capture both quantitative and qualitative attributes in a simple manner [72, 24, 73, 2].
- Popularity [74, 75, 46, 15, 76, 77, 42, 78, 79, 80].
- Simplicity in implementing and interpreting [81, 82].
- Capability in handling sparse or poor quality data [73].
- Consistency test to ensure judgments quality [69].

AHP has the drawback of including the potential internal inconsistency. The questionable theoretical foundation of the rigid scale[83]. Inconsistency can increase when the process contains a number of criteria that exceeds the human short-term memory [28]. The process can also be affected, due to time taken to complete the experts judgments [84]. For Jahan et al.[2] it only can compare a limited number of decision alternatives, which is usually not greater than 15. To deal with the uncertainty and ambiguity better AHP could be combined with fuzzy logic [42, 85, 86, 87, 88, 89, 90]. Use of Delphi method combined with selection of appropriate and relevant number of decision criteria for pairwise comparisons can address this drawback[91].

AHP is also combined with other methods: such as Simple Additive Weighting (SAW), Grey Relational Analysis (GRA), ANP. This approach ought to be used to ensure reliability of criteria weights [92].

AHP technique fist step, is to decompose the problem organizing objectives, criteria and alternatives hierarchically. Decomposition should occur from the general to specific direction which could be noted in figure 3. The second step is the comparison of

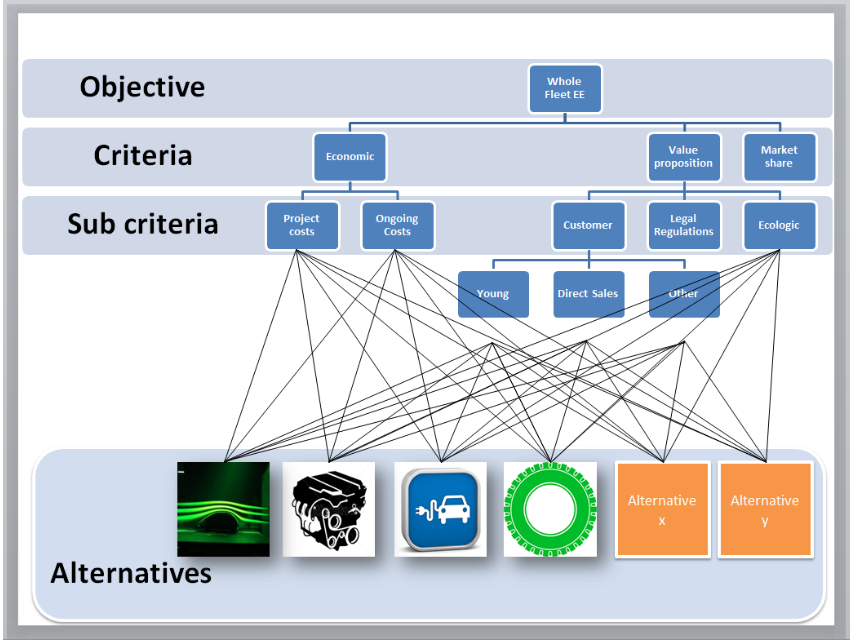

Figure 3 – AHP hierarchy and structure. Font: own author.

alternatives and criteria in order to determine the relative importance within each level [24].

The criteria are compared pairwise, according to their levels by experts. To create a comparison matrix with the relative importance of criteria, respecting the objective, we use the fundamental scale of pairwise comparisons, which is given in table 9 (see appendix). Based on the pairwise comparison judgments, AHP is able to reduce complex problems into a simple hierarchical model to determine the weights of each criteria [24]. In the comparison matrix, criteria are disposed in lines and columns. Assuming a criteria, the pairwise comparison of criterion i with criterion j yields a square matrix where a_{ij} denotes the comparative importance of criterion i with respect to criterion j. In this matrix, $a_{ij} = 1$ when $i = j$ and $a_{ij} = 1/a_{ji}$. Comparison matrix is exhibit in equation 2–1. Next step, requires to normalize column data by equation 2–2 and calculate the eigenvector. Which is the weight of each criterion w_c, by the average values of each criteria row using formula 2–3.

$$A = \begin{pmatrix} 1 & a_{12} & a_{13} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & a_{23} & \dots & a_{2n} \\ \dots & a_{ij} & \dots & & \vdots \\ \frac{1}{a_{n1}} & \frac{1}{a_{n2}} & \dots & \dots & 1 \end{pmatrix} \tag{2–1}$$

$$a_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2–2}$$

$$w_c = \frac{\sum_{j=1}^{n} a_{ij}}{n} \tag{2–3}$$

The comparison matrix and eigenvector are used to estimate the maximum eigenvalue by formula 2–4. The aim of this step is to establish priorities among the elements of hierarchy by making a series of judgments based on pairwise comparisons of the elements. Consistency index (CI) can be calculated as a measure to reflect the coherence of expert's judgments, this index is calculated by equation 2–5.

$$\lambda_{max} = \frac{1}{n} \sum_{i,j=1}^{n} \frac{w_j * a_{ij}}{w_i} \tag{2–4}$$

$$CI = \frac{\lambda_{max} - N}{N - 1} \tag{2–5}$$

We obtain the random index (RI) for the number of factors which are used in de process according to table 10 (see appendix) and finally calculate the Consistency Ratio (CR). In case of CR is smaller than or equal to 0.1, the pairwise comparison passes the consistency test. Otherwise, judgments ought to be reviewed [68]. CR is calculated by formula 2–6.

$$CR = \frac{CI}{RI} \tag{2–6}$$

Finally, rank of preference order based on AHP identifies the most recommended alternatives to a specific MCDM problem.

2.2.3 Energy Efficiency Measurement

Although for most people, vehicle EE is the amount of kilometers traveled with a certain amount of fuel (kilometers per litre, miles per gallon) more rigor is required to measure EE under a scientific inquiry or a public policy. EE alone is a generic term and brings together equivocal quantitative measure [13]. Having U as useful output of a process, E as energy input to a process, Energy Efficiency EE can be calculated by 2–7.

$$EE = \frac{U}{E} \tag{2–7}$$

EE can be classified in four groups: thermodynamic, physical-thermodynamic, economic-thermodynamic or economic [13]. Vehicle EE is being measured by physical-thermodynamic because combines thermodynamic indicators, used for measuring the amount of energy, together with physical units which are intended to measure the service delivery of the process.

The effects of different fuel types ought to be normalized, since it has distinct amounts of thermodynamic energy. Fuels calorific value is defined as the amount of internal

Table 1 – Calorific values of each fuel [4].

Fuel	Calorific values	Density	MJ/L	Reference Diesel
	(MJ/Kg)	Kg/l		
Gasoline E00	43,06	0,74	31,65	1,13
Gasoline E22	38,92	0,75	28,99	1,23
Ethanol	24,80	0,81	20,09	1,77
Diesel	42,93	0,83	35,65	1,00

energy contained on it, and the higher the calorific value, greater will be energy. Since fuel energy amount is directly proportional to its mass, and this in turn varies with temperature, pressure, concentration to specify rules to regulate these tests is necessary. Just as an example, the standard measure of NBR 6601 is megajoules (MJ) [93], an MJ is the amount of energy required to raise the temperature of 10 liters of water to 23,8ºC. Table 1 summarizes these differences for each of the fuels [4]. Note that C gasoline used in Brazil includes 27% of alcohol, according to current law in August 2015. In spite of that, tests are completed with E22, which contains 22% of alcohol according to NBR. MJ is essentially a thermodynamic indicator that can be used to normalize different types of fuel used in vehicles. The overall industry EE curve is calculated by weighted average using formula 2–8 [6], where F means the whole universe of vehicles analyzed and Q means the quantity of vehicles sold during the period analyzed.

$$\text{Overall Energy Efficiency} = \frac{\sum_{n=1}^{F} EE_{\text{vehicle n}} * Q_{\text{vehicle n}}}{\sum_{n=1}^{F} Q_{\text{vehicle n}}} \tag{2–8}$$

On vehicle EE of output process efficient is better measured by physical indicators such as Kilometers meaning the travelled distance. In order to do that properly a detailed test should be followed. These tests are named driving cycles and vary for countries and regions. Examples of existing driving cycles include US FTP-72/75 cycle, NBR 6601:2012 Brazil, improved European cycles, Athens driving cycle, Perth driving cycle (Australia), Melbourne peak driving cycle (Australia), Sydney driving cycle (Australia), Bangkok cycle (Thailand), Pune driving cycle (India), German motorway driving cycle, Beijing driving cycles for classified roads and many others. The full review of existing driving cycles is reported in literature by Samaras e Meisterling[94].

The measurement in Brazil, includes an urban cycle which lasts about 41 minutes divided into three phases: cold start, stopping at the end of this phase for 10 minutes and warm start [93]. This cycle is approximate 17.9 km, with a maximum speed of 91.3 km/h and average speed of 34.3 km/h [93]. And a highway cycle lasts approximately 25 min, divided into two phases: the heating cycle and the test. Are approximate 33 km, being only 16.5 km of sampling, with a maximum speed of 96.4 km/h average speed of 77.4 km/h [95]. Figure 4 illustrates the cycle of measurement process based on NBR 6601. The amount of fuel used for complete tests it is converted to MJ, to become fuel independent, and it is used as denominator in equation 2–7. The useful output is calculated considering the vehicle's weight.

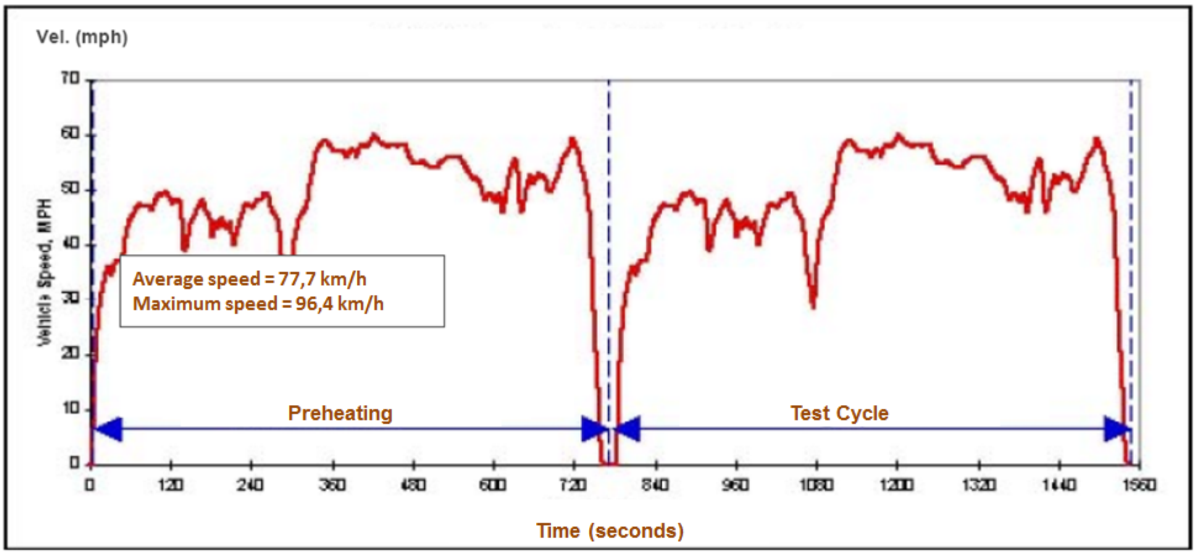

Figure 4 – Energy measurement cycle. Font: own author.

Fuel consumption is influenced by a number of factors such as: mass, aerodynamics, speed, choice of gears and for many mechanical factors and projects ranging from car to car. Most of the energy generated by the combustion engines is lost in the process, more than 60 % only by engine [3], as can be seen in the figures 5 for urban and highway cycles respectively.

2.2.4 Neural Networks and Time Series Forecasting

Artificial neural network (ANN) with supervised learning are very prominent field of research. New applications arise often because flexibility of nonlinear models enable discover pattern adaptively from the data. It has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from data and estimate any complex functional relationship with high accuracy [96, 97].

Characteristics of ANN includes:

- ANNs have ability to learn from experience is useful for many practical problems since it is often easier to have data than to have good theoretical guesses [98, 99].
- ANNs can generalize. After learning the ANNs can often correctly infer the unseen part of a population even [96].
- ANNs are universal functional approximators. It has been shown that a network can approximate any continuous function to any desired have more general and

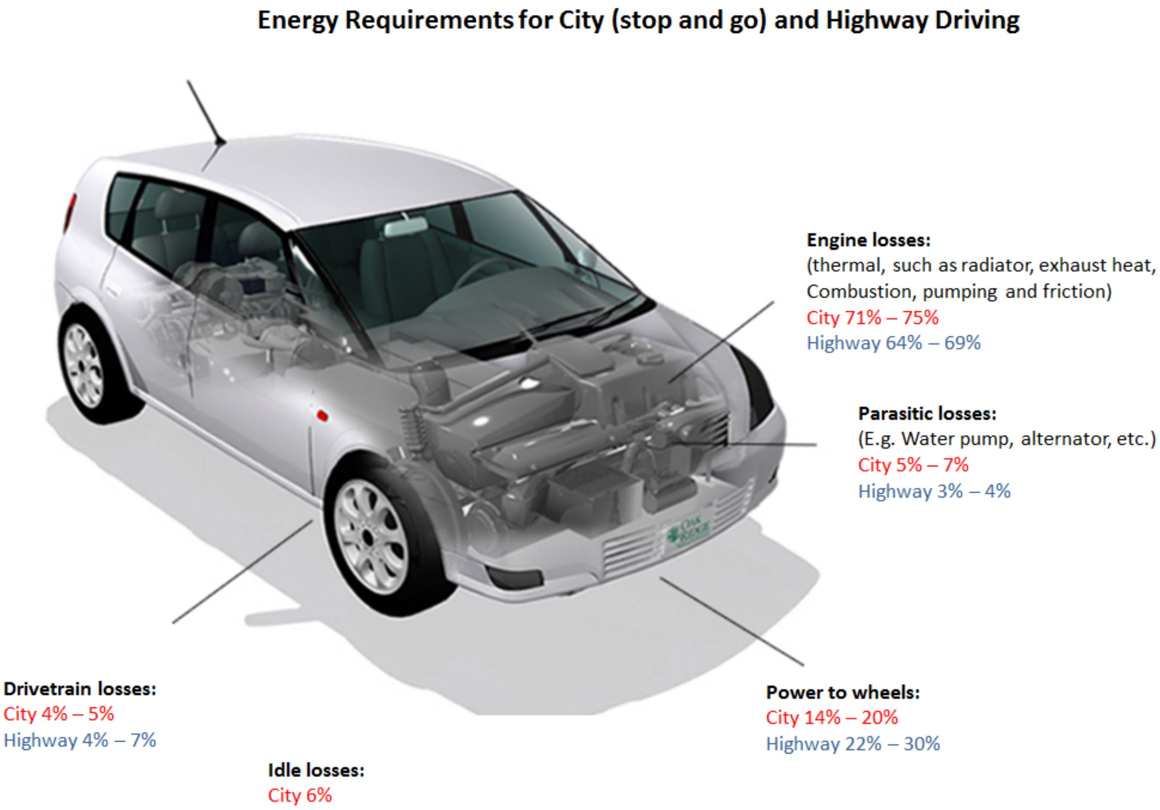

Figure 5 – Estimated energy losses in urban and highway cycle. Font: U.S. Department of Energy[3]

flexible functional forms than the traditional statistical methods can effectively deal with[96, 99].

- ANNs are nonlinear[96, 99].

Many different ANN models have been proposed since 1980s. Perhaps the most influential models are the multi-layer perceptrons (MLP). MLP is one of most prevalent neural networks and could be used to approximate nonlinear functions [99].

One major application area of ANNs is forecasting of the multivariate nonlinear nonparametric statistical [100]. As forecasting is performed via prediction of future behavior from examples of past behavior, ability to generalize is essential [96].

Time series forecasting (TSF) is done by analysis of past data [101]. Time series (TS) are defined as a set of sequential observations which can be either continuous or discrete [102]. ANNs are considered useful approaches for addressing problems of time series forecasting (TSF) [103].

MLP with backpropagation and stochastic time strength function is powerful forecasting model [99].

Tkáč e Verner[104] evaluate 412 articles from 1994 until 2015 and conclude that majority of reviewed articles applied networks with supervised learning. Although many types of neural network models have been proposed, the most popular one is the feedforward network model which includes applications for time series forecasting [96]. Sharda[100] found out backpropagation is most common. Ansuj et al.[105] argued that conventional backpropagation network outperformed ARIMA model with interventions and provided better forecasts.

Sales forecasting methodology have the following steps: data gathering and processing, choosing the model for forecasting, forecasting the results and evaluating the results[106].

2.2.5 Fuzzy Numbers

Pairwise comparison is the foundation for a lot of MCDM methods. Pairwise comparison is a rate between two options. In Saaty's original proposal a rigid scale is used to measure this relation. A fuzzy approach uses a less rigid scale to define the strength with which one option dominated other [107]. To ensure the proper reflection of experts judgments by making reference to the uncertainty, fuzzy numbers are used to integrate linguistic assessments [108]. Fuzzy are a common approach to represent mathematically the human uncertainty and vagueness in pairwise comparison[42]. Fuzzy help experts to express approximate ratio instead of exactly[107].

The membership function represents this ratio in equation$f_a(x) \in [0,1]$. A positive trapezoidal fuzzy number (PTFN) n can be defined as $(n1, n2, n3, n4)$ if $n2{=}n3$, then n is called a triangular fuzzy number (TFN) [109, 107]. Figure 6 shows a graphical representation of this function. The membership function for TFN and PTFN can be seen in equations 2–9 and 2–10 respectively.

Mathematical approaches are used to convert a fuzzy number in a set of weights for one judgment. Which allows fuzzy to be combined with many different methods such as TOPSIS [110, 111, 112, 113, 91, 46, 18], AHP [88, 86, 85, 42, 87, 89, 90],ANP [114, 26],VIKOR[115, 56, 116],DEMATEL [45, 117, 118].

$$f_a(x) = \begin{cases} 0 & : x < a, x > c \\ \frac{x-a}{b-a} & : a \leq x \leq b \\ \frac{c-x}{c-b} & : b \leq x \leq c \end{cases} \tag{2–9}$$

$$f_a(x) = \begin{cases} 0 & : x > a \\ \frac{x-a}{b-a} & : a \leq x \leq b \\ 1 & : b \leq x \leq c \\ \frac{d-x}{d-c} & : c \leq x \leq d \\ 0 & : x > d \end{cases} \tag{2–10}$$

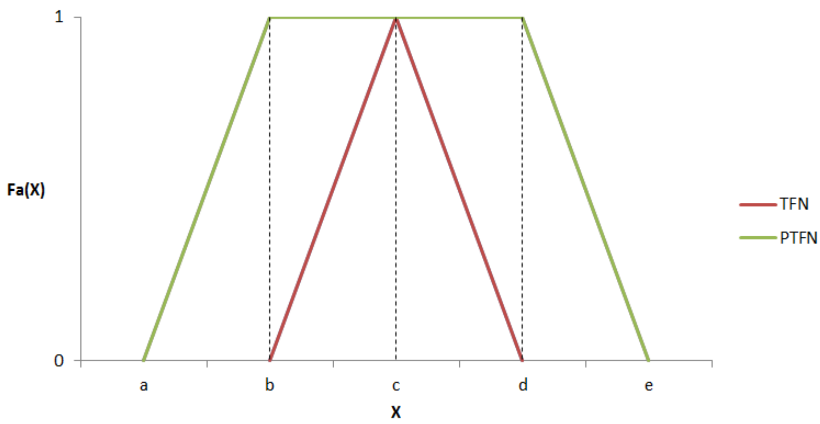

Figure 6 – Positive trapezoidal fuzzy number and triangular fuzzy number. Font: own author.

2.3 Related Work

Related work are listed on table 2. This list includes work of researchers that focus on MCDM method specifically or focused on particular field of interest.

Table 2 – Related Work

Author	Topic	Period	Papers	Findings
Pérez, Carrillo e Montoya-Torres[80]	MCDM review concerning design and operation of urban passenger transport systems	between 1982 and 2014 (up to May)	86	AHP popularity. The number of papers increased from 2000, with a surprising small amount of publications between 2003 and 2006. It is to note that from the total number of papers published in these 30+ years, 48.86% were published between 1982 and 2007, while 51.14% were published during the last 6 years (between 2008 and 2014).
Behzadian et al.[14]	Review focused on TOPSIS applications	Between 2010 and 2012	266	Among numerous MCDM methods, TOPSIS continues to work satisfactorily across different application areas.

Continued on next page

Table 2 – continued from previous page

Author	Topic	Period	Papers	Findings
Jahan et al.[2]	Review about material screening and choosing methods	Until 2009	95	TOPSIS, ELECTRE and AHP have been the most popular state of the art methods in material choosing.
Govindan et al.[74]	Identify MCDM approaches for green supplier evaluation and selection	from 1996 to 2011	33	AHP is the most widely MCDM method and also for green supplier evaluation and selection. Single technique is more common than integrated approach. Interestingly, many of the identified papers e twenty five papers (77.77%) are still utilizing a single technique in their analysis. Eight papers (22.22%) utilized an integrated approach, with the objective of trying to achieve a more realistic application given the complexities of a real-world decision process.
Ilgin, Gupta e Bataïa[119]	Environmentally conscious manufacturing and product recovery (ECMPRO)	between 1996 and 2014	190	Increase in the number of publications concerning the use of MCDM techniques in recent years. MCDA is more popular than MODM in ECMPRO. Among the most frequently used techniques, one can find AHP. Significant increase in the number of publications in recent years.
Scott, Ho e Dey[120]	MCDM review concerning bioenergy sector	from 2000 to 2010	57	Optimization methods are most popular with methods choosing between few alternatives being used in 44% of reviewed papers and methods choosing between many alternatives being used in 28%. The most popular application area was to technology selection with 27% of reviewed papers followed by policy decisions with 18%.

2.4 Research Methodology

This work conducted a systematic literature review (SLR) of MCDM applications and techniques available to solve the problems in automotive industry. SLR's are organized reviews based on clear search strategy to ensure rigor, completeness and repeatability of the process which means identify, evaluate and interpret all available research relevant to a particular question [121]. The main reason to perform a SLR is to build a solid theoretical foundation for this study. Usual reasons for performing a SLR include:

- To summarize the existing evidence concerning one technology [121, 122].
- To identify gaps in current research to suggest areas for further investigation.
- To provide a framework/background to appropriately position new research activities.

SLR are going to help this paper to support a model which decisions are based on facts and agreed between all experts instead of just opinions. SLR are useful to identify methods and procedures in a field of knowledge[122]. This SLR comprehends two major steps. First, a Bibliometric Study was conducted to understand the universe around this theme. Second, papers were reviewed to understand MCDM techniques used by automotive industry given specified attention to energy efficiency. MCDM applications were identified and classified according to table 6 (see appendix). This strategy was used also to narrow the results of SLR following Staples e Niazi[123] recommendations.

It is important to note that searching in just one database and only in titles for MCDM or multi-criteria we got more than 12.000 results. Some reviews use the strategy of limit the application of MCDM technique to specific field [74, 124, 80, 15, 120], others limit by the MCDM method [17, 14, 1] and some limit by both [2]. Since one of the main purposes is to compare MCDM methods, this study narrow the results limiting the subject to automotive industry.

The procedure of systematic review includes the following steps: planning, defining research questions, searching databases, discussion of validity, data extraction, and synthesis of the results[121]. Next subsections describes these steps.

2.4.1 Planning

The goal of systematic review is to find out how the authors have, in the literature, used MCDM to help in automotive decision making process. We developed a review protocol at the beginning of the systematic review, to make sure that the research is undertaken as planned and not driven by researcher expectations. The protocol includes research background, the research questions, search strategy, study selection criteria and procedures, quality assessment, data extraction, and data synthesis strategies. The research questions and article identification strategies are described in the following subsections.

2.4.2 Research questions

Specifying the research questions is the most important part of any systematic review [121]. The present paper attempts to answer the following questions:

- **RQ1:** Which MCDM methods were most frequently used?
- **RQ2:** How rate of combined approaches instead of single method used? Or a specific method could be killer for a specific problem?
- **RQ3:** What applications of MCDM were most frequently?
- **RQ4:** How fuzzy logic have been used to deal with uncertainty? How frequently?

The main objective of RQ1 and RQ2 is to understand which are most common methods and combinations. Finally, RQ3 gets a whole picture of paper, identifying who the authors are, which are the publishers that usually publish more and what are the most frequent words related to these papers. In order to group the papers application categorization proposal was applied according to table 6 (see appendix).

2.4.3 Research strategy and search process

This study was planned to find relevant literature about the link between MCDM and automotive industry.

Just indexed journals and papers written in English were considered. Usage of indexed journals is a common strategy [125]. No additional filter related to type of publication was done in the initial step, so books were included. Searches were conducted in four electronic databases: Science Direct, Emerald, IEEE Xplorer, Springer.

In the searches, were used the same conceptual research string. The results of these researches were 215 results from Science Direct, 113 from Springer, 20 from IEEEXplorer and 4 from Emerald totalizing 352 results.

This study uses the following search string : ("Multi-criteria decision-making") OR ("multiple-criteria decision analysis") OR ("MADM") OR ("MODM") AND ("vehicle" or "vehicular" or "automotive") AND ("fuel" or "emission"). Synonyms, abbreviations, and alternative spellings were created in other to cover relevant topics as suggested by [121]. The search string tries to filter papers that treat MCDM and have some link to EE in automotive industry in the same time. It was used on the electronic databases on 22 of September 2015.

After duplicate papers were removed by Zotero tool [126], 339 papers remained. After removing the papers that are out of the inclusion criteria, 45 papers remained to be analyzed. The analyses and conclusions about the final selected papers were conducted by author. Inclusion and exclusion criteria are explained bellow.

The paper is kept in the study if it satisfies all of the inclusion criteria:

- Academic papers published on journals or conferences.
- Papers related MCDM and to automotive industry, at same time.
- Papers that have clear concepts about MCDM.
- Papers written in English.
- Studies published until September 22 of 2015.
- Papers that have explicited on it, which MCDM method or combination of methods were used.

The paper is kept out if it satisfies any of the exclusion criteria:

- Duplicate papers found on the digital libraries.
- Books, thesis, editorials, prefaces, article summaries, interviews, news, reviews, correspondence, discussions, comments, reader's letters and summaries of tutorials, workshops, panels, and poster session.
- Papers written in other languages than English.
- Studies that are only available as abstracts.

2.4.4 Threats to Validity

The goal of this study is to cover, as many as possible, the relevant research papers about the link between MCDM and automotive industry. The approaches below follows Kitchenham et al.[121] guidelines. We adopted precautions in order to avoid that relevant papers have not been included. First, since in the English language, there is some ambiguity we used different terminology in the search in order to cover much related terms as possible. Search included documents keywords, title, and abstract according to [127].

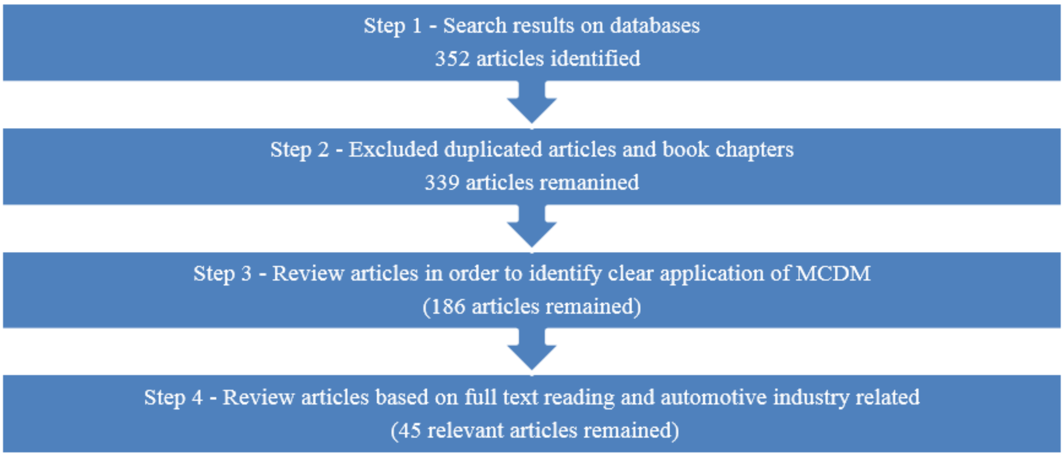

Figure 7 – Step by step of research process. Font: own author.

Second, search was carried out in well-known journals and proceedings which are included in the electronic databases that were searched. ScienceDirect has over than 3,800 journals [128], Springer has over than 2,500 journals[129], Emerald 593 journals [130] and IEE Xplorer more than 3,9 million of items[131]. To avoid limitations of search in one or two databases[127], we included four databases in the search. Third, in order to avoid paper have been rejected incorrectly selection process was included specific questions. Figure 7 summarizes this process.

The following measures have been taken to improve the validity of the research and to minimize the number of missed papers. The inclusion and exclusion criteria at every step were explicitly defined and reviewed by author. Clear criteria were adopted to allow the correct paper categorization and also to assure quality of analyzed papers such as:

- Is it clear the correlation to automotive industry?
- Is it clear what techniques were used to construct each model?
- Is it clear how accuracy was measured?
- Indicators/Criteria are clear defined?
- Linguistic terms are clear defined?
- Ranking are clear defined?

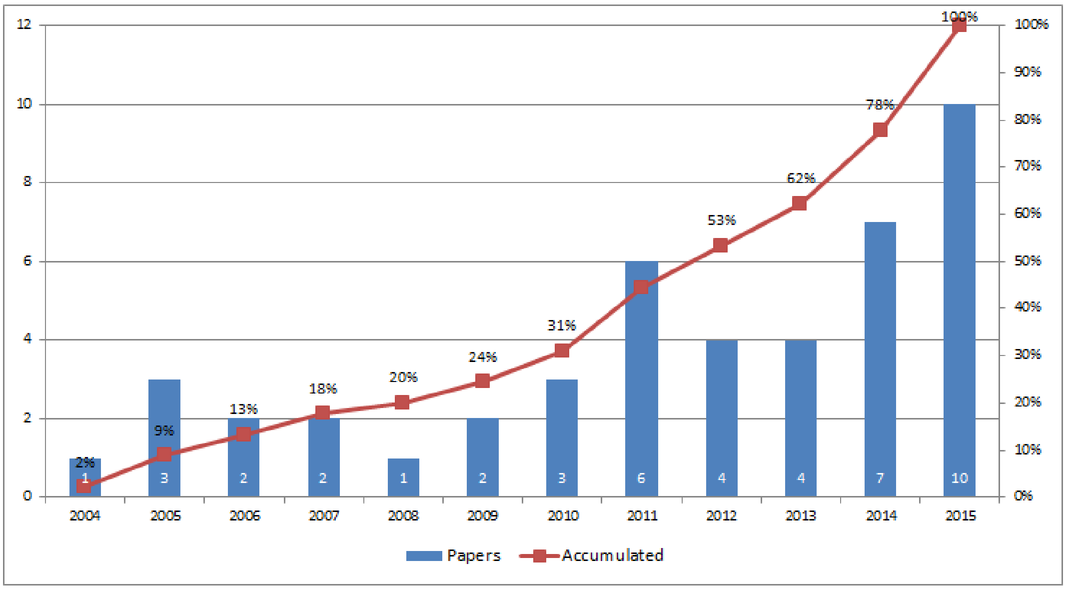

Figure 8 – Published papers by year related to MCDM and automotive industry. Font: own author.

2.4.5 Data extraction and synthesis

After identification of the relevant papers, the following data were extracted: the source (journal or conference), title, authors, publication year, MCDM methods and a basic evaluation of applied technique such as accuracy, criteria, indicators, ranking and linguistic terms if applicable. The data extracted from each paper were maintained through the whole review process. Based on the criteria for classifying the papers, all relevant papers were reviewed. The corresponding data were extracted.

It is not easy and, because of this, further criteria for classifying the papers were defined, based on what information was available in the papers. The data synthesis was specified in the review protocol from the beginning of the systematic review. It is reasonable combine selected studies, because despite different applications and different MCDM techniques the overall purpose of all of them is to aid the automotive ecosystem. The final list of papers analyzed is present in table 7 (see appendix).

2.5 Results

We identified the most frequently methods to solve decision making problems related to automotive industry. We also evaluate a number of publications per year and evaluation of authors, publishers. All papers found were categorized according to Behzadian et al.[14].

Considering the number of publications by year according to figure 8 it is noted that the number of publications is growing up exponentially.

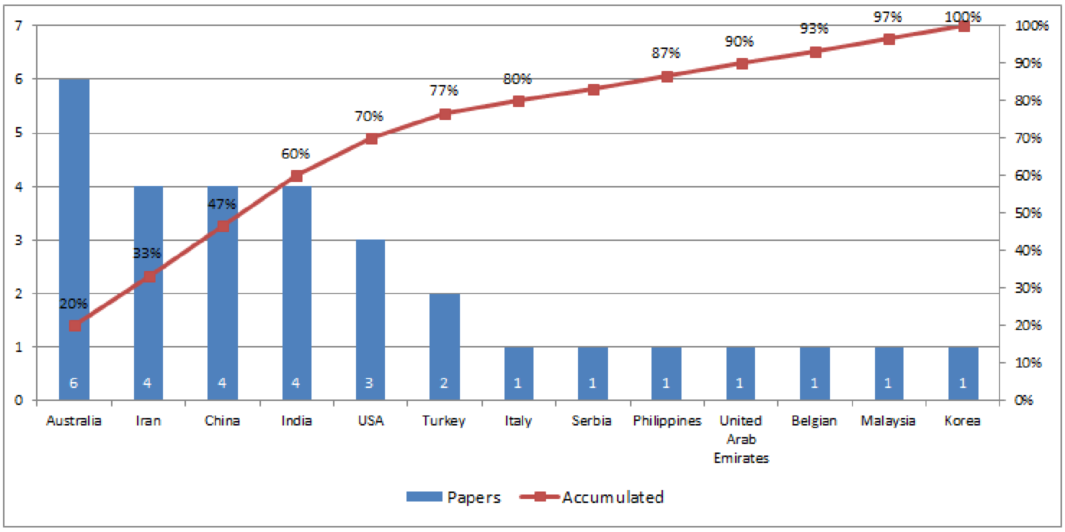

Figure 9 – Published papers by country related to MCDM and automotive industry. Font: own author.

MCDM applications by country are show in figure 9 it is noted that Australia has major publications followed by Iran, India and China.

Evaluation of authors data according to ideas created by Lotka(1926) known as “the inverse square law of scientific productivity” shows that only a small number of authors produces more than one document. In the set of papers selected at this search, just 10 authors published more than 1 document. In the top 5 a group lead Ayoko, Godwin (7 publications), follow by 2 others members with 4 publications and others 2 with 3 publications. Those researchers that published more than one paper, usually do that about same MCDM methods.

A frequency distribution analysis over words used in titles and keywords was evaluated. As expected, the most common words are "Decision making" (7 times), followed by "Supply chain management", "Multi-criteria decision making" and TOPSIS all of them with 3 occurrences each. Since the value proposition was to analyze important words, prepositions and articles were removed, so we cannot verify first Zipf law. However we verify that words with low frequency got similar values of occurrence.

Expert Systems with Applications and Atmospheric Environment are the most active publishers with 4 paper each. Total of 33 publishers for a total of 45 selected papers show how dispersed is this type of publication.

2.5.1 MCDM Methods

Figure 10 shows absolute frequency of MCDM methods founded in selected papers. Between the main groups of MCDM, MADM is far most common with 91% of papers against 9% of MODM. The number of methods is greater than documents analyzed since

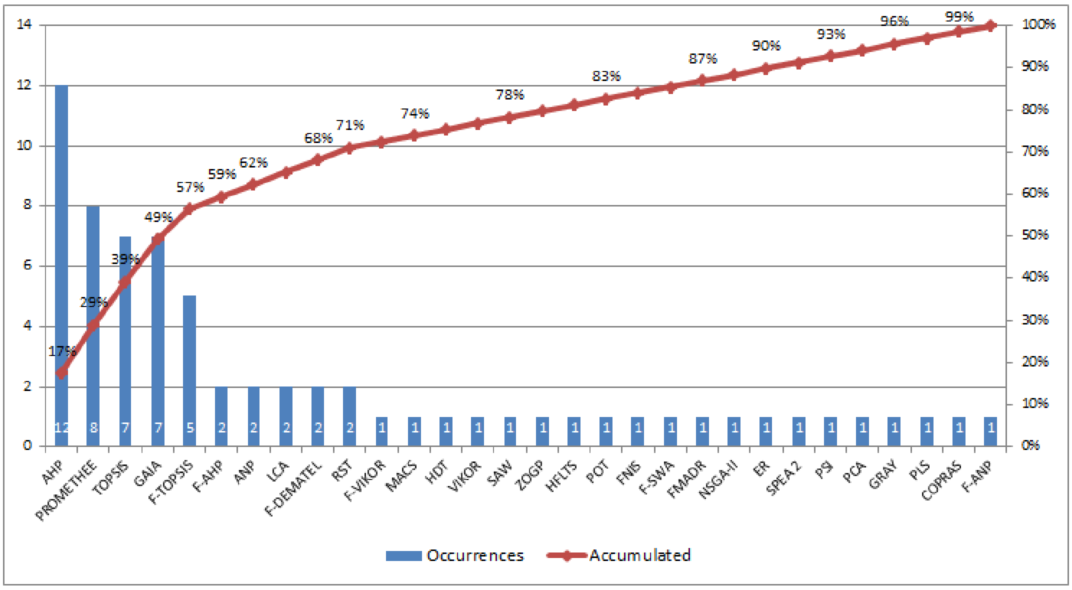

Figure 10 – MCDM methods occurrences in analyzed papers. Font: own author.

it is usual combination of methods. **Answering RQ1**, our analysis shows that AHP (12 ocurrences) is the most popular method in this context, followed by PROMETHEE (8 times which 6 from Australia). This is coherent with increasing popularity of the PROMETHEE in different activities [132].

It is noteworthy that if we consider all 186 analyzed papers, which method application is clear and consistent, we still conclude the most popular method is AHP (19,5%) followed by TOPSIS (12,4%), F-AHP (7,38%) and Promethee (7,1%) and F-TOPSIS(4%). This result is coherent with others studies, about AHP popularity in terms of number of journal publications. AHP is still considered most popular of MCDM methods [15, 46, 79, 78, 74, 75] the most applied for transport projects evaluation [77, 15, 75], for supplier evaluation [42], for green supplier evaluation [74] and for solid waste management [76]. Ho (2010) found DEA as most popular individual approach for supplier selection. However, it was noticed that the integrated AHP approaches are more prevalent [72]. TOPSIS and AHP are the widely used decision-making methods [133]. As well as, TOPSIS is also one of the most well-known and widely accepted methods for MCDM [134]. Fuzzy was the most common alternative proposition, present in 17% of analyzed methods, this number is also coherent with Vinod's (2015) numbers between 10% and 15% [42].

Answering RQ2, our analysis shows that combined approaches are more frequently over single method. The rate of integrated approachs (62,2%) are greater than individual approaches (37,8%). Since there is no distinguished superiority of one MCDM technique over the others, it is difficult to determine the best decision making method for a given scenario independently of approach [135, 72].

Integrated approaches seems to be a better solution to surpass weaknesses. This

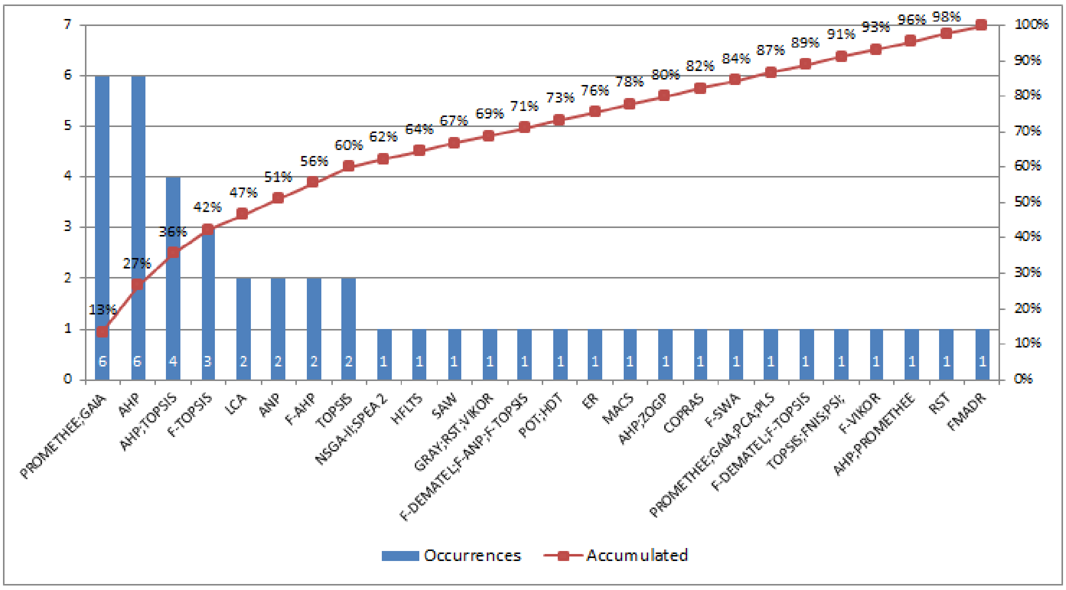

Figure 11 – MCDM methods combined in analyzed papers. Font: own author.

procedure explains why Fuzzy is so common, fulfills the uncertainty gap. **Answering RQ4**, where the information is deficient, intangibility, arising from human qualitative judgments, uncertainties, vagueness or preferences available are subjectives and imprecise fuzzy logic is required [56, 18, 45]. Another usual approach for fuzzy is to avoid rigid scale. Authors used seven linguistics terms to assess the level of the performance criteria with TFN [113], gray numbers [27] and PTFN [136, 56]. Despite one occurrence of TFN combined with eleven linguistics terms[45]. We observed in our research that five linguistics terms with TFN with six cases is used frequently [85, 27, 42, 137, 118, 89]. This integrated approach also helps to eliminate the disadvantages of AHP[42].

Those cases where the optimal alternative should not have the worse performance in some criteria are usually solved by integrated approaches. In this cases AHP is used for obtaining the weights of attributes and TOPSIS is responsible for calculating the ratings and ranking the alternatives [39, 79, 44, 138].

Figure 11 shows absolute frequency of MCDM method or combination found out in analyzed papers. PROMETHEE and GAIA (6 times) overcomes the most notorious combination of AHP and TOPSIS (4 times) found out in selected papers, in **response to RQ2**. When we consider grouped methods, fuzzy becomes even more popular as variation achieving 20%.

2.5.2 MCDM Application

Answering RQ3, this research analyzed the application of MCDM technique in selected papers to understand the most frequently applications. We categorized them in 9 groups as proposed by [14]. As expected, the main group was Design, Engineering and

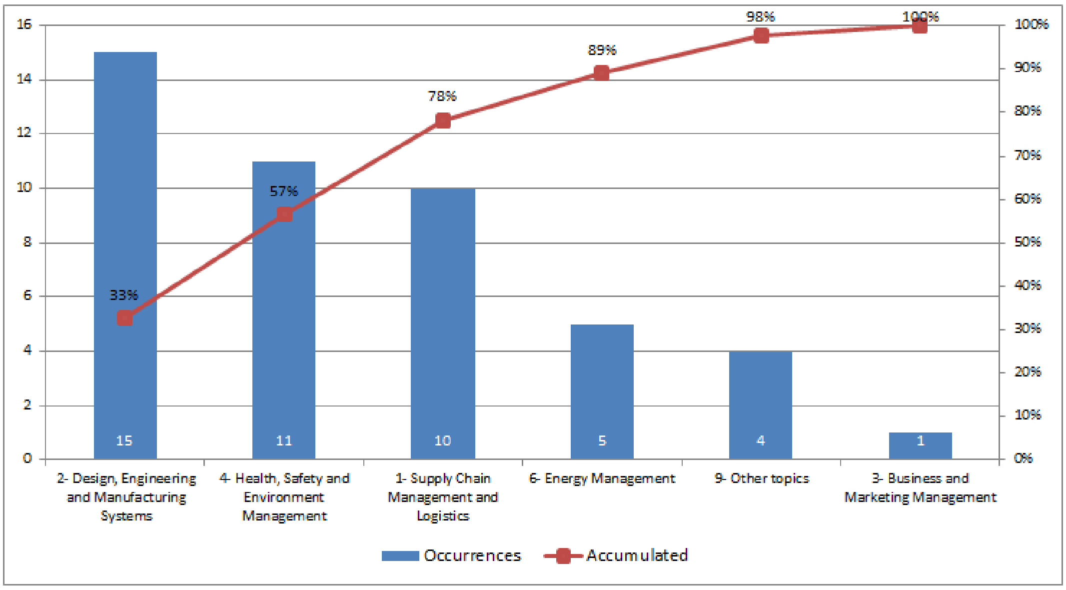

Figure 12 – Applications of MCDM methods in analyzed papers. Font: own author.

Manufacturing systems, results are show in figure 12.

Considering the link between the five categories of application and MCDM methods the results are present in figure 13. It is noteworthy that most part of applications combined method PROMETHEE and GAIA are related to Health and Environment. TOPSIS can fit requirements of different areas [14], AHP too, because they were found out in four of nine proposed areas within our research scope.

Among numerous MCDA/MCDM methods developed to solve real-world decision problems, TOPSIS continues to work satisfactorily across different application areas [14]. TOPSIS is the most frequent method applied in Supply chain and Logistic field [14, 1].

Since there are a lot of methods with only one application they were grouped into others. Use of Fuzzy techniques is also common for Supply Chain managements and Logistics.

2.6 Discussion

This study attempted to review papers published until October 2015 about MCDM in Automotive industry in popular international journals. The research methodology and research questions were described in Section 2.4. A list of analyzed papers qualified by the method in table 8 (see appendix) shows all the selected papers.

In general, MCDM techniques are popular and correctly applied in many different applications and fields. This can be noted by the number of different journals that bring papers related to MCDM subject.

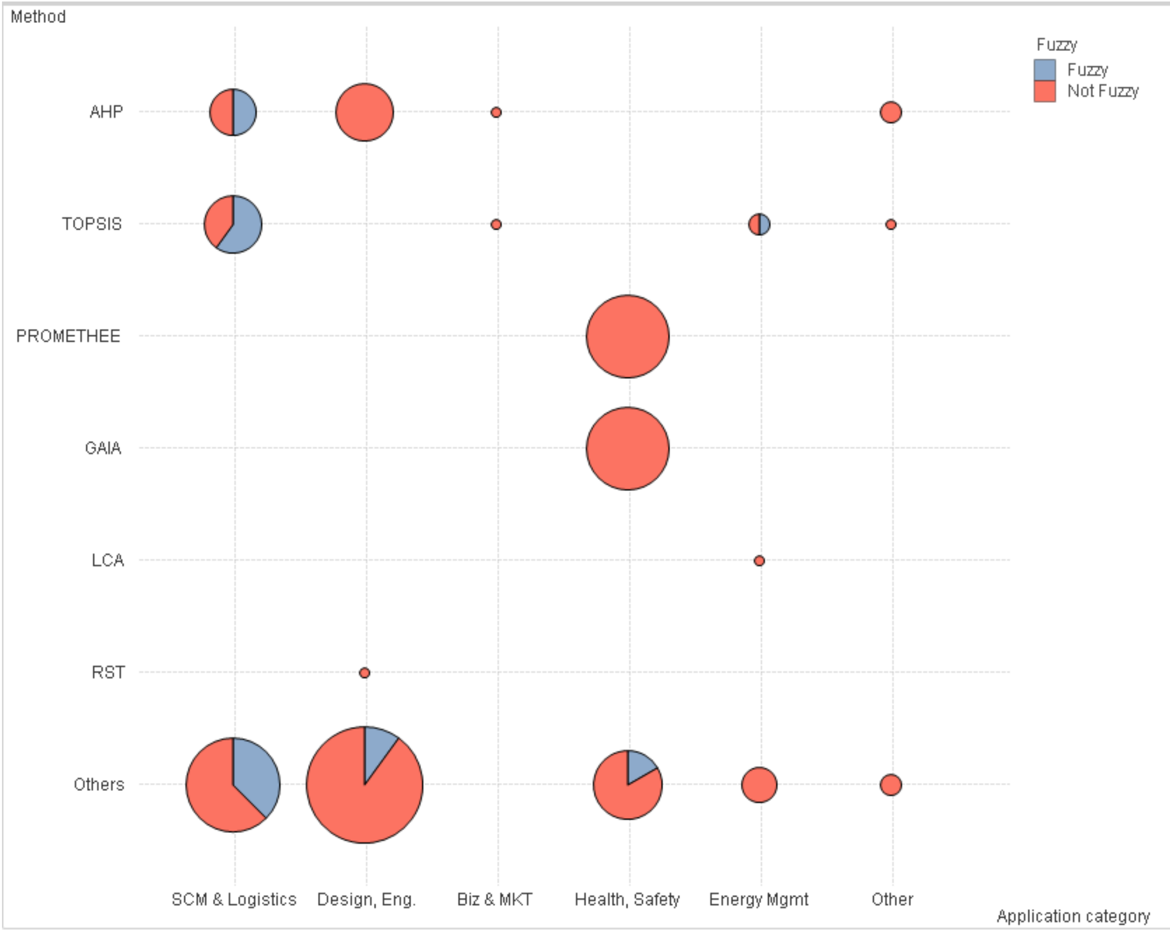

Figure 13 – Applications of MCDM techniques in analyzed papers. Font: own author.

The number of methods, combinations and variations show that a common standard was well understood, at same time many researchers are trying to enhance decision-making processes to next level. In this direction it is clear an increasing tendency to combine fuzzy logic techniques with other MCDM methods to deal with uncertainty and vagueness inherent in decision-making processes, especially those with large number of stakeholders are involved.

It seems that in spite of popularity and applicability of same methods, there is no killer method. However, it is clear that correct criteria and alternatives structure it is a important step. Since most part of methods rely on experts to assist criteria, a process of identify inconsistencies is very important. This could be one of the reasons for AHP popularity.

Methods specialization was also perceived, researchers seems to have their preferred methods that are basis for variations or are applied in different problems. This can explain why it is more common reviews and applications about one method than comparisons between methods.

2.7 Conclusion

This paper carried out a unique literature review to classify MCDM techniques with focus on automotive industries. The review categorized 45 scholarly papers from 33 journals until October 2015 into 5 application areas. They are further classified by publication year, publication journal, country of application. Overall, we found that MCDM techniques have been successfully applied to a wide range of applications in automotive industry. The methods were observed to be most frequently in engineering design followed by environment and supply chain. It was observed that AHP was the most consistently technique followed by PROMETHEE. Integrated approaches were more usual than individual ones. Application of fuzzy methods to tackle uncertainties in the data was also observed in the published literature [134, 42, 113, 56, 18, 139, 45, 118, 88]. Despite many studies it is still hard determine the best decision making method for a given scenario.

There is a gap on use of MCDM for automotive design focused in EE. Although, a review of the published literature on automotive industry analyzed here indicates greater applicability of MCDM methods for dealing with complex decision-making in various applications and automotive sectors with different subjects and terms. None of them focused on EE for automaker point of view. There are papers for fleet selection [27, 140, 88] and fuel selection [141, 142, 35, 136, 143]but none of them is focused on support a rational decision of which features should be adopted on each vehicle in order to enhance EE. The methods have been widely used to take care of multiple, conflicting criteria to arrive at better solutions. On the other hand, the increasing popularity and applicability of these methods beyond 2010 indicate a paradigm shift in MCDM approaches.

3 Brazilian Energy Efficiency Evaluation and Forecast

3.1 Introduction

Following other countries, Brazilian government introduces in 2012 the Inovar-Auto [6] program. Automotive sales achieve a remarkable number of 2,99 millions of units sold in Brazil in 2012. An accumulated increase of 56% since 2006. There were no reason to be afraid of keep exploring all the market opportunities. However, the main goal of the program is to improve the energy efficiency (EE). Minimum required improvement of 12% in comparison with EE obtained in 2011. And, all Brazilian automakers agreed with this new rules, including a possible additional reduction of taxes in 1 % for those who increase EE by 15.4% and to 2% for those who achieve 18,8%. If compared to Europe or United States, the ratio of person by vehicles remains low in Brazil. Which is clear signal of opportunities. The country continue to arouse interest of automakers worldwide. However, those which do not achieve the minimum requirement will put the business under risk due to fines.

There are few researches about the potential effect of Inovar-Auto over Brazilian automotive market. Many questions need to be answered. How far are the general market of minimum target requirement? How is the EE curve over last years? Has EE been improving since Inovar-Auto was launched? Has automotive industry applying technical evolutions to improve EE? Which technology should be adopted by each car segment to improve the whole manufacturer EE? How sales forecast for first year of Inovar-Auto can impact automakers decision about which kind of technology should be adopted? To answer questions like that we analyze Brazilian sales numbers with focus on how the overall market numbers are facing the new regulations. This study will not answer all questions, but undoubtedly can help others researchers to understand what can happen in the future. Specific cases could be studied, after sales numbers become public and company's strategy be revealed. Brazilian peculiarities and obscure effects of Inovar-Auto provide unique characteristics which justify creation of a specific model to guide decision making.

The main goal of this study is to develop a decision-making model capable of support a better decisions about the suitable strategy to be adopted to achieve expected EE in future sales without compromise the deal. We propose a model capable of evaluate the most suitable technology that should be adopted by each vehicle segment. After, we calculate the impacts of this improvement using next year sales forecast estimated by

ANN. Therefore, we can anticipate if results are good enough to achieve the Inovar-Auto targets.

This study intends to generate knowledge and solve real world problems, enhancing existing forms of doing something [144]. It is also experimental, from technical point of view, since different models were tested to find out the best performance according to goal criteria. The nature of this research is applied because methods and techniques were used to solve issues [145]. Regarding procedures, this research is bibliographical, because intends to review previous works, analyzing multiple approaches to solve a problem [144].

3.2 Research Design

In this work, we propose an approach that combines Delphi technique together AHP[24] to identify and prioritize factors for improving EE. A Delphi group was carried out to structure the problem hierarchically using objectives come from Inovar-Auto. It was used a set of engineering alternatives and mainly to define the evaluation criteria. Since the hierarchy was defined, AHP technique was used to prioritize the alternatives with special attention to consistency check. To verify the results in EE, a sales forecast model was developed using a neural network and the last 10 year of vehicle market data. A comparison with initial objectives are going to provide insights for decision makers and planners aiding the overall process. The Figure 14 summarize this approach. The methodologies details used in this work are discussed below.

Steps adopted for the AHP method in this work follows [24], Delphi procedure was also to achieve a mutual consensus. The consistency of judgment data provided by a group of experts and prioritize the hierarchy was also part of AHP methodology [24].

3.3 Inovar-Auto Objectives

Inovar-Auto objectives includes many topics such as: accept be part of Brazilian labeling project named PBE (*Programa Brasileiro de Etiquetagem*), have at least 6 local steps of vehicle production carried out in Brazil are also a requirement. However, in this work we focus only in EE. We summarize Inovar-Auto objectives linked to EE as follow:

- Achieve a minimum energy efficiency of 12% over EE obtained in 2011.
- Verify if it is worth a possible additional taxes reduction in 1% by achieving 15.4% of EE.
- Verify if it is worth a possible additional taxes reduction in 2% by achieving 18.8% of EE.

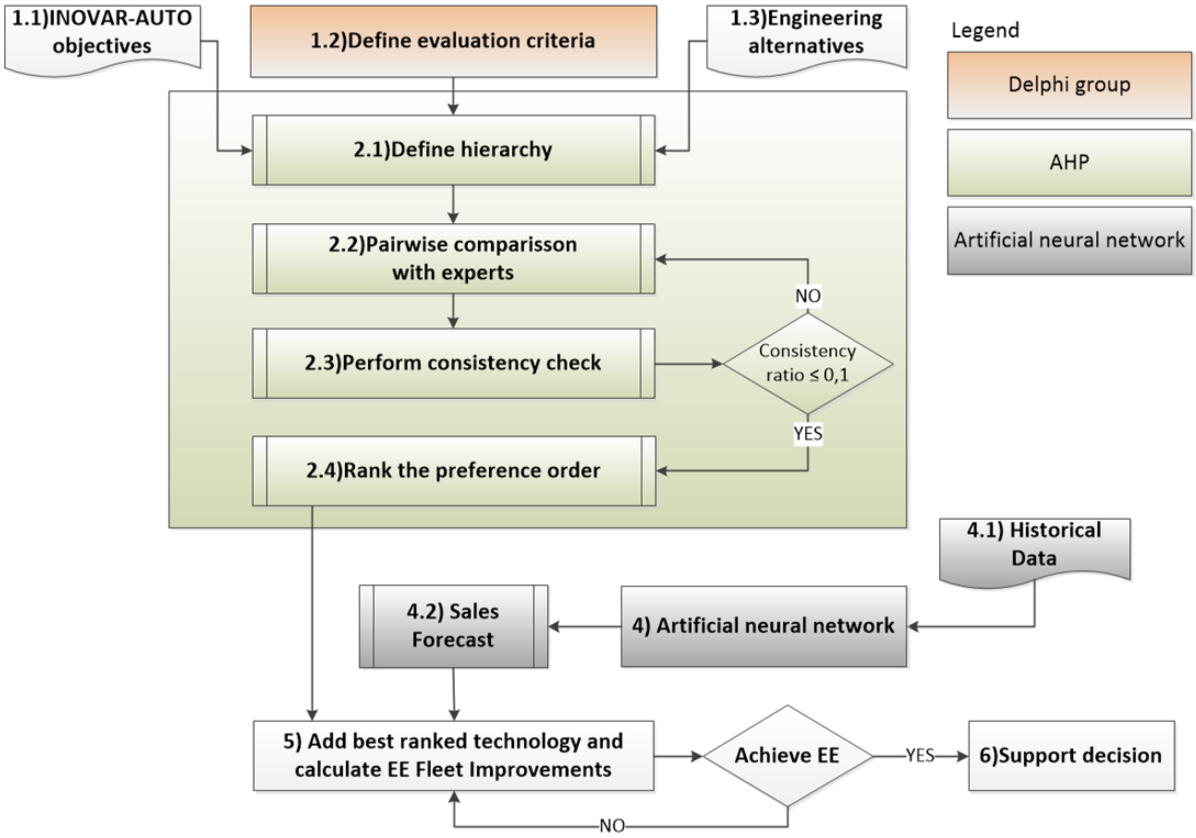

Figure 14 – Methodology Approach. Font: own author.

3.4 Engineering alternatives

Engineering alternatives to improve EE are explained in details on table 11 [146](see appendix). These alternatives changes from one automaker to another, from vehicles, models and even from versions of the same model. Of course, gains obtained are also different. For this reason we use ranges to evaluate the potential benefits. Commercial names of this technologies can also change from one automaker to another due to marketing reasons. The alternatives proposed here are bare engineering! Any resemblance to market names is coincidental. The effects of technologies applied on vehicles to improve EE are based on a literature review of benefits acquired in real applications and supported by engineering calculations [147]. All of engineering alternatives used here exists in at least one mass market vehicle worldwide.

3.4.1 Defined evaluation criteria

In order to obtain reliable criteria for evaluating acceptable approaches to improve EE for each vehicle category according to Inmetro, a Delphi procedure was applied. Delphi method carried out by a panel of experts from automotive industry, academic institutions and consulting firms who were focused on automotive marketing. Combination of Delphi technique and MCDM is usual, Delphi method accumulates and analyzes the results of experts feedback on a particular topic which is also analyzed with AHP [34, 148, 140, 149, 23] or other MCDM technique [150, 151]. Experts help to decomposes complex problem into sub-problems with clear criteria and decision alternatives hierarchically organized as proposed by Saaty[24].

3.4.2 AHP and Delphi Group

A good decision making model needs to tolerate vagueness or ambiguity, because human judgments and preferences are often subjective and uncertain [149]. AHP is a common approach for analyzing various types of decision making situations in many fields of science and technology [54], mainly used to solve decision problems with vague and with multiple criteria characteristics [2]. Furthermore, criteria, alternatives and especially how each criterion impacts the attributes, leading us to a model able to tolerate uncertainty [152]. As we discussed in chapter 2, AHP is indicated to be used in automotive industry dealing with ambiguity. In order to support AHP, a Delphi group with experts was used to define the evaluation criteria and hierarchy.

3.4.3 Calculate EE Fleet Improvements

Artificial neural network (ANN) with supervised learning are very prominent field of research, new applications arise often because flexibility of nonlinear models enable discover pattern adaptively from the data. It has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from data and estimate any complex functional relationship with high accuracy [96, 97]. Although many types of neural network models have been proposed, the most popular one for time series forecasting is the feedforward network model [96]. Details about ANN to time-series forecast can be see in [153, 98].

Historical license registration data used as input for ANN will forecast demand with combined with Inmetro data, and preferences for EE improvement on each vehicle category obtained by AHP will enable to carry out an analysis in order to validate the adherence to initial objectives. The steps for calculate EE are described below and follow Inovar-Auto rules:

- Calculate EE from September 2011 until August 2012.
- Estimate sales from September 2016 until August 2017 using ANN at vehicle category level using last 10 years of historical data.
- Calculate EE for estimated sales.

- Verify if improvements where enough to achieve requirements according to specified objectives.

- If results were not satisfactory the previous steps should be executed again.

This model will be an effective and helpful study for the decision makers and planners optimize the most appropriate engineering alternative available to enhance not only the EE of automotive industry but also sustainability too. In this model, the main goal of the problem is placed at the top which means keep the same model for one specific vehicle or automaker. The model is subject to two important uncertainties: it relies on experts judgments and do not use precise engineering solutions. This approach was chosen in order to avoid the requirement of a non disclosure agreement. As an example, this model can be used for one automaker to choose the engineering alternatives that will not only improve EE, but also keep vehicle attractive from customer point of view at the same time keep automaker cost under control.

3.4.4 Sample Data

Since the goal is to understand effects of EE on automotive market in Brazil, a detailed analysis should be carried out over existent license registration. For this reason, we got registrations from DENATRAN since 2006 until September of 2016 which is a open information [10]. These dataset consist of a record for each vehicle sold in Brazil containing date of license registration, automaker, vehicle details accounting 33,8 millions of units sold. We got from Inmetro, data available in Brazilian program of labeling (*Programa Brasileiro de Etiquetagem*), which contains vehicle information, automaker, fuel consumption and energy efficiency. Inmetro have evaluated 692 different models and versions of vehicles in 2015, which were classified across 14 categories. Instead of analyze individual vehicles, in this work we analyzed only the most representative categories of Brazilian market.

Inmetro categories were regrouped into six different categories to know: mini, small, compact, medium, medium-large and large. AHP analysis was done considering small (or subcompact), compact and medium (or midsize) vehicles which represents 97% of Brazilian market. Table shows vehicle area reference for each category, it is important to notice that regulation admits 0,1m ^{2} variation. Inmetro also classify vehicles based on end use: sports, off-road, light commercial and cargo vehicle (based on passenger car). However, in this work only size parameter was used in the analysis.

Figure 15 show market share for each segment over the time period analyzed. This input can se used by expert to select most adequate technologies to be incorporated consider the vehicle niche.

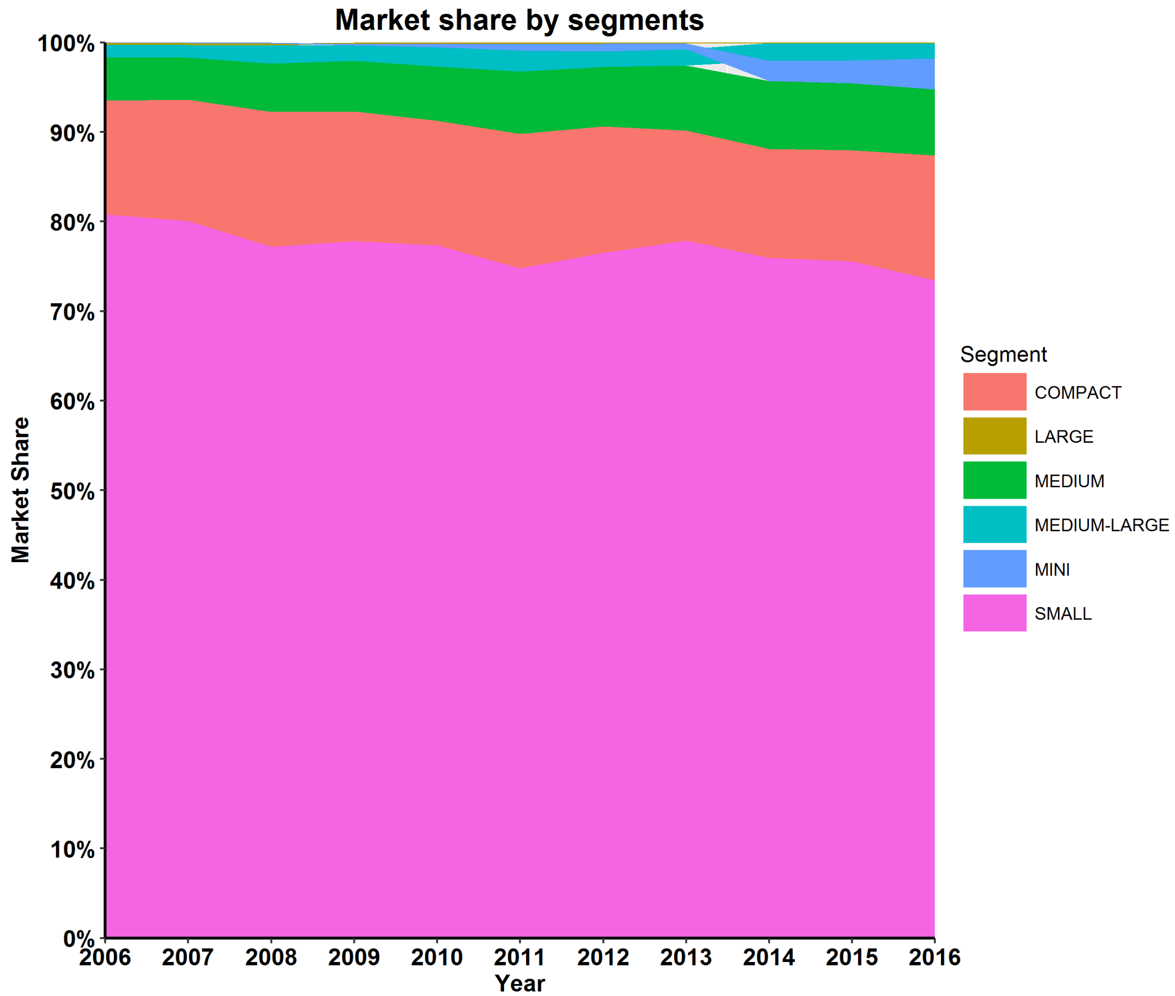

Figure 15 – Market share for each segment over the time period analyzed. Font: own author.

Categories	Nominal vehicle area
Mini	$\leq 6.0m^2$
Subcompact	$6.0m^2 \leq x \leq 6.5m^2$
Compact	$6.5m^2 \leq x \leq 7.0m^2$
Midsize	$7.0m^2 \leq x \leq 8.0m^2$
Large	$\geq 8.0m^2$

Table 3 – Vehicle categories size parameters according to Inmetro. Font: own author.

3.4.5 Tools

Statistical analyses requires to deal with datasets, because of that use it is mandatory softwares support. R is tool composed by a statistical programming languages and an open source software which popularity have being increasing. R language is based on S language [154]. Both languages are based on General Public License (GPL) which is open source. Despite many good softwares for this goal are available in the market, in this paper we use just R, due to facility to extend the language with packages. The R packaging system has been one of the key factors of the overall success of the R project [155].

3.5 Results and Discussion

3.5.1 AHP

Experts judgments were compiled and priorities were calculated by AHP [24]. Results are listed on specific appendix in tables 18, 26 and 34 respectively for small cars, compact and medium cars. Results were consolidated in table 4.

	Small	Compact	Medium
Turbo or supercharged engines	0.17	0.18	0.23
Hybrid-electric Vehicles (HEVs)	0.10	0.12	0.16
Integrated Start Generator	0.14	0.15	0.15
Reduced weight	0.21	0.18	0.12
Automated manual/dual clutch transmissions	0.10	0.10	0.09
Manual 6-speed transmissions	0.20	0.19	0.16
A continuously variable transmission (CVT)	0.08	0.08	0.09

Table 4 – Preferred choice calculated using AHP according to experts judgments. Font: own authors.

For small cars, the best choice is reduce cars weight, which is supported by absence of impact in after sales costs and good EE results. Cheah[166], suggest that new vehicles should focus in become lighter, and most of them will use more fuel-efficient powertrains, such as smaller turbocharged engines and/or hybrid-electric drives. Lowering vehicle weight reduces tire rolling resistance, therefore the energy spent to accelerate a vehicle to a given speed; hence it increases EE [7]. Benefits for weight reduction could be better than references used for this analysis [7], which suggests that with higher benefits this item could be used also on another vehicle segments. Medium-size vehicles will be able to reduce an average of 50 kg in the near term. In the medium term, can be reduced by up to 300 kg through the use of composites and hybrid solutions [167].

According to Cheah e Heywood[7] average fleet weight in USA in 2009 was 1,730KG against 1,224 Brazilian fleet, however as we can see in figure 16 weight is increasing. Ullman[168] analyze 13 year span of data (2001 to 2013) to find that vehicle weight and technological progress are major factors in determining fuel economy among all vehicle segments. Specifically, a reduction in weight is most impactful in sub-compact segment. European Union and Japan, increased fuel efficiency by focusing on smaller and lighter vehicles [164]. Automakers has indicated that weight reduction is a key part of its strategy to improve fuel economy by 40% by the year 2020[167].

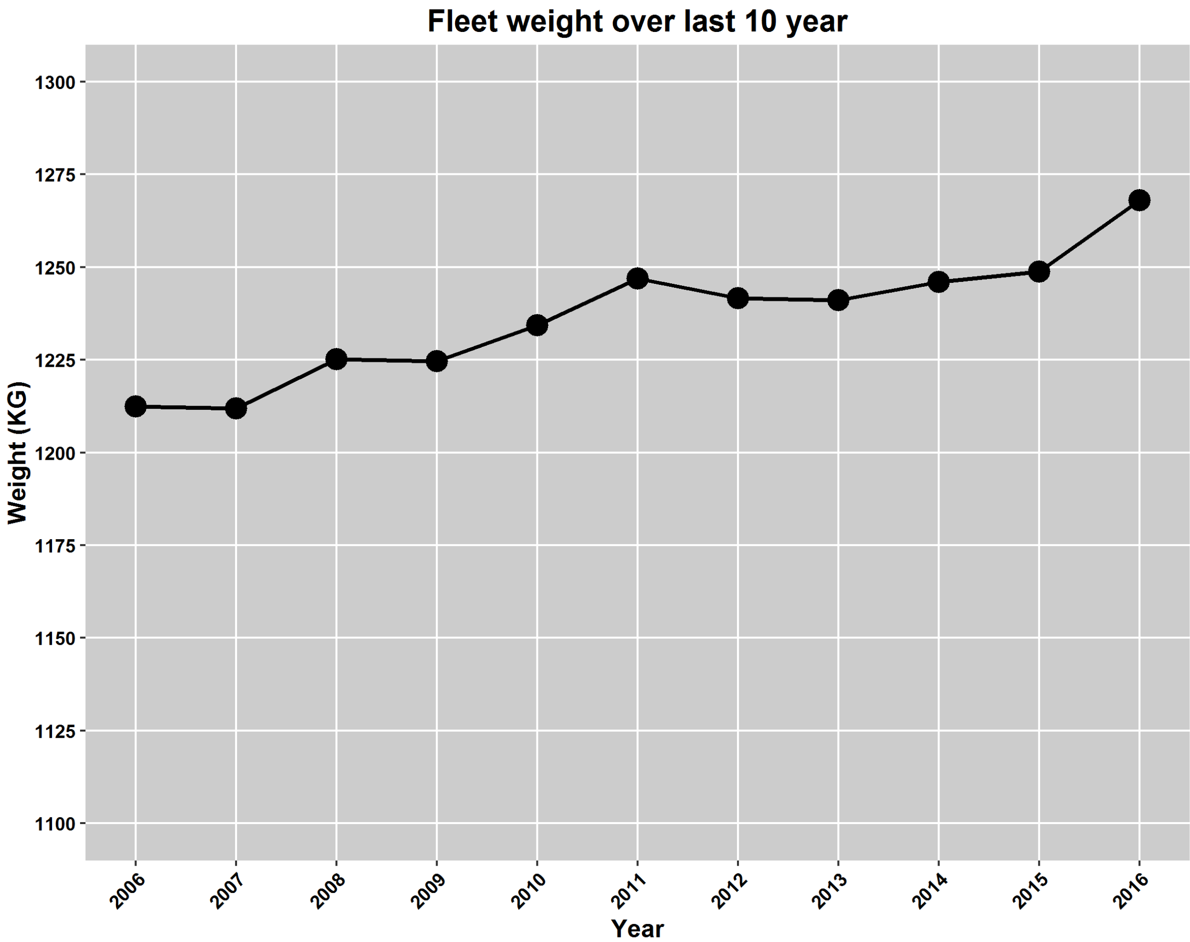

Figure 16 – Fleet weight over last 10 year. Font: own author.

For compact cars, three different alternatives were scored very close including manual 6-speed transmissions, turbo or supercharged engines and reduced weight followed by Integrated Start Generator. For medium size cars, preference is for turbo or supercharged engines and automated transmissions with 6 speed or more. A turbo charger, by increasing the amount of air flow into the engine cylinders, allows an engine to be downsized while delivering the same power [7]. Having more gears allows smaller, more economical engines to power larger vehicles and improves the efficiency of existing engines. In 2010 the number of car with six or more speed exceed five or four in USA [168].

3.5.2 Sales forecast

According to our ANN forecast model in 2017 the market will be around 1.9 Millions of units. This number are similar to numbers obtained in 2008. Small and compact vehicles continue to dominate Brazilian automotive industry. This group have a strong dominance in such way it can solve EE problem alone. If we took just one measure for EE improvement in this segment we solve the entire industry challenge. In figure 17 we

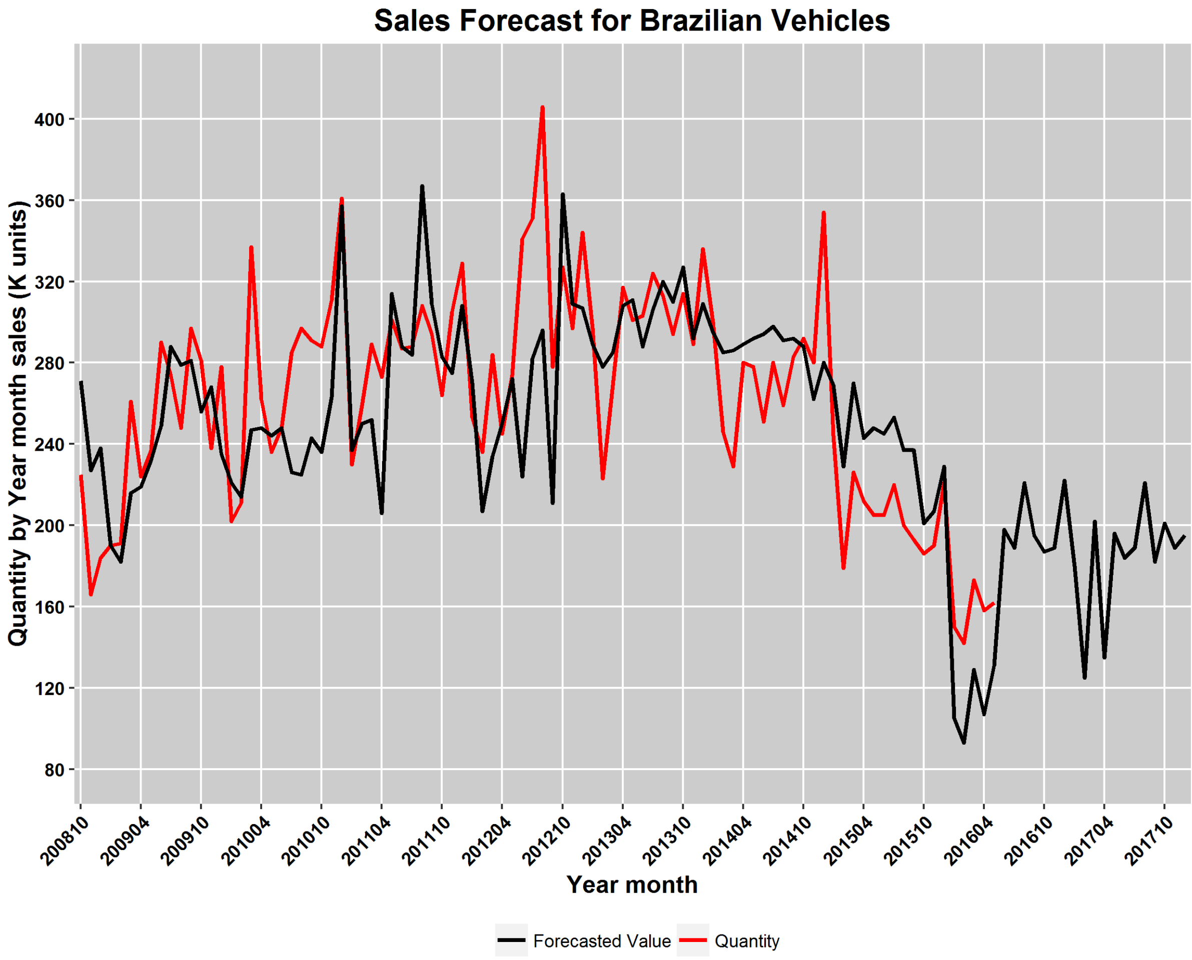

Figure 17 – Sales forecast for Brazilian vehicles. Font: own author.

can see the Brazilian curve for the first year of Inovar-Auto resolution. The mean average percentage error (MAPE) is about 15%. This result is not good enough to surpass pure statistical methods such as ARIMA or SARIMA, but it was selected due to ability to deal with many variables.

3.5.3 Energy Efficiency

In our modeling effort, we adopt a less detailed approach to vehicle segmentation, and focus on the key technologies and design options should be fitted for an specific segment, since our purpose is to provide broader insight on how to solve this challenge.

According to our analysis, we can conclude that EE remains unchanged over the last 10 years.

We also confirm that EE does not improved significantly until now, after Inovar-auto agreement. This does not means that automakers in general can not achieve the government thresholds. In the graph 18, it is clear how far categories are from target.

Graph 19 has two parts. First graph show how overall EE remains practically unchanged over last 10 years. Second graph show weight by each segment. Zielinski, Andreucci e Aktas[164] points that in spite of efforts and regulations, fuel economy in the United States has remained unchanged since 2001. This can be also confirmed by table 5.

	Year	Licensed Vehicles	Weight	MJ/KM
1	2006	1321502	1212.4	2.09
2	2007	1763973	1211.9	2.09
3	2008	1998890	1225.1	2.12
4	2009	2312078	1224.6	2.11
5	2010	2539723	1234.3	2.12
6	2011	2604189	1246.9	2.13
7	2012	2988619	1241.6	2.13
8	2013	3146282	1241.0	2.13
9	2014	2955786	1246.0	2.13
10	2015	2241189	1248.7	2.13
11	2016	1330403	1268.1	2.14

Table 5 – EE over last years. Font: own author.

Cheah e Heywood[7] suggest that in spite of automotive engineers have worked hard to steadily improve EE, have not resulted in reducing the vehicle's fuel consumption. We also find out the same results looking Brazilian last 10 years data. This should not be mistaken for lack of gains in technical efficiency. The gains have been taking place, but have instead been used to offset the negative fuel consumption impacts of improving other vehicle attributes such as vehicle horsepower, comfort and size. Which can be seen in figure 21 and 16. It is noticed that vehicle horsepower increased 18.9% since 2006 and 10.0% since 2012 when Inovar-auto was signed. Borba[169] also confirms the increase in 1000cm3 light vehicles analyzing data from 1994 to 2004.

Therefore this is present in all of segments, which can be seen in graph 20. However, segments with low volumes are more affected by specific vehicle niches such as mini and large. For example, large vehicles segments were influenced in 2012 by Dodge Ram pick-up. The quantity of units sold is not enough to impact the whole market, but it is noticed in the segment.

We do not find similar research for Brazilian market, but increase potency it is beneficial for automakers. Since consumers are willing to pay \$160–\$5500 more from an additional 0.1 hp/lb in acceleration performance [162]. Most consumer do not evaluate the long term savings [170].

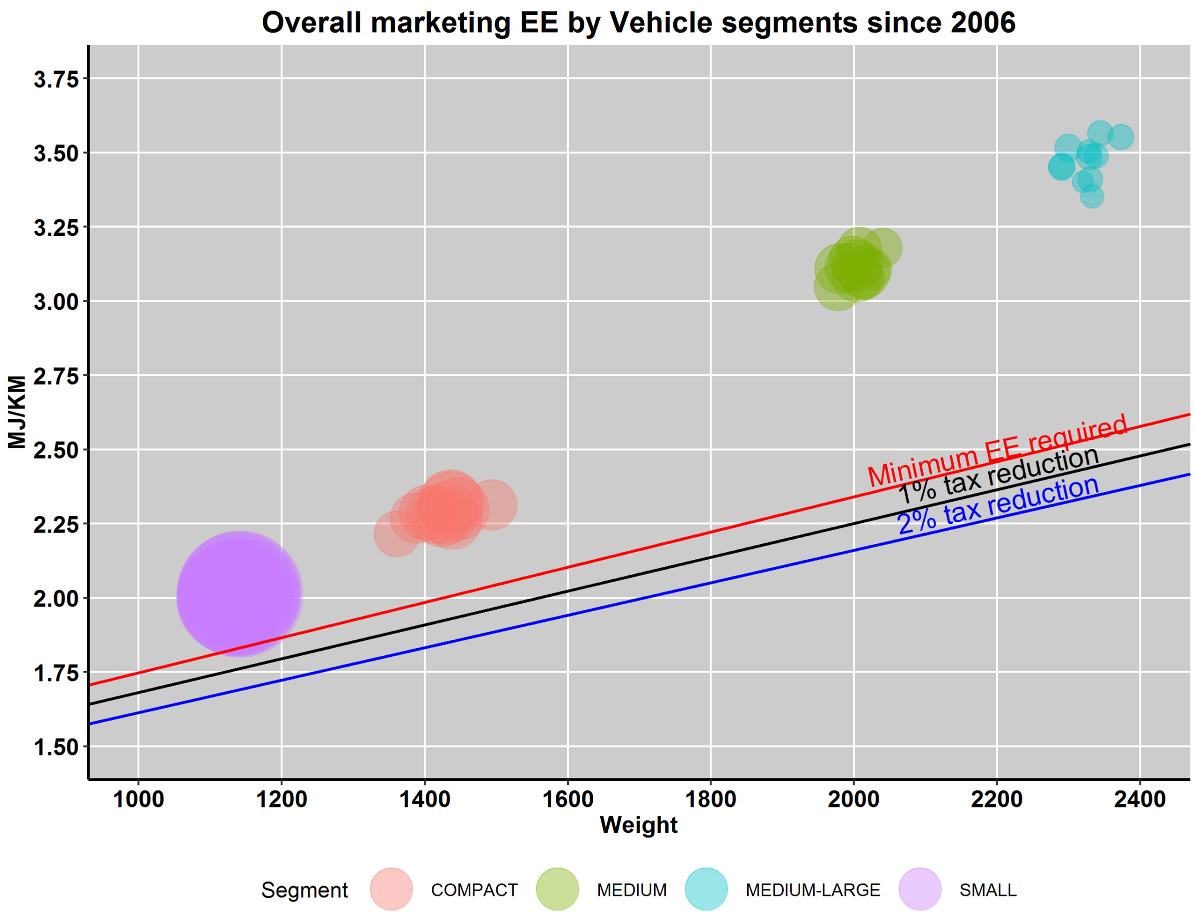

Figure 18 – EE by vehicle segment. Font: own author.

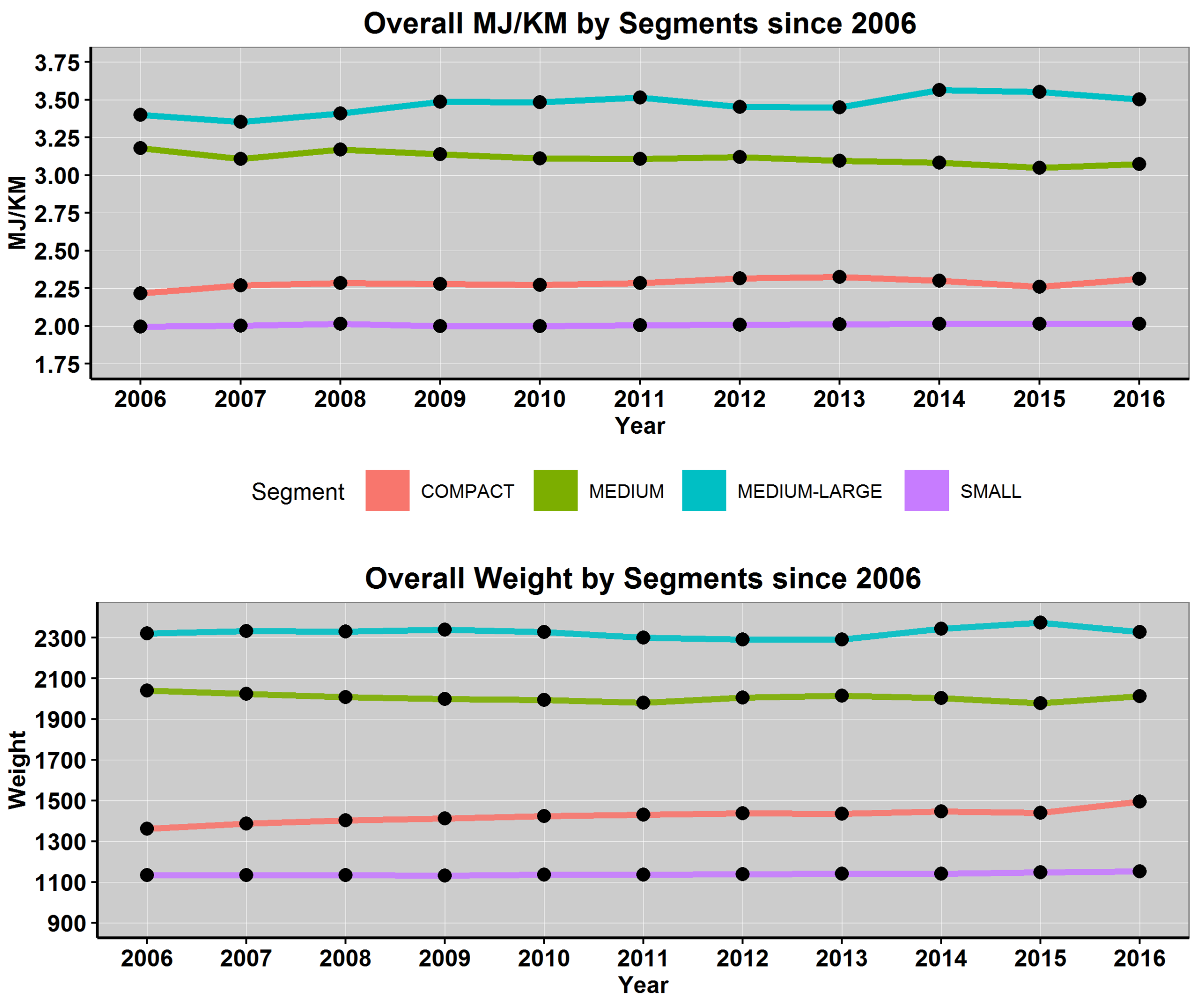

Figure 19 – MJ and weight per year. Font: own author.

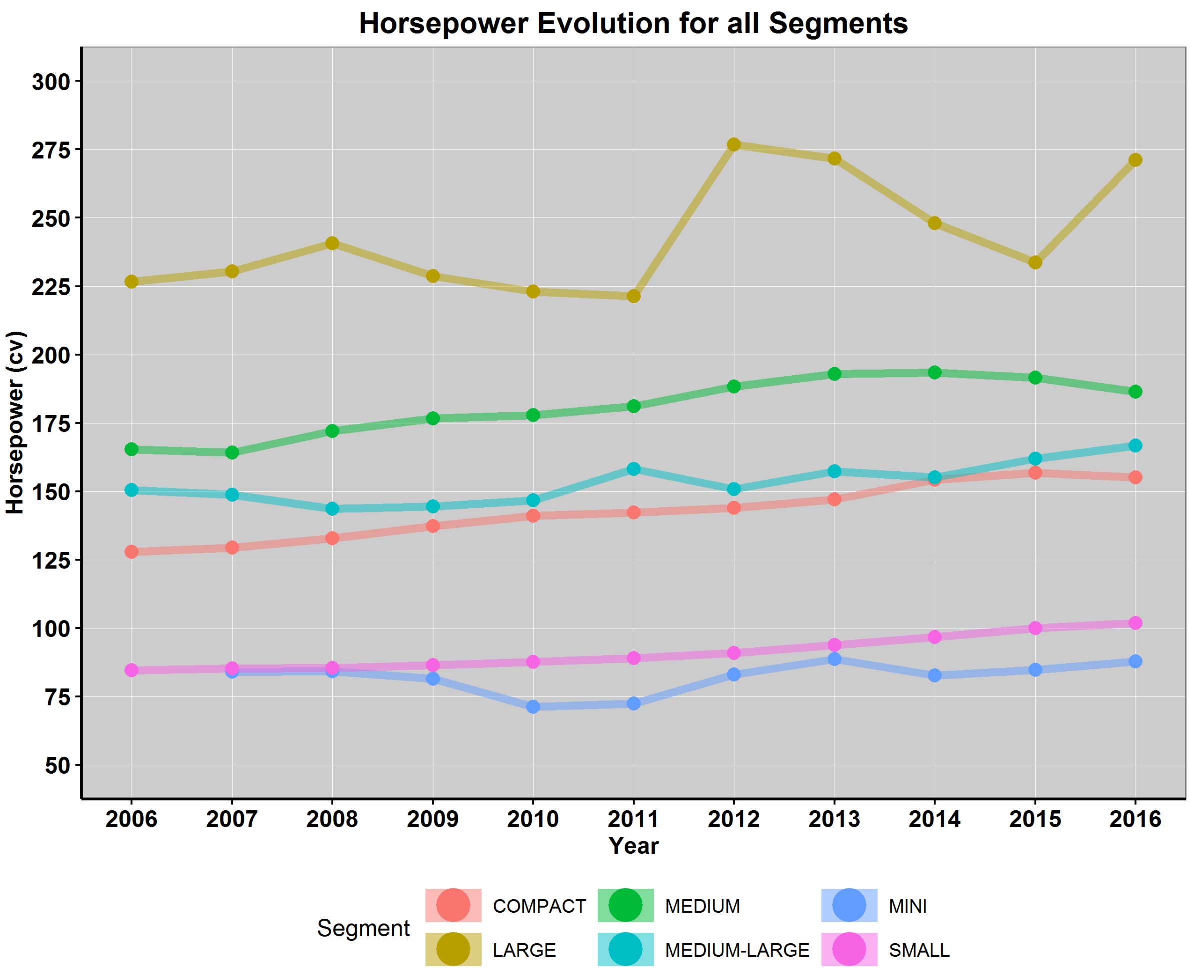

Figure 20 – Horsepower evolution by all market segments. Font: own author.

Fischer[171] pointed out that since today we do not know the true cost of enhancing EE, we do not really know how manufacturers and consumers will react. Overall cost includes not only the direct costs of producing EE vehicles, but also how consumers will rate fuel saving.

Busse, Knittel e Zettelmeyer[172] print out that effect of EE savings is greater on used cars that the new ones. A difference of $1,945 in the relative price of the highest fuel economy and lowest fuel economy quartile of used cars against only $354 for new cars. Which suggest that consumers of new cars are less sensitive to EE. Busse, Knittel e Zettelmeyer[172] also suggest that EE and fuel price can affect market share of new vehicles.

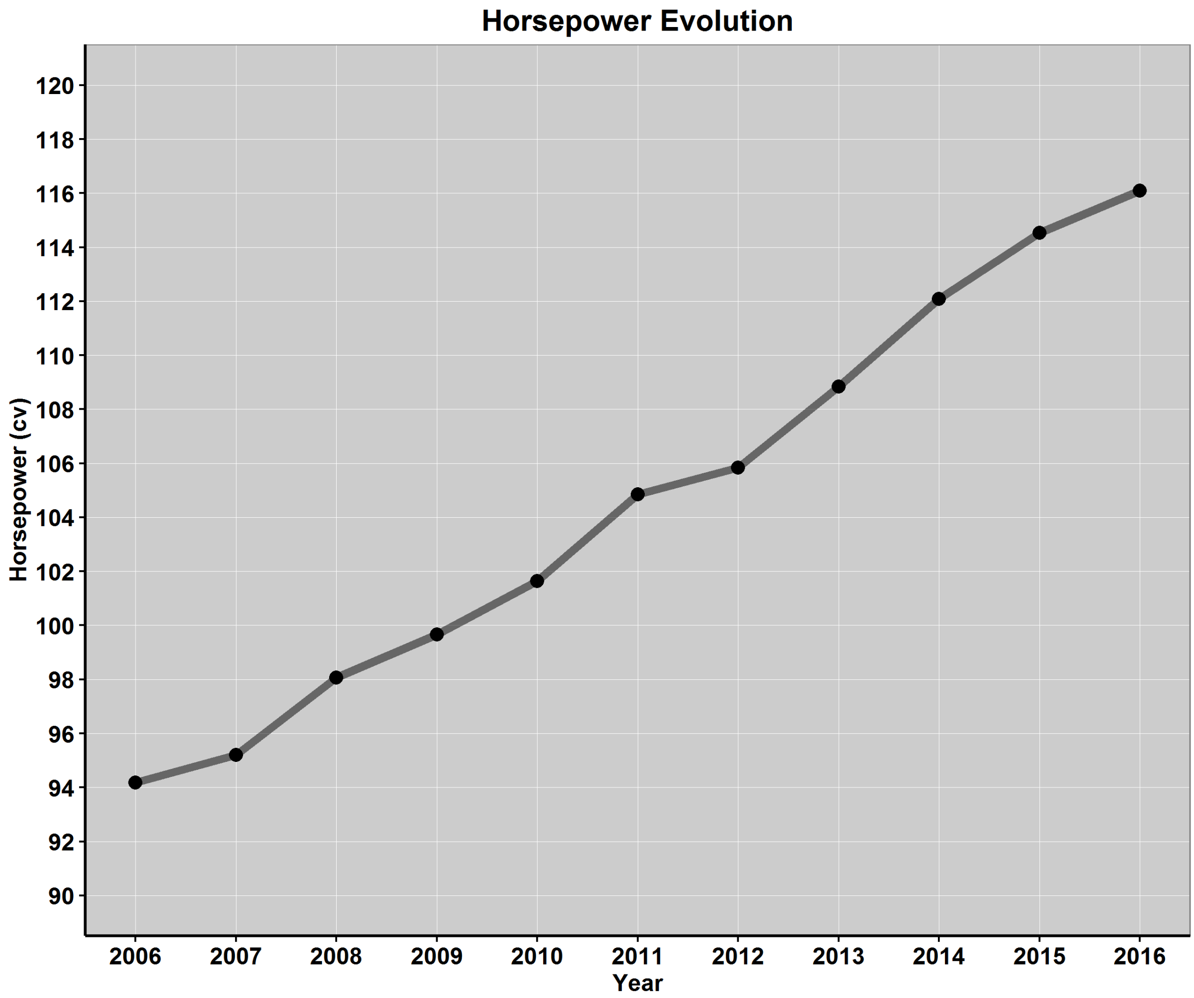

Figure 21 – Horsepower evolution over last 10 years. Font: own author.

3.6 Related Work

In spite of 23% of the Brazilian Industrial Gross Domestic Product (GDP) in 2013 came from the automotive industry [156], there are fewer studies about Inovar-Auto. None of them related to a method to choose which features that could be added in Brazilian fleet to improve EE. Science direct [128], which is an online database, had just 3 papers referencing Inovar-Auto until 2016. Since the whole regulation is new, there are some hindrance to measure EE precisely for past years for those vehicles that were not in labeling program [157].

Mello, Marx e Motta[158] explore the benefits of Inovar-Auto but highlights that more ambitious and longer term projects eventually can not be completed before the program's first phase. The main goal is to provide a in-depth analyze about R&D projects developed by the Brazilian Automotive Industry. It also noticed that Brazilian EE target is not a technical challenge for the automotive industry since the technologies already exists. This result is aligned with ours.

Lima e others[159] notice that automakers should invest at least 0.5% of gross revenue in R&D between 2015 and 2017. However, highlights that the European Union and Japan claim for dispute settlement in World Trade Organization (WTO) with respect to certain measures concerning taxation and charges in the automotive sector due to Inovar-Auto. Brazil report in WTO that its Inovar-Auto programme, set to expire in December 2017, aims only to encourage technical development, raise environmental standards and improve the quality of cars in Brazil. It said the incentives depend on the energy efficiency of vehicles [160]. One of main concerns regarding this point is how this dispute can affect the continuity of Inovar-Auto program. Lima e others[159] also points that Inovar-Auto is a emergency and short term policy instead of long term policy which incentivize structural transformations. The lack of regulations for period after 2017 it is a strong argument in favour of short term view of programme.

Menezes, Maia e Carvalho[161] study how policy incentives stimulate low-carbon development strategies in São Paulo. However, their focus is on pollutant reduction.

According to Sallee e Slemrod[12] automakers respond to these local incentives by fine tuning fuel economy to reach minimum expected levels maximizing gains and reducing investment. Analyzing USA vehicle efficiency label of fuel economy ratings of vehicles between 1991 and 2009 (which are measured as integers). Shows that models at whose rating ends in .5 are 50% more common then rating ends in .4. Which means a probability of just 0.0007 in a binomial distribution.

Whitefoot e Skerlos[162] argued that corporations have shifted away from the kind of price competition strategies they practiced in the past and moved in the direction of designing vehicles with superior EE in order to comply with the new regulations. It is one of the points that Brazilian law wants to reinforce. However, automakers tend to disrespect regulations when the penalties value set to low values [163].

Zielinski, Andreucci e Aktas[164] points that CAFE have a goal of encouraging increased fuel economy and reduced dependence on foreign energy supply. However, in spite of this efforts, USA cars and light trucks are ranked as being the heaviest of any nation. On top of that, fuel economy in the United States has remained unchanged from 2001 to 2015 and continue to have low EE vehicles. Brazilian fleet is lighter than American, however we are far from Europe or Japan in EE. The benefits of reduce foreign energy dependence in Brazil cannot be evaluated in short term.

Andress et al.[165] reviews the current status of light duty vehicles in the USA and discusses policies to improve fuel efficiency, advanced electric drives. The paper describes the cost, technical, infrastructure, and market barriers for alternative technologies. It also notice that while diesel is the primary fuel in heavy-duty vehicles, the penetration of diesel engines in the US market is very small. This contrasts sharply with the situation in Europe, where over 50% sales are diesel. Brazilian laws restricts diesel for vehicles with four-wheel drive or at least one tonne of cargo capacity. Which restrict this fuel for specific niches.

3.7 Conclusion

The future vehicle scenarios presented confirm that in addition to the magnitude, the timing of more stringent EE standards is also important in determining the feasibility of meeting the requirements.

Answering the question, how far are the general market of minimum target requirement? We confirm that EE do not improve in the last 10 years. We also confirm that technological gains are not primary applied to EE until now. It is clear that gains have been used mainly to increase vehicle potency and size. Expressive gains in horsepower contrasts with average speed reported by urban mobility studies.

According to our analysis we conclude that EE remains steadily since Inovar-Auto was launched. This can be explained by scenario which automakers do not always start with a clean slate and work on brand new designs for all their product lines. It is also important to remember the long development cycles. It is interesting to notice that, if an automaker started improvements in 2012 they will begin to release this innovation by 2016/2017 due to long development cycles. This is also coherent with vehicle development cycle which is around 4 to 5 years [11, 12].

Although EE remains steadily, the fuel economy improvement achievable is significant. The proposed method find out the technical evolutions that fits to each vehicles segments and can help automakers to achieve the government thresholds. Delphi group helps to identify and evaluate most significant criteria. Pairwise comparison done by experts using AHP assure consistency. Instead of focus on specific engineering items, we run this model using a set of existent alternatives. However, this approach can be reviewed to include other technical solutions. Combining this scenario with sales forecast of next year, we calculate future EE after technology adoption.

Small and compact car are the key segment to tackle with EE problem. Our model shows that just one effective measure applied over this segment allows Inovar-Auto requirements to be achieved. For small cars we suggest weight reduction and improve transmission as main solution to enhance EE. In the compact cars segment turbo engines also appears as alternative. Since the segments continue to dominate Brazilian automotive industry, it can solve EE problem alone.

4 Final Conclusion

In this work, we proposed a model to aid automotive industry to find out technical alternatives that fits better to Inovar-Auto requirements. In the Systematic literature review we research a method that assists a decision-making process capable of deal with unprecedented changes in automotive industry. AHP was selected due to capability of deal with tangible and intangible criteria, uncertainty and incomparable units. AHP popularity and applicability in large range of business was another factor that driven adoption. AHP was combined with Delphi group to identify technologies that can improve vehicle EE ensuring the judgments quality.

In the chapter 3, we study Brazilian numbers related to EE and understand where technical gains have been used in the last 10 years. Main vehicle segments were identified to support a coherent decision process. In order to assure that results are good enough, ANN model was used to forecast next year sales and make sure that expected results will be achieved. If we look last 10 years evolution seems that government target are very audacious, since EE is not improving. However, it is also clear that technological gains are not primary applied to EE until now. We also understand the reasons behind this poor improvements. Long development cycles help to understand because even after automakers sign the Inovar-Auto agreement, none or little progress was achieved.

Therefore, when we look to EE opportunities, we believe industry reach expected levels. We conclude that based on premise that focus will be moved to EE. Since as we see in this work focus is not EE until now. We believe that delay to get results of EE improvement are consequence of long development cycles. Three additional factors drive this expectation. First of all the fines applied will be big enough to put operations at risk. Which undoubtedly will guide automakers efforts to increase EE. Secondly, due to a very competitive marketing when price is always a very important factor. Which can give a significant competitive advantage for those who surpass minimum levels as described in the law. Specially in entry segments where price is one of the most important criteria from consumer point of view. Thirdly, by taking into consideration Brazilian engagement in such programs such as sugar cane alcohol the possibilities are very good. The virtuous cycle can lead tax reduction, encourage fleet renewal and boost automotive economy again. The economic impacts goes to oil consume reduction until competitive advantage in exportation which is exactly what the government wants. Of course, trade offs are always present.

4.1 Future research directions

As future research we are planning to create a multi-objective model to determine the better production mix for an automaker combining all the main constraints related to the decision. The main restrictions are commercial, finance, industrial and EE. Since interests are contradictory we have a clear opportunity to use a mathematical methods to aid players to reach a consensus. We are also planning study how Inovar-Auto can impact oil consume in Brazil.

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Appendix

APPENDIX A – List of Analyzed Papers

Table 6 – Classification of papers application

Shortname	Fullname
1- Supply	1- Supply Chain Management and Logistics
2- Design	2- Design, Engineering and Manufacturing Systems
3- Business	3- Business and Marketing Management
4- Health	4- Health, Safety and Environment Management
5- Human	5- Human Resources Management
6- Energy	6- Energy Management
7- Chemical	7- Chemical Engineering
8- Water	8- Water Resources Management
9- Other	9- Other topics

Table 7 – Final list of analyzed papers on the systematic literature review.

Database	Articles
Emerald	[42]
IEEE Xplore	[173], [113], [174], [175], [176], [177], [39], [43]
Science Direct	[178], [179], [180], [88], [181], [138], [182], [183], [184], [118], [185], [45], [139], [141], [18], [142], [23], [71], [75], [186], [187], [188], [44], [77], [189], [190], [35], [56], [79], [191], [136], [140]
Springer	[134], [143], [41], [27]

Table 8 – Papers, year of publishing and methods applied.

Title	Year	Methods
Sustainable transport fleet appraisal using a hybrid multi-objective decision making approach	2015	VIKOR, RST, three-parameter interval grey numbers.
Strategies for utilizing alternative fuels by Iranian passenger cars	2006	Partial order theory, Hasse diagram technique.
An analytic network process-based multicriteria decision making model for a reverse supply chain	2013	ANP
An exploration of green supply chain practices and performances in an automotive industry	2013	TOPSIS

Continued on next page

Table 8 – continued from previous page

Title	Year	Methods
Multi-criteria decision making for supplier selection using fuzzy AHP approachnull	2015	AHP
Network selection delay comparison of network selection techniques for safety applications on VANET	2011	AHP
On the Causes of Road Accidents: Fuzzy TOPSIS	2010	TOPSIS
ANP based vertical handover algorithm for vehicular communication	2012	ANP
Semantic Multi-Criteria Decision Making SeMCDM	2009	AHP
Integration of an EMO-based preference elicitation scheme into a multi-objective ACO algorithm for time and Space Assembly Line Balancing	2009	MACS
Fuzzy Multiple Attribute Decision Routing in VANETs	2014	FMADR
A Multiple Attribute-based Decision Making model for autonomous vehicle in urban environment	2014	AHP, TOPSIS
Customer order dependent supplier selection	2011	SAW
A systems approach to improving fleet policy compliance within the US Federal Government	2010	AHP
Two novel FMCDM methods for alternative-fuel buses selection	2011	TOPSIS, FNIS, PSI,
Robust evidential reasoning approach with unknown attribute weights	2014	ER
An integrated group decision making model and its evaluation by DEA for automobile industry	2010	AHP, TOPSIS
Application of fuzzy VIKOR and environmental impact analysis for material selection of an automotive component	2012	VIKOR
Mathematical analysis of fuel cell strategic technologies development solutions in the automotive industry by the TOPSIS multi-criteria decision making method	2011	TOPSIS
Influence of fuel composition on polycyclic aromatic hydrocarbon emissions from a fleet of in-service passenger cars	2007	PROMETHEE , GAIA
Rule-based life cycle impact assessment using modified rough set induction methodology	2005	RST

Continued on next page

Table 8 – continued from previous page

Title	Year	Methods
A combined AHP-PROMETHEE approach for selecting the most appropriate policy scenario to stimulate a clean vehicle fleet	2011	AHP, PROMETHEE
A comprehensive environment friendly approach for supplier selection	2014	AHP–TOPSIS
Characterization of elemental and polycyclic aromatic hydrocarbon compositions of urban air in Brisbane	2005	PROMETHEE, GAIA
Multi-criteria ranking and receptor modelling of airborne fine particles at three sites in the Pearl River Delta region of China	2011	PROMETHEE, GAIA
Combined Application of Multi-Criteria Optimization and Life-Cycle Sustainability Assessment for Optimal Distribution of Alternative Passenger Cars in U.S.	2015	LCA
Selection of CO2 mitigation strategies for road transportation in the United States using a multi-criteria approach	2014	AHP
A multi-dimensional framework for evaluating the transit service performance	2013	TOPSIS
A multiple stakeholders' approach to strategic selection decisions	2008	AHP, ZOGP
Multi-criteria evaluation of alternative-fuel vehicles via a hierarchical hesitant fuzzy linguistic model	2015	hesitant fuzzy linguistic term sets (HFLTS)
Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective	2015	TOPSIS
POLCAGE 1.0—a possibilistic life-cycle assessment model for evaluating alternative transportation fuels	2004	LCA
A fuzzy logic-based approach to determine product component end-of-life option from the views of sustainability and designer's perception	2015	
A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers	2012	DEMATEL, ANP, TOPSIS
Characterization of VOCs from LPG and unleaded petroleum fuelled passenger cars	2014	PROMETHEE, GAIA

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Table 8 – continued from previous page

Title	Year	Methods
Integrating fuzzy DEMATEL and fuzzy hierarchical TOPSIS methods for truck selection	2013	DEMATEL, TOPSIS
Effect of fuel composition and engine operating conditions on polycyclic aromatic hydrocarbon emissions from a fleet of heavy-duty diesel buses	2005	PROMETHEE, GAIA
Public engagement in strategic transportation planning: An analytic hierarchy process based approach	2014	AHP
Optimal driving during electric vehicle acceleration using evolutionary algorithms	2015	NSGA-II, SPEA 2
Selection of City Distribution Locations in Urbanized Areas	2012	AHP, TOPSIS
The effects of fuel characteristics and engine operating conditions on the elemental composition of emissions from heavy duty diesel buses	2007	PROMETHEE, GAIA, PCA, PLS
Two-step algorithm for the optimization of vehicle fleet in electricity distribution company	2015	AHP
A comparative study of the elemental composition of the exhaust emissions of cars powered by liquefied petroleum gas and unleaded petrol	2006	PROMETHEE, GAIA
Predicting the potential of agro waste fibers for sustainable automotive industry using a decision making model	2015	AHP
Crashworthiness analysis and design of multi-cell hexagonal columns under multiple loading cases	2015	COPRAS

APPENDIX B – Methodology Support Tables

Table 9 – AHP - Scale of importance

Reference	Scale	Explanation
1	Equally preferred	pair activities contribute equally to the objective
3	Moderately	Experience and judgment slightly favor one activity over the other
5	Strongly	Experience and judgment slightly favor one activity over the other
7	Very strongly	An activity is strongly favored over the other and its dominance demonstrated in practice
9	Extremely	The evidence favoring one activity over the other is of the highest degree possibility affirmation
2,4,6,8	Intermediate values	Used to represent compromise between the preferences listed above

Table 10 – AHP - Random Index (RI) table.

n	3	4	5	6	7	8	9	10	11
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Table 11 – Alternatives to be evaluated

Alternative	**Gain**	**Explanation**
Turbo or supercharged engines	Potential fuel economy benefit – [2-5%]	Increases the available airflow and specific power level, allowing a reduced engine size while maintaining performance. A supercharger is an air compressor used for forced induction of an internal combustion engine. The greater mass flowrate provides more oxygen to support combustion than would be available in a naturally-aspirated engine, which allows more fuel to be provided and more work to be done per cycle, increasing the power output of the engine.

Continued on next page

Table 11 – continued from previous page

Alternative	Gain	Explanation
Hybrid-electric Vehicles (HEVs)	Potential fuel economy benefit - [30-50%] Mild hybrid potential fuel economy benefit – [5-7%]	Hybrid-electric vehicles (HEVs) use two power sources, a petrol or a diesel engine, and a battery pack that also powers the vehicle. These vehicles generally shut the engine off when it is appropriate to run on the batteries, thereby improving fuel consumption.
Integrated Start Generator	Potential fuel economy - [5%]	An integrated starter generator provides idle-stop capability and uses a high voltage battery with increased energy capacity over typical automotive batteries. This higher voltage allows many of the engine-driven belts to be removed reducing the load on the engine, thereby improving efficiency. Using a higher voltage battery also allows the engine to be shut off when the vehicle is stopped in traffic. The engine will then restart when the throttle is depressed. This saves fuel because the engine is not running when a car would normally be in idle mode. Fuel economy is improved by up to 5%and city emissions are reduced by up to 30% [192].
Reduced weight	Potential gain of 10%	Reduced weight would enable the same performance to be achieved with a smaller engine. The King Review found that such "lightweighting" could offer efficiency gains of 10%, at a cost of £250 - 500 per vehicle.
Automated manual/dual clutch transmissions	Potential fuel economy benefit – [4-8%]	An automated manual transmission is a manual transmission with no clutch. Shifts are controlled electrically and hydraulically. Dual clutch transmissions contain two separate clutches and are like a manual transmission, but the vehicle controls shifting and launch functions. A separate clutch is used for the even number gears and the other clutch is used for the odd numbered gears. This allows for faster and smoother shifting.

Continued on next page

Table 11 – continued from previous page

Alternative	Gain	Explanation
A continuously variable transmission (CVT)	Potential fuel economy benefit – [4-8%]	Uses V-shaped pulleys connected by a metal belt rather than gears to provide the ratios for operation. Unlike manual and automatic transmissions with fixed transmission ratios, CVTs can provide fully variable transmission ratios with an infinite number of gears, so the engine can operate at higher efficiency.
Manual 6-speed transmissions	Potential fuel economy benefit – [3-5%]	Offer an additional gear, usually a higher overdrive ratio, than a 5-speed manual transmission. This improves efficiency by reducing engine revolutions per minute when on the highway.
Six, seven and eight speed automatic transmissions	Potential fuel economy benefit – [3-5%]	Six, seven, eight and nine speed automatic transmissions are becoming available. These transmissions have gear ratio spacing optimized for a broader range of operating conditions and better efficiency.

APPENDIX C – AHP Results

Criteria Evaluation	A1	A2	A3	A4	A5	A6
Performance[A1]	1.00	0.50	0.20	0.33	0.20	0.14
Confort[A2]	2.00	1.00	0.14	3.00	0.50	0.20
AfterSaleCosts[A3]	5.00	7.00	1.00	9.00	3.00	0.33
Feature Perception[A4]	3.00	0.33	0.11	1.00	0.20	0.11
Energy Efficiency[A5]	5.00	2.00	0.33	5.00	1.00	0.33
Engineering Maturity[A6]	7.00	5.00	3.00	9.00	3.00	1.00

Table 12 – Criteria evaluation for subcompact Cars. Font: own author.

Performance	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	5.00	3.00	5.00	5.00	5.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	7.00	3.00	3.00	3.00	3.00
Integrated Start Generator[A3]	0.20	0.14	1.00	0.20	0.33	0.14	0.33
Reduced weight[A4]	0.33	0.33	5.00	1.00	3.00	2.00	3.00
Automated manual/dual clutch transmissions[A5]	0.20	0.33	3.00	0.33	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	0.20	0.33	7.00	0.50	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.20	0.33	3.00	0.33	0.33	0.33	1.00

Table 13 – Performance evaluation for subcompact Cars. Font: own author.

Confort	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.20	0.20	1.00	0.33	3.00	0.20
Hybrid-electric Vehicles (HEVs)[A2]	5.00	1.00	3.00	7.00	5.00	7.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	5.00	3.00
Reduced weight[A4]	1.00	0.14	0.20	1.00	0.20	0.33	0.20
Automated manual/dual clutch transmissions[A5]	3.00	0.20	0.33	5.00	1.00	3.00	0.33
Manual 6-speed transmissions[A6]	0.33	0.14	0.20	3.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	5.00	0.20	0.33	5.00	3.00	3.00	1.00

Table 14 – Confort evaluation for subcompact Cars. Font: own author.

After sales cost	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	0.33	0.11	0.20	0.14	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	0.20	0.11	0.20	0.14	0.33
Integrated Start Generator[A3]	3.00	5.00	1.00	0.14	0.50	0.20	3.00
Reduced weight[A4]	9.00	9.00	7.00	1.00	7.00	3.00	7.00
Automated manual/dual clutch transmissions[A5]	5.00	5.00	2.00	0.14	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	7.00	7.00	5.00	0.33	3.00	1.00	7.00
A continuously variable transmission (CVT)[A7]	0.33	3.00	0.33	0.14	0.33	0.14	1.00

Table 15 – After sales cost evaluation for subcompact Cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.14	0.20	0.33	0.33	3.00	0.33
Hybrid-electric Vehicles (HEVs)[A2]	7.00	1.00	3.00	7.00	7.00	5.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	3.00	3.00
Reduced weight[A4]	3.00	0.14	0.20	1.00	0.33	1.00	0.33
Automated manual/dual clutch transmissions[A5]	3.00	0.14	0.33	3.00	1.00	3.00	0.33
Manual 6-speed transmissions[A6]	0.33	0.20	0.33	1.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	3.00	0.20	0.33	3.00	3.00	3.00	1.00

Table 16 – Consumer feature evaluation for subcompact Cars. Font: own author.

	A1
Turbo or supercharged engines[A1]	5.00
Hybrid-electric Vehicles (HEVs)[A1]	7.00
Integrated Start Generator[A1]	5.00
Reduced weight[A1]	3.00
Automated manual/dual clutch transmissions[A1]	4.00
Manual 6-speed transmissions[A1]	4.00
A continuously variable transmission (CVT)[A1]	7.00

Table 17 – Expected energy efficiency improvement for subcompact Cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	9.00	3.00	3.00	3.00	1.00	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.11	1.00	0.20	0.20	0.14	0.11	0.20
Integrated Start Generator[A3]	0.33	5.00	1.00	3.00	3.00	0.33	3.00
Reduced weight[A4]	0.33	5.00	0.33	1.00	3.00	1.00	3.00
Automated manual/dual clutch transmissions[A5]	0.33	7.00	0.33	0.33	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	1.00	9.00	3.00	1.00	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.33	5.00	0.33	0.33	0.33	0.33	1.00

	Performance	Confort	Costs	Feature	EE	Maturity
Turbo or supercharged engines	0.37	0.05	0.05	0.05	0.14	0.27
Hybrid-electric Vehicles (HEVs)	0.22	0.40	0.02	0.42	0.20	0.02
Reduced weight	0.14	0.03	0.45	0.05	0.09	0.14
Manual 6-speed transmissions	0.12	0.04	0.25	0.04	0.11	0.24
Automated manual/dual clutch transmissions	0.07	0.10	0.11	0.09	0.11	0.09
A continuously variable transmission (CVT)	0.05	0.15	0.04	0.13	0.20	0.06
Integrated Start Generator	0.03	0.22	0.08	0.21	0.14	0.17

Table 18 – AHP results for subcompact cars. Font own author.

	A1	A2	A3	A4	A5	A6
Performance[A1]	1.00	0.50	0.33	2.00	1.00	0.14
Confort[A2]	2.00	1.00	0.33	3.00	3.00	0.20
AfterSaleCosts[A3]	3.00	3.00	1.00	3.00	2.00	0.33
Feature Perception[A4]	0.50	0.33	0.33	1.00	0.33	0.11
Energy Efficiency[A5]	1.00	0.33	0.50	3.00	1.00	0.33
Engineering Maturity[A6]	7.00	5.00	3.00	9.00	3.00	1.00

Table 19 – Criteria evaluation for medium cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	5.00	3.00	5.00	5.00	5.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	7.00	3.00	3.00	3.00	3.00
Integrated Start Generator[A3]	0.20	0.14	1.00	0.20	0.33	0.14	0.33
Reduced weight[A4]	0.33	0.33	5.00	1.00	3.00	2.00	3.00
Automated manual/dual clutch transmissions[A5]	0.20	0.33	3.00	0.33	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	0.20	0.33	7.00	0.50	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.20	0.33	3.00	0.33	0.33	0.33	1.00

Table 20 – Performance evaluation for medium cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.20	0.20	1.00	0.33	3.00	0.20
Hybrid-electric Vehicles (HEVs)[A2]	5.00	1.00	3.00	7.00	5.00	7.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	5.00	3.00
Reduced weight[A4]	1.00	0.14	0.20	1.00	0.20	0.33	0.20
Automated manual/dual clutch transmissions[A5]	3.00	0.20	0.33	5.00	1.00	3.00	0.33
Manual 6-speed transmissions[A6]	0.33	0.14	0.20	3.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	5.00	0.20	0.33	5.00	3.00	3.00	1.00

Table 21 – Confort evaluation for medium cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	0.33	0.11	0.20	0.14	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	0.20	0.11	0.20	0.14	0.33
Integrated Start Generator[A3]	3.00	5.00	1.00	0.14	0.50	0.20	3.00
Reduced weight[A4]	9.00	9.00	7.00	1.00	7.00	3.00	7.00
Automated manual/dual clutch transmissions[A5]	5.00	5.00	2.00	0.14	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	7.00	7.00	5.00	0.33	3.00	1.00	7.00
A continuously variable transmission (CVT)[A7]	0.33	3.00	0.33	0.14	0.33	0.14	1.00

Table 22 – After sales cost evaluation for medium cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.14	0.20	0.33	0.33	3.00	0.33
Hybrid-electric Vehicles (HEVs)[A2]	7.00	1.00	3.00	7.00	7.00	5.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	3.00	3.00
Reduced weight[A4]	3.00	0.14	0.20	1.00	0.33	1.00	0.33
Automated manual/dual clutch transmissions[A5]	3.00	0.14	0.33	3.00	1.00	3.00	0.33
Manual 6-speed transmissions[A6]	0.33	0.20	0.33	1.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	3.00	0.20	0.33	3.00	3.00	3.00	1.00

Table 23 – Consumer feature evaluation for medium cars. Font: own author.

	A1
Turbo or supercharged engines[A1]	5.00
Hybrid-electric Vehicles (HEVs)[A1]	7.00
Integrated Start Generator[A1]	5.00
Reduced weight[A1]	3.00
Automated manual/dual clutch transmissions[A1]	4.00
Manual 6-speed transmissions[A1]	4.00
A continuously variable transmission (CVT)[A1]	7.00

Table 24 – Expected energy efficiency improvement for medium cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	9.00	3.00	3.00	3.00	1.00	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.11	1.00	0.20	0.20	0.14	0.11	0.20
Integrated Start Generator[A3]	0.33	5.00	1.00	3.00	3.00	0.33	3.00
Reduced weight[A4]	0.33	5.00	0.33	1.00	3.00	1.00	3.00
Automated manual/dual clutch transmissions[A5]	0.33	7.00	0.33	0.33	1.00	0.33	3.00
Manual 6-speed transmissions[A6]	1.00	9.00	3.00	1.00	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.33	5.00	0.33	0.33	0.33	0.33	1.00

Table 25 – Tecnology engineering maturity for medium cars. Font: own author.

	Performance	Confort	AfterSaleCosts	Feature	EE	EngMaturity
Turbo or supercharged engines	0.37	0.05	0.05	0.05	0.14	0.27
Hybrid-electric Vehicles (HEVs)	0.22	0.40	0.02	0.42	0.20	0.02
Reduced weight	0.14	0.03	0.45	0.05	0.09	0.14
Manual 6-speed transmissions	0.12	0.04	0.25	0.04	0.11	0.24
Automated manual/dual clutch transmissions	0.07	0.10	0.11	0.09	0.11	0.09
A continuously variable transmission (CVT)	0.05	0.15	0.04	0.13	0.20	0.06
Integrated Start Generator	0.03	0.22	0.08	0.21	0.14	0.17

Table 26 – AHP results for medium cars. Font own author.

	A1	A2	A3	A4	A5	A6
Performance[A1]	1.00	2.00	5.00	3.00	5.00	0.20
Confort[A2]	0.50	1.00	5.00	3.00	3.00	0.20
AfterSaleCosts[A3]	0.20	0.20	1.00	0.20	0.33	0.11
Feature Perception[A4]	0.33	0.33	5.00	1.00	3.00	0.20
Energy Efficiency[A5]	0.20	0.33	3.00	0.33	1.00	0.20
Engineering Maturity[A6]	5.00	5.00	9.00	5.00	5.00	1.00

Table 27 – Criteria evaluation for medium-large cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	5.00	3.00	5.00	5.00	5.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	7.00	3.00	3.00	3.00	3.00
Integrated Start Generator[A3]	0.20	0.14	1.00	0.20	0.33	0.14	0.33
Reduced weight[A4]	0.33	0.33	5.00	1.00	3.00	2.00	3.00
Automated manual/dual clutch transmissions[A5]	0.20	0.33	3.00	0.33	1.00	0.33	3.00
Six, seven and eight speed AT[A6]	0.20	0.33	7.00	0.50	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.20	0.33	3.00	0.33	0.33	0.33	1.00

Table 28 – Performance evaluation for medium-large cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.20	0.20	1.00	0.33	3.00	0.20
Hybrid-electric Vehicles (HEVs)[A2]	5.00	1.00	3.00	7.00	5.00	7.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	5.00	3.00
Reduced weight[A4]	1.00	0.14	0.20	1.00	0.20	0.33	0.20
Automated manual/dual clutch transmissions[A5]	3.00	0.20	0.33	5.00	1.00	3.00	0.33
Six, seven and eight speed AT[A6]	0.33	0.14	0.20	3.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	5.00	0.20	0.33	5.00	3.00	3.00	1.00

Table 29 – Confort evaluation for medium-large cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	3.00	0.33	0.11	0.20	0.14	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.33	1.00	0.20	0.11	0.20	0.14	0.33
Integrated Start Generator[A3]	3.00	5.00	1.00	0.14	0.50	0.20	3.00
Reduced weight[A4]	9.00	9.00	7.00	1.00	7.00	3.00	7.00
Automated manual/dual clutch transmissions[A5]	5.00	5.00	2.00	0.14	1.00	0.33	3.00
Six, seven and eight speed AT[A6]	7.00	7.00	5.00	0.33	3.00	1.00	7.00
A continuously variable transmission (CVT)[A7]	0.33	3.00	0.33	0.14	0.33	0.14	1.00

Table 30 – After sales cost evaluation for medium-large cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	0.14	0.20	0.33	0.33	3.00	0.33
Hybrid-electric Vehicles (HEVs)[A2]	7.00	1.00	3.00	7.00	7.00	5.00	5.00
Integrated Start Generator[A3]	5.00	0.33	1.00	5.00	3.00	3.00	3.00
Reduced weight[A4]	3.00	0.14	0.20	1.00	0.33	1.00	0.33
Automated manual/dual clutch transmissions[A5]	3.00	0.14	0.33	3.00	1.00	3.00	0.33
Six, seven and eight speed AT[A6]	0.33	0.20	0.33	1.00	0.33	1.00	0.33
A continuously variable transmission (CVT)[A7]	3.00	0.20	0.33	3.00	3.00	3.00	1.00

Table 31 – Consumer feature evaluation for medium-large cars. Font: own author.

	A1
Turbo or supercharged engines[A1]	5.00
Hybrid-electric Vehicles (HEVs)[A1]	7.00
Integrated Start Generator[A1]	5.00
Reduced weight[A1]	3.00
Automated manual/dual clutch transmissions[A1]	4.00
Six, seven and eight speed AT[A1]	4.00
A continuously variable transmission (CVT)[A1]	7.00

Table 32 – Expected energy efficiency improvement for medium-large cars. Font: own author.

	A1	A2	A3	A4	A5	A6	A7
Turbo or supercharged engines[A1]	1.00	9.00	3.00	3.00	3.00	1.00	3.00
Hybrid-electric Vehicles (HEVs)[A2]	0.11	1.00	0.20	0.20	0.14	0.11	0.20
Integrated Start Generator[A3]	0.33	5.00	1.00	3.00	3.00	0.33	3.00
Reduced weight[A4]	0.33	5.00	0.33	1.00	3.00	1.00	3.00
Automated manual/dual clutch transmissions[A5]	0.33	7.00	0.33	0.33	1.00	0.33	3.00
Six, seven and eight speed AT[A6]	1.00	9.00	3.00	1.00	3.00	1.00	3.00
A continuously variable transmission (CVT)[A7]	0.33	5.00	0.33	0.33	0.33	0.33	1.00

Table 33 – Tecnology engineering maturity for medium-large cars. Font: own author.

	Performance	Confort	AfterSaleCosts	Feature	EE	EngMaturity
Turbo or supercharged engines	0.37	0.05	0.05	0.05	0.14	0.27
Hybrid-electric Vehicles (HEVs)	0.22	0.40	0.02	0.42	0.20	0.02
Reduced weight	0.14	0.03	0.45	0.05	0.09	0.14
Six, seven and eight speed AT	0.12	0.04	0.25	0.04	0.11	0.24
Automated manual/dual clutch transmissions	0.07	0.10	0.11	0.09	0.11	0.09
A continuously variable transmission (CVT)	0.05	0.15	0.04	0.13	0.20	0.06
Integrated Start Generator	0.03	0.22	0.08	0.21	0.14	0.17

Table 34 – AHP results for medium-large cars. Font own author.