Multi-objective Decision-making Methods for Optimising CO_2 Decisions in the Automotive Industry

Nassir Ibrahim, Sharon Cox, Robert Mills, Andrew Aftelak, Hanifa Shah

Faculty of Computing, Engineering and the Built Environment.

Birmingham City University, Birmingham, UK

ABSTRACT

Multi-objective optimisation (MOOP) methods are used heavily to support decision-makers in addressing problems with conflicting objectives. With global CO_2 emission legislation becoming stringent, automotive OEMs face a challenge to balance conflicting commercial and environmental objectives simultaneously. Automotive OEMs seek to maximise profits by stimulating global sales volumes whilst also minimising CO_2 management costs. MOOP methods can quantify CO_2 management costs to optimise decisions in response to the increasingly regulated business environment. Whilst automotive OEMs are modelling the dynamic knock-on effects of pursuing multiple objectives, there is also a need to formulate their decision objectives, decision criteria and decision options to be considered as part of CO_2 management decisions first. A systematic literature review offers a detailed account of how automotive OEMs can optimise CO_2 management decisions.

The multiple decision objectives, decision criteria and CO_2 management decision options considered by automotive OEMs are first categorised. The systematic literature review reveals that evaluating decision criteria such as the vehicle fleet portfolio, customer demand, market requirements and financial cost can assist automotive OEMs select the optimal CO_2 management decision in a given scenario. Next, reconfiguring vehicle features, investing in technology, restricting sales and paying CO_2 tariffs are identified as the most common CO_2 management decisions taken by automotive OEMs. Then MOOP methods are critiqued for their suitability, before a novel decision support model, which adopts an automotive OEMs' perspective for mitigating CO_2 management costs is proposed. It is found that interactive and objective decision making approaches such as MOOP opposed to classical Multi Criteria Decision Making (MCDM) methods can more precisely quantify the commercial implications of the stricter global CO_2 emission legislation now imposed on automotive OEMs. If automotive OEMs adopt the proposed model, they can effectively model future CO_2 management scenarios and pre-emptively prevent counter-productive decisions by minimising CO_2 management costs.

Key words: CO_2 tariff minimisation; Profit maximisation; Financial cost; Multi-objective optimisation; Decision support model; Automotive OEMs

1. Introduction

The transportation industry is one of the largest emitters of CO_2 (EPA, 2019). CO_2 emissions are a major concern for decision-makers throughout the product lifecycle, particularly during the use phase (Russell, 2019). Decision-makers seek to quantify the compliance and noncompliance costs associated with CO_2 legislation and to enumerate the extent to which the increasingly regulated business environment impacts the sales of vehicles (Morris et al., 2009). The commercial implications of CO_2 legislation need to be considered prior to the sale of goods to avoid automotive

OEMs incurring substantial CO_2 tariff costs for noncompliance with emission targets in global sales markets (Niese & Singer, 2013). In order to effectively measure the costs associated with vehicle CO_2 emissions, the commercial implications must be captured and quantified by ascribing a monetary cost (Engau & Hoffmann, 2011).
By factoring in the commercial implications of CO_2 legislation into decision-making, automotive OEMs can mitigate the commercial implications of CO_2 emissions throughout various stages of the product lifecycle (Nieuwenhuis et al., 2012). Factoring in the commercial implications of CO_2 legislation brings about an extra layer of complexity into the already intricate production processes involved in the automotive industry (Jasiński et al., 2016), especially during car production. Automotive OEMs carefully consider production measures such as Takt time, production line balancing, tooling and manpower planning (Roy et al., 2011), hence embedding CO_2 management into the decision-making equation brings about an extra layer of complexity for automotive OEMs (Shaik & Rodrigues, 2018). After all, automotive OEMs already produce countless different vehicle permutations, fitted with unique feature combinations, across a wide portfolio of vehicle models, as part of international vehicle fleets to cater for a global customer population (PA Consulting, 2019). Automotive OEMs need to handle the dynamics involved in the decision-making process by factoring in the costs associated with CO_2 management by modelling the interrelated criteria involved when optimising CO_2 decisions (Hao et al., 2016).

Numerous methods are used by manufacturers in existing approaches to manage the commercial implications of CO_2 legislation. Nevertheless, there is a deficiency of frameworks that assess criteria holistically, whilst utilising dynamic models (Carmona-Benítez et al., 2017; Khoo & Teoh., 2014) and that also offer a manufacturers perspective (Wellmann et al., 2017). This study builds upon previously developed methods that quantify the commercial implications of CO_2 legislation via optimisation methods. This paper progresses the work of Lee & Hashim, (2014), who modelled CO_2 mitigation strategies for electricity generation, by integrating CO_2 reduction costs with maximising profit, to achieve Pareto optimal outcomes. In addition, this paper follows the work of Müller et al. (2018), by recognising that businesses which operate globally are required to comply with different CO_2 emission legislations. Moreover, this paper extends the work of Nazari et al. (2015) by acknowledging that methods designed for CO_2 management should be dynamic whilst also appreciating the non-linear nature of how CO_2 tariff costs are incurred in reality as done in the work of Yang, (2018).

Automotive OEMs utilise a range of decision support methods with different purposes to investigate design variations and make cost-effective configurations even before the first vehicle prototype has been built. The methods used by automotive OEMs include but are not limited to Fords' product sustainability index and environmental failure mode effect analysis (FMEA), Volvos' life cycle analysis and design for recycling, Nissans' design for recycling, Renaults' life cycle management, Volkswagens' life cycle analysis, PSA (Peugeot-Citroens') eco-design, Fiats' life cycle analysis, Daimlers' design for environment and Toyotas' ecological vehicle assessment (eco-vas) (Nieuwenhuis & Wells, 2003). Other notable methods employed by automotive OEMs include CO_2 Model for PAssenger and commercial vehicles Simulation (CO_2MPAS), Vehicle Energy Consumption Calculation Tool (VECTO), Passenger Car and Heavy Emission Duty Model (PHEM), Passenger Car fleet emissions Simulator (PyCSIS), Simulation of Urban Mobility (SUMO) and Anstalt für Verbrennungskraftmaschinen List (AVL) Cruise. Notwithstanding the usefulness of the plethora of methods that are available, global emission legislation has given birth to a range of commercial implications for automotive OEMs that existing methods fail to fully address (Ricardo, 2018).
With the advent of stricter emission legislation, automotive OEMs are increasingly concerned with how CO_2 management decisions can be optimised and the combination of criteria that should be considered to effectively mitigate the costs associated with global emission legislation (PA

Consulting, 2019). In this regard, Multiple Criteria Decision Making (MCDM) methods can be employed to solve the automotive OEMs' CO_2 management decision problem (Zopounidis & Doumpos, 2002). Despite the abundance of published reviews on the subject of CO_2 emissions, the commercial implications of CO_2 emission legislation have received less coverage than the social, environmental, legal and technological implications brought about by CO_2 emission legislation. The explicit focus of this study is to address the commercial implications of CO_2 legislation with a conceptual decision support model. The model assists automotive OEMs to optimise CO_2 management decisions by concentrating solely on commercial objectives, such as minimising the financial costs associated with CO_2 management decisions whilst seeking to maximise profits for automotive OEMs.

The contributions provided by this systematic literature review are two-fold. Firstly, the gaps in knowledge pertaining to the commercial implications of CO_2 legislation are identified. The gaps in the body of knowledge that need to be filled are:

1. formulating the key objectives involved in dealing with the commercial implications of CO_2 emission legislation;
2. identifying the most effective combination of criteria to be evaluated by automotive OEMs in the CO_2 management decision problem in order to achieve optimal decisions;
3. and identifying the decision options that lead to achieving Pareto optimal outcomes as part of an automotive OEMs CO_2 management strategy.

Secondly, a decision support model that acts as a mechanism for automotive OEMs to mitigate the commercial implications of CO_2 legislation is proposed via a systematic literature review. The paper is organised as follows. Before the model is presented, section 2 of this article outlines the process of the systematic literature review. Section 3 covers the decision objectives, options and criteria that automotive OEMs can evaluate to solve the CO_2 management decision problem. Section 3 also includes a critique of MCDM methods and then categorises methods based on their individual characteristics. Section 4 covers the lessons that can be learned from existing approaches that utilise MCDM methods, to solve similar CO_2 management problems. Section 4 also includes a critical review of the effectiveness of employing particular MCDM and MOOP methods to mitigate CO_2 management costs across various industries. The findings from the literature on MCDM methods valuably inform the development of the proposed decision support model designed for automotive OEMs. Finally, section 5 concludes the paper.

2. Method

For the systematic literature review conducted in this study, keyword searches were carried out on academic databases such as Science Direct, IEEE, Web of Science, Scopus and Google Scholar. Some of the search terms used in database queries were: ['CO_2 emission costs' OR 'carbon footprint costs' AND 'decision support systems' OR 'decision analysis' OR 'multi-criteria decision analysis' OR 'MCDA' AND 'multiple objective optimisation' OR 'MOOP']. After records were generated from several searches on various academic databases, records were screened for relevance by assessing titles and abstracts of records. Duplicates were then removed which produced a collection of 183 sources of literature, ready for analysis. Due to the multidisciplinary nature of the CO_2 management decision making subject matter, a wide range of search term combinations in addition to the aforementioned search terms were employed. See the supplementary material for further details on the literature search.

A set of selection rules were set up to ensure that only relevant pieces of literature were included in this study:

- Inclusion of any type of study (published, whether peer-reviewed or not)
- Inclusion of any study on CO_2 management decision problems (automotive or not)
- Inclusion of studies of any geographical scope
- Exclusion of studies adopting a non-technocratic approach due to the study adopting a manufacturers perspective and the industry strongly favouring technocratic approaches
- Exclusion of studies in languages other than English (the languages fluently handled by authors of this study)
- Exclusion of studies focusing predominantly on ethical, social and political issues of CO_2 management decision problems as the focus of this review is on the commercial implications of CO_2 legislation
- Exclusion of duplicates. For example if a technical report was transformed into a peer-reviewed article then only the peer-reviewed article

The content of selected studies were mapped by extracting information using the following questions:

- What were the aim(s) of the study?
- What type of frameworks, models, methods or tools and techniques (approaches) were used in those studies?
- How were the approaches used in those studies to solve the CO_2 management decision problem?
- Did the study focus on the commercial implications of the CO_2 management decision problem?
- What were the conclusions of the studies regarding the effectiveness of the various existing approaches in solving the CO_2 management decision problem?

The CO_2 management decision problem has received significant attention especially as the environmental legislative landscape has become more stringent. In between the transition of NEDC and WLTP, the number of academic publications have increased as seen in Figure 1. In the advent of new global environmental legislation, academic publications have continuously reported the challenges facing manufacturers. Table 1 conveys the top academic journals that have reported the CO_2 management decision problem according to the bibliometrics of this study. This study found that the Journal of Cleaner Production, European Journal of Operational Research, and Energy Policy publish comprehensively on the CO_2 management subject matter in addition to the Society of Automotive Engineers. However, a significant amount of literature can also be found in white papers and consultancy reports produced by Ricardo, Netherlands Organisation for Applied Scientific Research (TNO), PA Consulting, European Environment Agency, JATO Dynamics and Just Auto, amongst many more. Based on the aforementioned selection rules, 201 publications were found, whereof 158 were peer-reviewed journal articles and 43 were other types of publications. Thirty-three percent of the publications focussed on the financial costs associated with CO_2 legislation with a further fifteen percent concentrating on the technological costs of CO_2 improvement during product development. Figure 1 shows that the number of publications in CO_2 management decision making has increased especially during the last decade (2010-2020), with a significant rise in 2017 particularly for the automotive industry during the advent of WLTP.

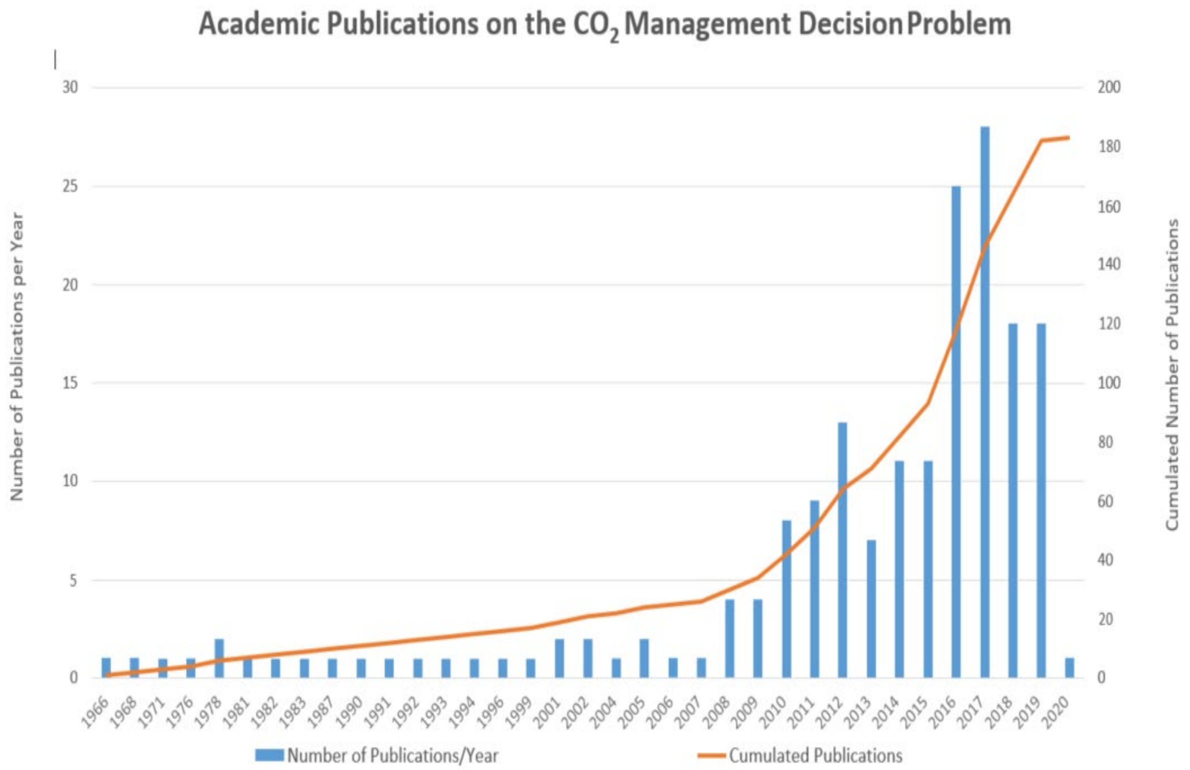

Figure 1: Academic publications on the CO2 management decision problems utilising MCDM methods (status: 11th January 2020)

Table 1: Top 12 academic Journals ranked by number of publications on the CO_2 management decision problem in this study

	Academic Journal	**Number of publications**
1	Journal of Cleaner Production	17
2	European Journal of Operational Research	13
3	Energy Policy	9
4	Society of Automotive Engineers	9
5	Renewable & Sustainable Energy Reviews	5
6	International Council on Clean Transportation	5
7	Energy	4
8	Applied Energy	3

9	Journal of Mechanical Design	3
10	Transportation Research Part D : Transport and Environment	2
11	Sustainability	2
12	Journal of Air Transport and Management	2

The key purpose of this paper is to collate existing literature on decision-making methods suitable for solving CO_2 management decision problems. First, the challenges global CO_2 emission legislation creates for manufacturing businesses, also known as Original Equipment Manufacturers (OEMs), will be explained. Second, the decision options of responding to global emission legislation are categorised, accompanied by the key criteria used by decision-makers when evaluating optimal responses to potential what-if scenarios. A review of existing decision-making methods is subsequently followed by an assessment of existing approaches to CO_2 management decision problems. Finally, MCDM methods are appraised on their suitability to support automotive OEMs mitigate the commercial implications of CO_2 legislation. The commercial implications of global CO_2 emission legislation will be discussed in the following section.

3. Results

The results of the systematic literature review will now be presented beginning with global emission legislation facing automotive OEMs.

3.1 Global emission legislation

Global CO_2 legislation is gradually becoming more and more stringent (The International Council on Clean Transportation (ICCT), 2016) by setting limits on CO_2 emitted throughout the product life cycle. OEMs have had to react to this legislative constraint by quantifying the costs associated with CO_2 emissions across the respective stages of the product life cycle (Rubin et al., 2015) as illustrated in Figure 2. Figure 2 highlights that even though global emission legislation is enforced on automotive OEMs, proactive design decisions can be made to mitigate the commercial implications of CO_2 legislation throughout the product life cycle. This study focuses on supporting automotive OEMs optimise CO_2 management decisions with an emphasis on the use phase of the product life cycle. The use phase involves the highest level of CO_2 emissions (Faria et al., 2013) and potential tariffs for noncompliance with emission targets. Non-compliance with emission targets could erode the profit margin and overshadow any profits to be achieved by automotive OEMs if not managed effectively (Matar & Elshurafa, 2017).

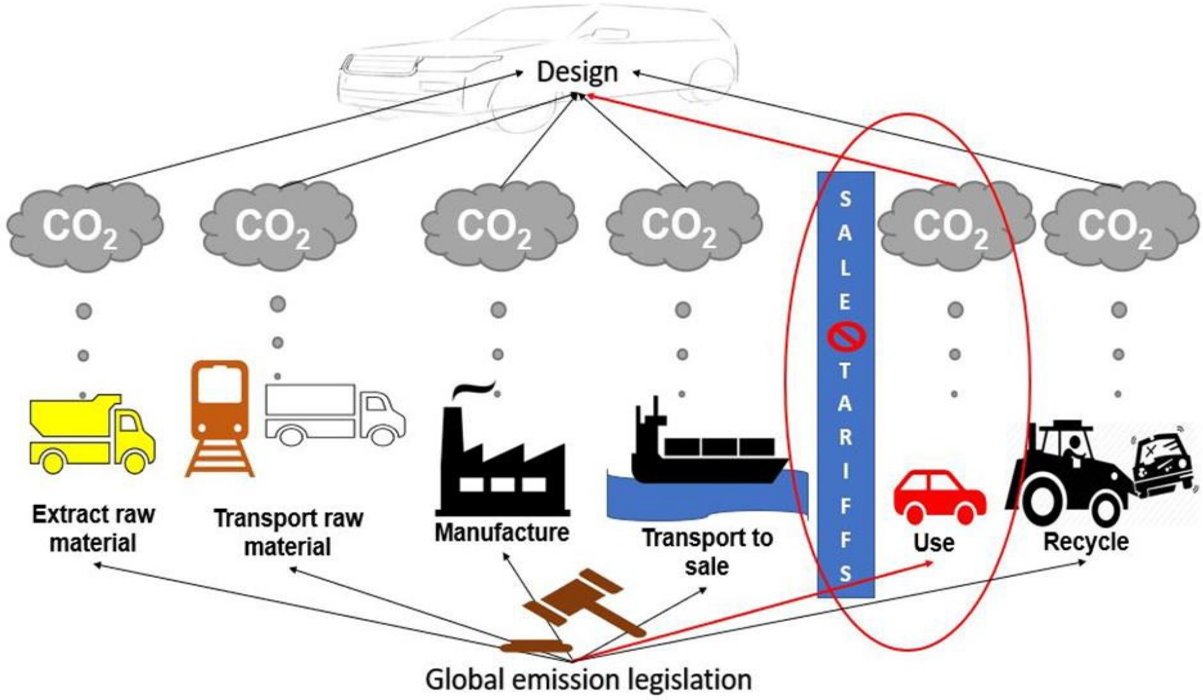

Figure 2: CO_2 emissions associated with activity across product life cycle

Global environmental legislation for automotive OEMs include CO_2 exhaust emission targets in the EU in 2021, fuel economy targets in the United States (US) in 2025 under corporate average fuel economy (CAFE) (Jenn et al., 2016), and the US National Highway Traffic Safety Administration (NHTSA), and the corporate average fuel consumption (CAFC) standard phase 4 in 2020, in China (Atabani et al., 2011). Table 2 shows existing and emerging global CO_2 emissions legislation for automotive OEMs. Whilst the EU measures a vehicle's environmental performance in CO_2 grams per kilometre (g/km), other markets such as China and the US use fuel economy in litres per kilometre (l/km) to indicate the environmental performance of vehicles. Automotive OEMs should factor in the commercial implications of global CO_2 emission targets into their decision-making.

Table 2: Global Passenger Vehicle Emission and Fuel Economy Legislation

Global Passenger Vehicle Emission Legislation – Use phase					
Region	**Period**				
	2015-2020		**2020 - 2025**		**2025-2030 (expected targets)**
China	Phase 4 Corporate Average Fuel Consumption (CAFC)	5.0 Litres (L) /100 km	Phase 5 CAFC	4.0 Litres (L) /100 km	-

EU	New European Driving Cycle (NEDC) Test	130g CO_2/km target	Worldwide Harmonised Light Vehicle Test Procedure (WLTP) + Real Driving Emissions (RDE) Test	95g CO_2/km target	WLTP + RDE	68 -78g CO_2/km target
India	Bharat Stage IV	130g CO_2/km target	Bharat Stage VI	113g CO_2/km target (from 2021)	WLTP	
Japan	Top Runner Program for passenger vehicles	16.8 L/km target	Top Runner Program for passenger vehicles	20.3 L /100 km target	-	
US	Corporate Average Fuel Economy (CAFE) Standards	6.63 L/ 100 km / 35.5 MPG	The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule	6.36 L/100 km target/ 37 US MPG (from 2021)	-	

For example, the Corporate Average Fuel Economy (CAFE) program in the US regulates vehicles to a fuel economy standard of 34.1 miles per gallon (MPG) requires automotive OEMs to tailor their future vehicle offerings to more fuel-efficient powertrains or propulsion systems whilst also reducing vehicle mass and size (Wolfram et al., 2016). The European Union (EU) has proposed regulation 443/2009 to control CO_2 emissions from new passenger cars (European Commission Climate Action, 2019). According to that regulation, the average CO_2 emissions for each automotive OEMs' new passenger cars registered in 2020, in the EU should not exceed the value of 95 grams (g) CO_2/km on the New European Driving Cycle (NEDC) (Bampatsou & Zervas, 2011). In addition to this constraint, the previous emissions testing process (NEDC) was changed to the more stringent Worldwide Harmonised Light Vehicles Test Procedure (WLTP) in 2018. WLTP intends to better reflect actual emissions compared to carrying out the test in a laboratory where certain variables could have been manipulated (Dimaratos et al., 2016). This further exacerbates the CO_2 management challenge for automotive OEMs.

Failure to comply with emission targets can have serious implications such as CO_2 tariffs being imposed on automotive OEMs (Brand et al., 2017). This prompts automotive OEMs to assess various CO_2 improvement measures in response to the legislative environment, hence, fuel efficiency and exhaust emission legislation have become key drivers of technological change for automotive OEMs. There is a challenge to better understand the commercial implications of CO_2 legislation in the automotive industry (González Palencia et al., 2015; Thiel et al., 2010) with respect to the potential costs (Hill et al., 2012; Ligterink et al., 2016) of future investments (Fox et al., 2017) or penalties to be incurred in different global sales territories.

There are various decision options automotive OEMs can consider in meeting emission targets such as vehicle mass reduction measures (Isenstadt et al., 2017), improving internal combustion engines (ICE) (Johnson & Joshi, 2018) and selling alternative fuel vehicles (AFVs), which consist of hybrid and battery electric vehicles (BEV) (Michalek et al., 2006). Automotive OEMs typically incorporate a mixture of complimentary CO_2 improvement measures as part of their vehicle fleet to offset the effect of high emitting vehicles affecting their fleet average emissions (Meszler et al., 2013). European CO_2 legislation was the predominant policy utilised to model CO_2 management costs in the publications found, followed by Chinese policy with American policy the least common. The decision maker's objectives and decision options of dealing with emission legislation will now be discussed.

3.2 Multiple objectives and decision options involved in CO_2 management decisions

Automotive OEMs typically seek to satisfy two competing objectives in dealing with emission legislation (Pasaoglu et al., 2012). In addressing the commercial implications of CO_2 legislation, these objectives are profit maximisation and emission minimisation for solving environmental problems (PwC, 2007). Finding a balance between commercial and environmental objectives is challenging, as emissions are a by-product of seeking profit maximisation (Tsai et al., 2012). Instead, automotive OEMs can identify the points at which they could incur CO_2 tariffs for not complying with global emission targets (Maddulapalli et al., 2012). This way, automotive OEMs could still pursue profit maximisation and minimise the cost of CO_2 tariffs by optimising decisions. When optimising decisions to satisfy multiple objectives, automotive OEMs should assess the effect of decisions on a vehicle fleet collectively, since the CO_2 tariff cost is based upon a collective vehicle fleet portfolio. A vehicle fleet portfolio is influenced by market requirements and driven by customer demand. As a result, automotive OEMs should observe the collective effects of decision options in dealing with emission legislation to mitigate the costs of CO_2 tariffs more effectively (Wells et al., 2010).

Figure 1 shows that CO_2 emissions can be mitigated at different stages of the lifecycle by product design decisions. There are a number of decision options available for automotive OEMs to choose from in order to respond to emission legislation, such as, investing in CO_2 technology, paying CO_2 tariffs, restricting sales and reconfiguring vehicle features (PA Consulting, 2019; ICCT, 2017, Ricardo, 2016; Ricardo, 2018). These options may not be mutually exclusive; hence automotive OEMs can make decisions about how to respond to the commercial implications of CO_2 legislation by combining decision options together, subject to the different potential scenarios in global markets. The CO_2 management decision options for automotive OEMs are discussed in the following section.

Decision Option I. Investing in CO_2 technology

There are a range of CO_2 improving technologies automotive OEMs can adopt in vehicle design to achieve favourable CO_2 performance, such as engine downsizing, electromechanical systems, regenerative braking systems (Silva et al., 2009), hybrid powertrains, battery-electric powertrains, fuel cells (Folkson, 2014) and alternative fuels, which include hydrogen, natural gas and biofuels (PwC, 2007). Toyota has taken a hybridisation route; however, they are returning to work on fuel cell technology; in contrast Nissan, Tesla and BMW have preferred battery electric vehicles (Mazur et al., 2015). The Renault-Nissan-Mitsubishi Alliance seeks to be the low-cost market leader for PHEV and BEV by 2022, Daimler has plans to launch a fully-electric brand, EQ by 2022 and after the PSA's merger with FCA, they plan to share technologies together and focus on selling small and compact vehicles with increased PHEV and BEV adoption (PA Consulting, 2020). Emission legislation can encourage or discourage investment in CO_2 improvement technologies (Lopez et al., 2017), however technologies are often dismissed due to a lack of customer demand (Coffman et al., 2017), their high associated life cycle costs (Ricardo, 2016) and the lack of available electric vehicle charging infrastructure (Wan et al., 2015). Upcoming legislation cannot be met without automotive OEMs deploying significant levels of technology in order to reduce CO_2 levels (Cheah et al., 2010; Walter et al., 2017). Not complying with CO_2 emission legislation means costly tariffs will have to be paid by automotive OEMs to authorities.

Decision Option II. Paying CO_2 tariffs to authorities for non-compliance with emission targets

An alternative to reducing CO_2 emissions is that automotive OEMs could decide to sell non-compliant vehicles and pay tariffs to authorities in their sales markets (Ciuffo & Fontaras, 2017). If, however, fleet average emissions do exceed the target threshold, there is a tariff incurred by the manufacturer of €95 per exceeding gram of CO_2/km against the total vehicle fleet in the respective sales markets in the EU (Mock, 2019). Similarly, automotive OEMs can be financially penalised for non-compliance with CAFC in China and CAFE in the US (Atabani et al., 2011). If CO_2 tariff costs are not mitigated they could overshadow any profits made on vehicle sales and hence erode the profit margins of automotive OEMs (Matar & Elshurafa, 2017).

Decision Option III. Restricting sales

Another way automotive OEMs could respond to CO_2 tariffs is to restrict their vehicle sales offering. Automotive OEMs sell vehicles in different global markets with varying emission targets, thus a viable decision could be to restrict product offering in specific markets. Automotive OEMs can sell individual vehicles with varying levels of CO_2 emissions as long as the average emissions of the total group of vehicles, also known as the vehicle 'fleet', within a specific market does not exceed the 130g CO_2/km target till 2020 and then the 95g CO_2/km target after 2021 in the EU (Regulation (EC) No 443/2009 of the EU). Automotive OEMs can respond to emission legislation by restricting the sales of highly polluting vehicles in markets with stringent legislation (Winter & Thierfelder, 2017). In the process sales restriction, automotive OEMs must also comply with Article 102 of the Treaty for the EU's antitrust policy (European Commission, 2014) and US antidumping laws which prohibit limiting the production of goods or charging unfair prices (Konings & Vandenbussche, 2013). Reconfiguring vehicle features across the global population of vehicle fleets in various markets could be an alternative option.

Decision Option IV. Reconfiguring vehicle features

Vehicle CO_2 emissions are largely influenced by the mass of an individual vehicle (Tsokolis et al., 2016), which is impacted by the features fitted to the vehicle (May et al., 2014); along with the vehicle engine type, aerodynamic drag, tyre rolling resistance and power-to-mass ratio (Galindo et al., 2017). Vehicle feature content could be reconfigured during product development to minimise CO_2 emissions and tariff cost incurred and thus mitigate the impact on the profit margin (JATO, 2017). Automotive OEMs could decide to review features offered to customers to reduce CO_2 emissions.

CO_2 emissions can be mitigated in a number of ways. Table 3 summarises automotive OEM's decision options for CO_2 management. A proactive approach can maximise the opportunities of automotive OEMs to satisfy both environmental and commercial objectives. Automotive OEMs are currently preparing scenario specific responses to CO_2 legislation by conducting what-if-scenario analyses to gauge product life cycle costs associated with current and future emission legislation targets in various international markets (Thiel et al., 2014). The following section will identify the criteria to consider when selecting between decision options for responding to CO_2 emission legislation.

Some of the many CO_2 management decision options available to automotive OEMs can be categorised into two well-known categories. The first category is investing in CO_2 improvement technology and includes electrification, developing advanced transmission systems, advanced engines and alternative fuel systems. The second category involves adopting vehicle mass reduction measures via the use of lighter materials or reconfiguring additional vehicle features (PwC, 2007). Although the academic literature provides insights into how automotive OEMs can optimise CO_2 management decisions via technology and product development, white papers and consultancy reports have shown that automotive OEMS can also elect to pay CO_2 tariffs for non-compliance with legislated CO_2 targets or also restrict global vehicle sales (PA Consulting, 2019; ICCT, 2017, Ricardo, 2016; Ricardo, 2018). Despite less scientific publications covering the latter two decision options, paying CO_2 tariffs and restricting vehicle sales are valid decision options for automotive OEMs dealing with the commercial implications of CO_2 legislation (Ito & Sallee, 2018). Table 3 tabulates the four key decision option categories extracted from the literature, available to automotive OEMs in response to the commercial implications of CO_2 legislation.

Table 3: Summary of decision options to deal with CO_2 emission legislation

Decision Options	**Decision options of dealing with CO_2 emission legislation**
Decision Option I. Investing in CO_2 technology	**Description:** There is a general consensus in the car industry that CO_2 improvement technology will be necessary for meeting global emission legislation.
	Advantage: the decision of investing in CO_2 technology is considered the most effective for reducing CO_2 emissions and automotive OEMs are rewarded with incentives such as CO_2 reduction credits and subsidies for investing in CO_2 technologies by policymakers (Wolfram et al., 2016)
	Disadvantage: The significant financial costs associated with investing in CO_2 improvement technology makes the decision of investing, cost prohibitive (Folkson, 2014).
Decision Option II. Paying CO_2 tariffs	**Description:** If the average emissions of an automotive OEM's fleet exceed the emission target, the automotive OEM has to pay a CO_2 tariff for each vehicle sold.
	Advantage: The payment of CO_2 tariffs permits vehicles which are noncompliant with global emission targets to still be sold hence enabling automotive OEMs to generate sales revenues which would otherwise have not been possible without paying tariffs (ICCT, 2016)
	Disadvantage: The payment of tariffs, also known as penalties, can negatively harm the brand image of automotive OEMs, particularly for the environmental impact created by products (Ferrell et al., 2017). As a result, automotive OEMs take Corporate Social Responsibility (CSR) seriously to protect brand image
Decision Option III. Restricting sales	**Description:** Automotive OEMs can restrict the sales volumes of specific vehicle models or vehicle features to mitigate fleet average emissions
	Advantage: Tariff costs can be avoided by restricting sales and automotive OEMs can use this opportunity make minor modifications in the product development cycle to improve CO_2 performance of future vehicles to be sold (PA Consulting, 2019)

	Disadvantage: There can be significant opportunity costs associated with restricting sales such as a reduction in market share and the lack of proactively dealing with the CO_2 management problem may cause automotive OEMs to incur greater financial costs in the long term compared to the benefits of avoiding tariff costs in the short term when restricting sales (PA Consulting, 2019)
Decision Option IV. Reconfiguring vehicle features	**Description:** Vehicle features offered to customers by automotive OEMs can be changed to satisfy emission targets
	Advantage: Vehicle mass is the dominant factor impacting the CO_2 emissions of internal combustion engine vehicles and reconfiguring vehicle features can improve vehicle emission performance (Tsokolis et al., 2016)
	Disadvantage: Whilst striving to improve emission performance, automotive OEMs should not neglect the preferences of customers by disregarding customer demand (Mills et al., 2016)

After discussing the most common decision options taken by automotive OEMs in response to the commercial implications of CO_2 legislation, now the decision criteria that has been used to evaluate the commercial implications of CO_2 management decisions will follow.

3.3 Decision Criteria to consider in selecting options to respond to emission legislation

There are multiple criteria to consider in the decision-making process for selecting appropriate decision options in response to global emission legislation as shown in Table 3. First, it is important to establish the particular CO_2 management strategy to be adopted by the automotive OEM prior to selecting decision criteria. CO_2 management strategies vary widely (Genta et al., 2014) and include, but are not limited to three main strategy categories which give birth to their related measures:

1) Alternative fuel technologies with measures such as Biofuels, Natural gas and Hydrogen;

2) Engine technologies with measures such as Electrification, Hybridisation, Fuel cells and Advanced ICE;

3) Non engine technologies such as Transmission, Energy storage, Rolling resistance and Aerodynamics

The relative effectiveness of these CO_2 management measures have been investigated in previous studies. For example, Türe & Türe (2020) investigated the use of lighter vehicle materials and considered criteria such as the amount of vehicle material type employed, the vehicle mass reduction achieved when substituting components and the resultant exhaust emission produced by the passenger car. Weiss et al (2019) assessed the cost-to-benefits of electrification and plug-in hybrid vehicles (PHEV) by considering criteria such as fuel and electricity prices, existing vehicle charging infrastructure and expected vehicle mileage. Conversely, Rosenfeld et al (2019) examined alternative fuel technologies using criteria like energy supply structure, electricity generation mix and transport distance travelled. The various possible CO_2 management strategies that automotive OEMs can adopt impacts both the measures that will consequently be available to them, and the decision criteria that they will evaluate as a result. Although the aforementioned criteria utilised in previous studies are valid, the evaluation of decision criteria is progressively becoming a commercial challenge for automotive OEMs who are seeking profitability and battling against CO_2 management costs (Idjis & da

Costa, 2017). The commercial challenge involves automotive OEMs having to consider criteria like the market requirements in their international sales territories, the customer demand for vehicles they produce, the subsequent financial costs of CO_2 management and the nature of their vehicle fleet portfolio. As previously mentioned in section 1, the aim of this study is to purely address the commercial implications of CO_2 legislation facing automotive OEMs and provide decision support from the manufacturers perspective. Future research is required to verify the viability of these decision criteria and will now be discussed in more detail.

Decision Criteria I. Optimise vehicle fleet portfolio

An automotive OEM's vehicle fleet portfolio is comprised of various vehicle models, all which proportionally contribute to the fleet average emissions in respective markets (Autovista, 2019). Vehicle models have a range of features. Automotive OEMs can optimise their vehicle fleet portfolio by maximising vehicle sales and minimising the CO_2 tariff cost incurred by reconfiguring vehicle features to satisfy CO_2 emission targets in (g/km), whilst also satisfying customer demand for a given selection of vehicle features (Sharif et al., 2019).

Decision Criteria II. Customer demand

Customer demand is another criteria automotive OEMs consider when responding to emission legislation. Customer demand determines the type of vehicles ordered and the individual features fitted to vehicles. Customers are still demanding heavy and high-emitting types of vehicles such as Sports Utility Vehicles (SUVs) even though legislation requires a reduction in vehicle emissions (Bampatsou & Zervas, 2011). As customers order vehicles with more optional features, the optional vehicle features impact a vehicles' mass, power consumption and CO_2 emissions (Martin et al., 2017). The manufacturer should acknowledge how customer demand for various vehicle types and individual features can be met whilst responding to emission legislation.

Decision Criteria III. Market requirements

The cost of market-specific tariffs for non-compliance of legislation has to be factored into the decision-making process as well as the compliance costs associated with CO_2 improving technologies (Ligterink et al., 2015). As part of their CO_2 management strategy, automotive OEMs can choose to respond to emission legislation by restricting the sales of highly polluting vehicles in markets with stringent legislation (Winter & Thierfelder, 2017). Depending on market requirements, automotive OEMs could opt to invest in CO_2 improving vehicle technologies (Werber et al., 2009); purchase carbon credits, which is effectively a mechanism of 'paying to pollute'; pay non-compliance tariffs (Pasaoglu et al., 2012) or pay another manufacturer to join their emissions pool in order offset potential high fleet average emissions. Ultimately, automotive OEMs can make different decisions in different markets as part of their CO_2 management strategy.

Decision Criteria IV. Financial cost

Financial cost is a key criterion for automotive OEMs in the consideration of selecting options to respond to emission legislation. Automotive OEMs need to weigh up the costs of tariffs paid for non-compliance with emission targets, versus the incremental investment cost to comply with emission targets. Automotive OEMs assess the potential costs of CO_2 improving technologies together with their CO_2 reduction potential against the potential costs of CO_2 tariffs (Ricardo, 2018). In addition to the potential costs of CO_2 improving technologies, automotive OEMs are also concerned with the shelf-life of CO_2 improving technologies (Fox et al., 2017).

As vehicle technology evolves, automotive OEMs are aware that multiple criteria have to be considered in the selection of CO_2 improving technologies such as engine e-boosting (Hu et al., 2017), 48 volt electrical systems (Brown et al., 2016), advanced driver assistance systems (ADAS)

(D'Amato et al., 2017) and sensor suites (Schaeffler Technologies GmbH, 2014). Customer demand, vehicle fleet portfolio, financial cost and sales markets are criteria which could all be evaluated in CO_2 management decisions. Table 4 shows the multiple criteria that could be considered by automotive OEMs when selecting decision options for CO_2 management as extracted from literature.

Table 4: Decision Criteria to consider in selecting decision options for CO_2 management

Reference	**Decision Criteria to consider in selecting options to respond to CO_2 emission legislation**			
	Decision Criteria I. Optimise vehicle fleet portfolio	**Decision Criteria II.** Customer demand	**Decision Criteria III.** Market requirements	**Decision Criteria IV.** Financial cost
Maddulapalli et al., 2012	✓	✓	✓	✓
Michalek et al., 2004		✓	✓	✓
Shiau et al., 2010	✓			✓
Reid et al., 2012	✓	✓		
Hoffenson and Söderberg, 2015		✓	✓	✓
Michalek et al., 2006	✓	✓	✓	✓
Takai et al., 2011	✓	✓		✓
Frischknecht and Papalambros, 2008	✓	✓	✓	✓
Siskos et al., 2014	✓		✓	✓
Tsokolis et al., 2016	✓		✓	
Silva et al., 2009	✓			✓
Thiel et al., 2010	✓			✓
Tsiakmakis et al., 2017	✓		✓	
Fontaras et al., 2018	✓		✓	
Al-Alawi & Bradley, 2014	✓		✓	✓

Decision-making methods can offer the perspective of policymakers, customers and manufacturers. Previous studies have modelled how decision-makers can make profit-optimal decisions whilst evaluating multiple criteria simultaneously. Although controlling financial cost is a key criterion for decision-makers seeking business profitability (Reid et al., 2012), understanding how the interrelationships between other criteria influences the objectives of the decision-maker is crucial when making decisions involving multiple criteria (Si et al., 2016). Multi-criteria decision-making (MCDM) is discussed in the following section.

3.4 Multi-criteria decision-making (MCDM) Methods

Decisions which involve making choices, ranking and sorting can be problematic due to the presence of several criteria (Ishizaka & Nemery, 2013). Decisions usually involve trade-offs whereby a decision-maker incurs a loss to make a gain elsewhere. In pursuit of making the optimal choice, the decision-maker considers a range of alternative options (Favi et al., 2016) to make a final choice, consequently sacrificing alternative choices. The process of foregoing alternative choices is referred to as the opportunity cost (Hahn et al., 2010). Usually, there is not a perfect decision that satisfies all criteria so a compromise must be found to achieve Pareto optimality (Tomoiagă et al., 2013). Pareto optimality can be defined as the state where resources are allocated as efficiently as possible so that improving one criterion will not worsen other criteria (Kennedy et al., 2008).

Multi-criteria decision-making (MCDM) is an approach for evaluating conflicting decision objectives in a structured manner (Nijkamp et al., 1990). Decisions are typically evaluated based upon long term prospects, level of uncertainty and risks. The MCDM process consists of defining objectives, choosing criteria for measuring objectives, specifying alternative decisions, transforming the criterion scales into measurable units by the same standard, allocating weights to criteria representing their relative significance, selecting and applying a mathematical algorithm for ranking alternatives and then choosing from set of alternative decisions (Ananda & Herath, 2009). Table 5 will now highlight the wide range of MCDM methods at the disposal of an automotive OEM for solving the CO_2 management decision problem in order to mitigate the commercial implications of CO_2 legislation.

Table 5: MCDM methods classification

MCDM methods classification			
Method	**School of thought**	**Merits**	**Limitations**
Analytic Hierarchy Process (AHP)	Full Aggregation	AHP has a prominent reputation for assigning weights to decision objectives which enables decision-makers to discern between objectives when making judgements (Ren et al., 2019)	The interdependence amongst criteria and decision alternatives can cause issues which can lead to discrepancies in the ranking of criteria and ultimately in decision-making judgment (Velasquez & Hester, 2013
Analytic Network Process (ANP)	Full Aggregation	ANP can handle the interrelationships between criteria thus allowing a more accurate ranking of criteria (Giannakis et al., 2020)	The priorities derived from the pairwise comparison matrices feeding into the weighted 'super matrix' and 'limit super matrix' involve subjective human judgements. Therefore, ANP is commonly supplemented with other methods to form hybrid decision methods (Chen et al., 2019)
ELECTRE	Outranking	ELECTRE is the best known and most widely used method for ranking problems due to the comprehensive ranking relationships produced by the method (Wen et al., 2016)	Although ELECTRE declares the decision-makers preferences, the method ignores the differences between decision alternatives in the process of determining the ranking order (Strantzali & Aravossis, 2016)
PROMETHEE	Outranking	PROMETHEE is easy to use, does not require criteria to be equally proportional and does not require normalisation hence overcoming the commensurability issue (Ishizaka & Nemery, 2011).	A limitation of PROMETHEE is that it lacks a clear system by which to assign weights (Macharis et al., 2004).

	Technique for the Order of Prioritisation by Similarity to Ideal Solution (TOPSIS)	Goal aspiration	TOPSIS involves a straightforward computation process, a weighing of decision criteria during the solution comparison procedure, whilst also enabling the best decision alternative for each decision criteria to be expressed in simple mathematical form, all, in a logical procedure for decision-makers' to easily follow (García-Cascales & Lamata, 2012)	1) TOPSIS is heavily dependent upon crisp values for assigning criteria weights however in most empirical decision problems, crisp values do not model decision problems accurately hence Fuzzy TOPSIS can be used in this case (Onu et al., 2017) 2) TOPSIS fails to acknowledge the relationships between decision criteria, consequently, decision-makers can encounter issues for weighing criteria consistently 3) TOPSIS suffers from the phenomenon of rank reversal subsequently violating the invariance principle of the utility theory (García-Cascales & Lamata, 2012)
	Evolutionary Algorithms	Goal aspiration	Evolutionary algorithms can solve complex optimisation problems and generate multiple Pareto optimal solutions in a single simulation considerably quicker than classical decision-making methods which have prohibitive execution times (Tomoiagă et al., 2013).	Mathematical problems which consist of a large number of design variables can be best solved by the Multi Objective Differential Evolution (MODE) algorithm with respect to convergence rate and running time. On the other hand, the MODE algorithm generates a smaller variety of solutions compared to the Multi-Objective Particle Swarm Optimisation (MOPSO) algorithm and the Non dominated Sorting Genetic Algorithm II (NSGAII) (Monsef et al., 2019)
	Quality Function Deployment (QFD)/ House of Quality (HOQ)	Product development	Applying QFD can reduce product design time and product costs whilst also increasing sale revenues (Carnevalli & Miguel, 2008)	Accurately interpreting the fuzzy desires of customers, modelling the relationships between the quality demanded by customers and the technical quality delivered by manufacturers is both a challenge and time consuming for decision-makers (Zhang et al., 2019)

	Goal Programming	Goal aspiration	GP presents decision-makers with helpful procedures such as the ability to relax decision constraints to better reflect the reality of decision problems (García-Martínez et al., 2019)	1) The 'satisfactory' solutions generated by GP are underpinned by Simons' theory of satisficing, hence GP can be criticised for the methods' failure to guarantee that Pareto optimal solutions are generated (García-Martínez et al., 2019) 2) GP is typically combined with other decision-making methods such as AHP due to the inability of GP to weigh coefficients
	Data Envelopment Analysis (DEA)	Nonparametric	1)The programming solvers embedded within the method facilitate the subjectivity issue associated with weight determination to be avoided by assigning efficiency scores to decision-making units (DMUs) instead (Liu et al., 2019) 2)The desirable and undesirable factors in decision-making can be differentiated well in comparison to multivariate analysis methods (Ai et al., 2019)	1)The trade-offs amongst multiple inputs as well as the desirable and undesirable outputs creates difficulty for decision-makers to capture and evaluate the empirical performance of systems (Xie et al., 2019) 2)The application of the method is more suited for production problems which have clear defined inputs and outputs (Wojcik et al., 2018)
	Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH)	Full Aggregation	MACBETH offers a simple and transparent approach for modelling complex, multidimensional problems and is extensively adopted for building value functions and to weigh criteria in additive models (Lopes et al., 2014)	Additive models are generally employed in MACBETH, however, additive models are criticised for violating conditional monotonicity (Lopes et al., 2014). Instead, non-additive measures such as interdependent elementary concerns (EC), also known as the decision-makers' 'point of view' can be used along with Choquet Integral (CI) operators, to be aggregated and create a key concern (KC).

	UTilités Additives (UTA)	Preference disaggregation - regression based	The methodological characteristics of UTA are favourable for decisions involving uncertainty due to methodological attributes such as estimating the additive utility value of decisions by ascertaining the decision-makers' global preferences, therefore UTA is commonly used for decision problems that involve ranking and sorting (Beuthe & Scanella, 2001)	The results generated by UTA can represent the decision-makers' preferences inaccurately by utilising the embedded piecewise linear marginal function value function within the method due to the methods' assumption that smoothness exists between first and second-order derivatives (Sobrie et al., 2018)
	UTADIS	Preference disaggregation - regression based	Instead of an additive model with piecewise linear marginal value functions, all non-decreasing marginal values are considered by UTADIS thus offering a more flexible preference model 2) UTADIS also offers a higher level of interaction with the decision-maker compared to variants of UTA methods (Greco et al., 2010)	The interactive process in UTADIS can be improved further to enable better support for the decision-maker and the practical usefulness of the method needs to be demonstrated by solving real world sorting decision problems (Greco et al., 2010)
	Rough Set Approach	Preference disaggregation	1) Extensions to method allow for inconsistent preference-ordered relations within decision criteria to be handled with via a) approximation by dominance relations and by incorporating b) analysis pairwise comparison table for choice and ranking problems 2) Preferential information is expressed comprehensibly via decision rule preference modelling (Greco et al., 2001)	Classical rough set theory approaches suffered from the issue of not detecting inconsistencies between criteria due to indiscernibility relations (Greco et al., 2001)

	Multi-attribute value theory (MAVT)	Full Aggregation	The method involves the relative global performance of every alternative is ranked opposed to ranking just the decision options hence enabling a transparent and structured decision making procedure. In addition, the method can compute a large number of alternatives with minimal impact on elicitation effort and without specialised software thus providing decision-makers with useful information (Ferretti, 2016)	The inherent process of eliciting the preferences of the decision-makers is restrictive which subsequently causes the method to inadequately represent preference information (Haag et al., 2019)
	Multi-attribute utility theory (MAUT)	Full Aggregation	MAUT usefully accounts for uncertainty (Scholten et al., 2015)	MAUT Demands strenuous efforts for decision-makers (Durbach & Stewart, 2012b) and the method necessitates precise preference information
	Simple Additive Weighting(SAW)	Goal Aspiration	The calculation procedure in SAW is intuitive and transparent, making the method popular and simple to use (Zionts & Wallenius, 1983)	The original method only employs crisp values which effectively disqualifies the method for solving decision problems involving imprecise values and uncertainty (Stević et al., 2017)
	Visekriteriijumska Optimizacija I kompromisno resenje (VIKOR)	Goal Aspiration	1) Useful for optimising multiple decision responses 2) ranking index accounts for group utility and minimal individual regret (Tian et al., 2019)	A significant methodological challenge has been handling imprecise information pertaining to decision values especially where criteria can not easily be expressed numerically (Xu et al., 2017). Fuzzy VIKOR method has been utilised to combat the challenge
	Value Analysis/Cost	Cost-Benefit	Value Analysis has been has been praised	Gathering and organising information is a frequently
	Management	Analysis	for the high degree of formalisation and found to increase product value whilst cutting product costs, importantly, without diminishing the value delivered to customers (Romano et al., 2010)	occurring issue in addition to the challenges of the potential counter-productiveness of group decision making and poorly organised data to the potential of the method producing effective results (Romano et al., 2010)

	Value engineering	Cost-Benefit Analysis/Cost Management	Value Engineering (VE) is systematic approach to attain desired functionality of products at a minimum cost by assigning a measurable 'value ratio'. VE seeks to ensure that the product achieves its basic function in a manner which satisfies the customer at an acceptable cost (Durga Prasad et al., 2014)	Despite the fact that achieving cost-effectiveness is significant for manufacturers, doing so at the early stage is rewarding but very difficult due to product concepts being formed when the major features and materials are determined at a later stage (Cho & Park, 2019)

Table 5 shows that there are two main schools of thought in MCDM (Wallenius et al., 2008); the American, full aggregation approach (Keeney & Raiffa, 1976) versus the French outranking approach (Roy, 1991). The full aggregation approach involves a score being evaluated for each criterion that is then synthesised into a global score whereby a criterion with a poor score can be compensated for by another criterion with a good score (Ishizaka & Nemery, 2013). Full aggregation methods include AHP (Saaty, 1987), ANP (Saaty, 1999), MAUT and MACBETH (Bana e Costa and Vansnick, 1994). In contrast, the outranking approach does not allow a poor score to be compensated for by a better score. PROMETHEE (Brans et al., 1986) and ELECTRE (Roy, 1991) are two methods built upon the outranking approach. Other major MCDA methods are based on goal aspiration that defines a goal for each criterion and then selects the nearest option to the ideal goal (Ishizaka & Nemery, 2013). TOPSIS (Hwang & Yoon, 1981), goal programming (Charnes et al., 1955) and data envelopment analysis (DEA) (Charnes et al., 1978) are examples of goal aspiration methods.

Over a dozen MCDM methods exist and various classifications exist for those respective methods as shown in Table 5. MCDM methods can primarily be classified according to the approach adopted by the method. For example, the value systems approach, the outranking relation approach, the disaggregation-aggregation approach or the multi-objective optimisation approach are the main four approaches adopted by MCDM methods (Siskos & Spyridakos, 1999). In addition to classifying methods according to their approaches, it is also possible to classify methods with respect to the differences between the types of decision problems that methods can solve. Decision problems normally involve either choosing, ranking, sorting or describing. Each method has its own merits, limitations and appropriateness depending on the nature of the decision problem to be solved. MCDM methods will now be discussed in further detail in section 3.5.

3.5 Full Aggregation Methods

- Analytic Hierarchy Process (AHP)

Analytic hierarchy process (AHP) is a multi-criteria decision-making method proposed by Saaty in 1980 which caters for both quantitative and qualitative data (Asabadi et al., 2019). Rather than the interval scale used conventionally by other decision-making methods, AHP uses a 1-9 ratio scale to compare preferences with a 1 out of 9 measure denoting least valued than the alternative; 1 denoting equally preferred to the alternative and 9 out of 9 denoting most important compared to alternative (Vaidya & Kumar, 2006). The AHP process involves the following steps:

1) Defining the problem

2) Developing a hierarchical structure

3) Constructing a pairwise comparison matrix

4) Performing judgment for pairwise comparisons

5) Synthesising pairwise comparisons

6) Checking for consistency

7) Developing an overall priority ranking

8) Selecting the best alternative (Velmurugan & Selvamuthukumar, 2012)

AHP is scalable to fit problems with a range of sizes and is not a data-intensive method; nevertheless the interdependence amongst criteria and decision alternatives can cause issues which can lead to discrepancies in the ranking of criteria and ultimately in decision-making judgment (Mahdiyar et al., 2020).

- Multi-Attribute Utility Theory (MAUT)

Keeney and Raiffa (1976) proposed multi-attribute utility theory (MAUT), a structured method that applies the utility concept to complicated decision problems that contain multiple attributes and multiple conflicting objectives (Sanayei et al., 2008). MAUT problems can be of two types. The first type is known as multiple criteria discrete alternative problems and involves choosing from a modestly sized set of alternatives or sorting between hundreds of alternatives (Zoupoundis & Doumpos, 2002). The second MAUT problem type is known as multiple criteria optimisation problems and contains a very large or even infinite number set of feasible alternatives. Alongside the differences in sizes of the feasible set of alternatives, multiple criteria discrete alternative and multiple criteria optimisation problems also differ in that discrete alternative problems tend to be modelled with uncertain values for criteria or alternatives. Utility or value functions are also accounted for differently in multiple criteria discrete and multiple criteria optimisation problems. The decision maker's utility is not captured mathematically in multiple criteria optimisation problems, instead the decision-maker is navigated towards their most preferred solution through an iterative and interactive process; whereas utility is in fact mathematically captured in multiple criteria discrete problems (Wallenius et al., 2008).

MAUT consists of the following five steps:

1. Defining alternatives and value relevant attributes
2. Evaluating each alternative separately on each attribute
3. Assigning relative weights to attributes
4. Aggregating weights of attributes and the single attribute evaluations of alternatives to obtain an overall evaluation of alternatives
5. Performing sensitivity analyses and making recommendations (Jansen, 2011)

MAUT usefully accounts for uncertainty (Scholten et al., 2015) and incorporates the decision maker's preferences (Durbach & Stewart, 2012). However, applying the method demands strenuous efforts on the decision-makers' part (Durbach & Stewart, 2012b) and necessitates the decision maker's preferences to be precise (Sarabando & Dias 2010).

3.5.1 Outranking methods

- PROMETHEE

PROMETHEE is an outranking method initially proposed by Brans in 1982 and developed further by Vincke & Brans in 1985 to solve MCDM problems (Brans & De Smet, 2016). PROMETHEE involves pairwise comparisons of alternatives with regards to each criterion, to obtain the ranking for all alternatives (Qi et al., 2019). PROMETHEE I consists of partial ranking whereas PROMETHEE II completely ranks a set of fixed alternatives from best to worst and PROMETHEE GAIA provides a visualisation of results (Talukder & Hipel, 2018). PROMETHEE II involves a stepwise procedure with the following five steps:

Step 1: Determine deviations based on pair-wise comparisons

Step 2: Apply the preference function

Step 3: Calculate overall or global preference index

Step 4: Calculate outranking flows also known as the PROMETHEE I partial ranking

Step 5: Calculate net outranking flow also known as the PROMETHEE II complete ranking

(Behzadian et al., 2010)

PROMETHEE is easy to use, does not require criteria to be equally proportional and does not require normalisation hence overcoming the commensurability issue (Ishizaka & Nemery, 2011). A limitation of PROMETHEE is that it lacks a clear system by which to assign weights (Macharis et al., 2004).

- ELECTRE

ELECTRE is a family of outranking decision-making methods initially proposed by Benayoun et al. (1966) and developed significantly throughout ELECTRE I (Roy, 1968), ELECTRE II (Roy and Bertier, 1971), ELECTRE III (Roy, 1978) ELECTRE IV (Roy & Hugonnard, 1982), ELECTRE TRI (Yu, 1992; Roy & Bouyssou, 1993) and ELECTRE IS (Roy & Bouyssou, 1993). ELECTRE I and IS methods can be used for choice problems to select from the smallest set of best alternatives (Kaya et al., 2019); whereas ELECTRE II, III and IV are used for ranking problems with the aim of ordering alternatives from best to worst. ELECTRE TRI, TRI-C and TRI-nC are used for sorting problems to allocate alternatives to a set of pre-defined categories.

ELECTRE methods collectively consist of two stages: an aggregation stage and an exploitation stage (Figueira et al., 2013). During the aggregation stage, pairwise comparisons of alternative actions against a given set of criteria are made; via numerous outranking relations, achieved by a Multiple Criteria Aggregation Procedure (MCAP). Outranking relations depend on the concepts of concordance and non-discordance (Govindan & Jepsen, 2016). Concordance requires the majority of criteria to be strictly in favour for an alternative in order for that alternative to be validly preferred over another. Once the concordance condition is satisfied, non-discordance requires none of the criteria in the remaining minority to oppose too strongly with the preferences made. The exploitation stage involves specific procedures to support various decision problems such as choosing from a restricted pool of the most appropriate actions by eliminating other actions, sorting those actions into categories from worst to best or ranking actions numerically from best to worst (Figueira et al., 2016).

Despite the fact that ELECTRE can handle both qualitative and quantitative data, and account for uncertainty and vagueness due to imperfect data, the underpinning outranking process can be burdensome, making the benefits and drawbacks of the various alternatives difficult to explicitly identify.

3.5.2 Goal aspiration methods

- Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The technique for order preference by similarity to ideal solution (TOPSIS) was proposed by Hwang & Yoon in 1981 and continues to be a versatile multi criteria decision-making method (Behzadian et al., 2012). The TOPSIS method involves the following steps:

1. Constructing a normalised decision matrix
2. Constructing a weighted normalised decision matrix
3. Determining positive ideal and negative ideal solutions from a finite set of alternatives
4. Calculating the separation measures for respective alternatives
5. Calculating the relative closeness of alternatives to the ideal solution

6. Selecting the alternative with the shortest distance from the ideal solution (Jahanshahloo et al., 2009)

Although TOPSIS is convenient for implementing in real life decision-making problems and follows a simple yet effective decision-making process, a major weakness of the method is the failure to acknowledge the relationships between decision criteria (Velasquez & Hester, 2013). As a result of the inter-relationships between criteria, decision-makers can encounter issues in weighing criteria consistently. Simple additive weighting is another commonly used decision-making method.

- ### Simple Additive Weighting (SAW)

Simple additive weighting (SAW) also known as weighted sum Model (SAW), is a simple method for solving MCDM problems proposed by Zionts & Wallenius (1983) and also by Kaliszewski and Podkopaev, (2016). The SAW method involves the following steps:

1. Determine the criteria that will be used as a reference in decision
2. Determine the suitability rating of each alternative for each criterion
3. Construct a decision matrix built upon the criteria
4. Normalise the matrix dependent on equations which will adjust attributes depending on whether attributes bring about gain (benefit) or a cost
5. Sum the multiplication of the normalised matrix with the weight vector in order to choose the largest value obtained as the best alternative (Haswan, 2019)

Even though SAW usefully permits criteria to be compensated, involves a simple calculation, and is implemented intuitively by decision-makers without the need for sophisticated software; yet still, the solutions generated by the method can be illogical hence misrepresent reality.

- ### Goal Programming (GP)

Goal programming (GP) is a commonly used MCDM method (Mardani et al., 2017), proposed by Charnes et al., (1955), and built upon on Herbert Simmons principle of satisficing (Tamiz et al., 1998). GP is an extension of linear programming (LP) and is designed to generate satisfactory solutions to problems with multiple conflicting goals, by assigning target values to a given set of goals (Jones et al., 2016). GP problems can be solved via lexicographic GP that integrates ordering and satisficing principles; weighted GP that combines optimising and satisficing principles; Chebyshev GP that unites satisficing and balancing principles (Broz et al., 2019); and extended GP that joins the respective principles together to form new frameworks (Jones & Romero, 2019). Lexicographic GP is applicable to decision problems where target goals can be clearly prioritised, whereas weighted GP is used for cross comparing objectives and Chebyshev GP is used to find a balance between competing objectives (Colapinto et al., 2017). Ultimately, GP involves setting a target value for each goal, listing target values along with their deviation variables, then weighing and adding together the undesirable deviations from the set of target values to create an achievement function (Huang et al., 2017).

GP can tolerate large problem sizes and yield infinite alternative solutions, however, the incapability of GP to weigh coefficients necessitates GP to be combined with another method for weighing coefficients.

- ### Evolutionary Algorithms (EA)

Evolutionary algorithms (EA) have become powerful decision support tools for decision-makers (Zhou et al., 2011) and are underpinned by a stochastic search mechanism, built upon the Darwinian principle of survival of the fittest (Elbeltagi et al., 2005). EAs generate solutions which mimic the natural process of evolution through reproduction (Elbeltagi et al., 2005). EAs are employed to generate a set of Pareto-optimal candidate solutions progressively. Trade-off information is provided by candidate solutions which are evaluated subject to the decision maker's preferences iteratively to refine goals and preferences (Qu et al., 2018).

The non-dominated sorting genetic algorithm (NSGA-II) is one of the first of such EAs and many other nature inspired algorithms have been developed to solve decision problems (Cortez, 2014). Although EAs can deal with large scale problems whilst generating near optimum solutions, a serious limitation of EA's is their long processing time for optimum solutions to evolve (Elbeltagi et al., 2005). To overcome the processing time issue, other EA algorithms such as memetic, particle swarm optimisation (PSO), ant colony and shuffled frog leaping algorithms have been proposed. Elbeltagi et al., (2005) found the PSO algorithm to perform best according to success rate in finding solutions, solution quality and ranked second best in with respect to processing time.

EAs can minimise the computation burden in finding multiple Pareto optimal solutions in just a single simulation compared to classical methods which involve prohibitive execution times (Tomoiagă et al., 2013). In spite of EAs generating solutions rapidly, EAs are criticised for not being able to detect changes occurring during the search process, thus failing to generate optimal solutions at all. EAs are also said to be ineffective in predictive approaches when data is non-linear or if changes in the dynamic environment are stochastic and consequently, the optimisation process can be slowed down by promoting diversity amongst solutions to prevent convergence (Nguyen et al., 2012).
With respect to MCDM methods, only two percent of the 183 publications reviewed utilised DEA whereas ELECTRE was utilised most frequently with a seven percent coverage. In comparison, Goal Programming, AHP or ANP, Genetic Algorithms, PROMETHEE and TOPSIS were utilised three percent each. Next, the existing approaches of decision-making methods sourced from the literature will be discussed.

4. Discussion

4.1 Existing approaches of MCDM methods to similar CO_2 management decision problems

The purpose of this study was to provide automotive OEMs with a decision support model to mitigate the commercial implications of CO_2 legislation. CO_2 management is becoming an increasingly important matter for global automotive OEMs. Employing an effective decision support model as response to the CO_2 management decision problem shows promise. CO_2 management decision problems involve a wide range of decision objectives, decision criteria and decision options. Factors may differ according to the priorities of the various automotive OEMs. Effectively identifying and combining the relevant factors is an important first step to optimise CO_2 management decisions. If automotive OEMs apply MCDM methods they can achieve Pareto optimal outcomes. Therefore automotive OEMs can mitigate the impact of CO_2 management costs and safeguard their profitability without sacrificing the requirements of customers, policymakers and business needs.

The methods, objectives and criteria utilised in previously conducted studies dedicated to measuring and controlling the costs of environmental impacts on businesses are shown in Table 7. Table 6 is an index table for Table 7. A range of decision-making methods have been applied across various industries, focusing on different stages of the product life cycle. Existing approaches from the literature have been tabulated and compared to contextualise the kind of decision-making methods that automotive OEMs could employ. Table 6 signifies the challenges that authors confronted in their approaches to solving CO_2 management decision problems in employing MCDM methods

Table 6: Challenges confronted by authors in the literature of existing approaches (utilising decision-making methods)

Challenges confronted by authors in the literature			
i	Determining optimal points where emission reduction measures become cost-prohibitive and negatively impact net profits causing businesses to incur losses should be explored	**v**	Methods such as multi-variate analysis which can handle complex, interrelated, non-linear data are required for modelling CO_2 problems
ii	Decision-making methods should enable parameters to be reconfigured to examine overall life cycle impacts	**vi**	Subjectivity involved in various stages of decision-making methods can cause inconsistent results to be generated
iii	Methods need to incorporate additional steps to generate more precise results	**vii**	Simulating objectives simultaneously whilst considering criteria holistically generates superior results
iv	Decision-making methods should be built upon stochastic models to tolerate uncertain data		

Table 7: Literature matrix of existing approaches

Reference	**Industry**	**Lifecycle stage focus**	**Method employed**	**Objectives**	**Criteria considered**	**Challenges confronted by authors in literature**						
						i	**ii**	**iii**	**iv**	**v**	**vi**	**vii**
(Matar & Elshurafa, 2017)	Cement production	Production	Multi Objective Optimisation	Maximise Profit Minimise CO_2 emissions	Investment cost of technology Electricity prices CO_2 tax prices	√						
(Mayyas, et al., 2012)	Automotive	ALL	Life Cycle Assessment	Estimate life cycle CO_2 emissions	CO_2 emissions per component produced Material type Mass Life cycle energy		√					
(Burke, et al., 2018)	Automotive	Use	Multivariate Analysis Partial Least Squares	Predict properties of product, determine which variables have greatest influence on output variables Reduce test to test variability	Vehicle chassis dynamometer recordings Vehicle power from torque and speed or voltage and current Humidity and temperature					√		
(Qiao, et al., 2017)	Automotive	Raw Materials, Production	Life Cycle Cost Analysis	Estimate life cycle CO_2 emissions	Production process fuel Material type CO_2 emissions per component produced			√				

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	ii	iii	iv	v	vi	vii
(Favi, et al., 2018)	Shipbuilding	Raw Materials, Production, Use, Recycling	Life Cycle Cost Analysis	Minimise lifecycle environmental impact Minimise lifecycle economic impact	Design configuration Fuel consumption Electricity consumption Recycling rate Operating costs				✓			
(Kumar, et al., 2014)	Automotive	Production	TOPSIS Entropy	Select Optimal Material Type	Surface hardness Core hardness Surface fatigue limit Bending fatigue limit Ultimate tensile strength Cost						✓	
(Tsai & Jhong, 2018)	Footwear manufacturing	Production	Activity Based Costing Mathematical Programming TOC	Maximise Profit Minimise Business Costs Minimise CO_2 tax	Product mix Direct labour Machine hours Batch level activity Product level activity					✓		

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	ii	iii	iv	v	vi	vii
(Igarashi, et al., 2016)	Recycling	Recycling	Multi Objective Optimisation	Minimise Total Recycling Cost Maximise Total Recycling Rate of Product Maximise total CO_2 saving rate of product	Total disassembly time Number of parts Recycling rate CO_2 saving rate Recycling cost Balance delay Smoothness index							✓
(Nadal-Roig, et al., 2018)	Animal husbandry	Transport	Multi Objective Optimisation	Maximise Profit Minimise CO_2 emissions	Batch size of pigs Cost per pig Selling price per pig Mean value of the live weight of pigs CO_2 emitted per kg of meat produced CO_2 emitted per trip of transporting pig by truck type Capacity of trucks Penalty per kg of CO_2 emitted	✓						

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	ii	iii	iv	v	vi	vii
(Tomoiagă, et al., 2013)	Power generation and distribution	Transport	Genetic Algorithms	Minimise Active Power Losses Minimise System Average Interruption Frequency Index	Total number of customers served Total number of customers supplied power from each load point (node) Total failure rate at the level at the level of the node Node Voltage limits Safeguard of power supplies for all customers						✓	

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	ii	iii	iv	v	vi	vi i
(Lee & Hashim, 2014)	Power generation and distribution	Production	Mathematical Programming	Minimise total costs with CO_2 emissions constraint	Type of fuel used in power plant Electricity power generation technology selected Capacity of boiler Total number of renewable energy (RE) power plants CO_2 emitted from various boilers using various fuels Fixed cost of boiler Operation time Price of fuel Price of RE sources CO_2 reduction target	✓						

(Müller, et al., 2018)	Aviation	Use	Mathematical Programming	Minimise the Net Present Value of periodic payments of investment	Optimal fleet size Optimal fleet composition Type of aircraft to operate in each period Quantity of new aircraft to be purchased in each period Quantity of aircraft to be sold in each period Quantity of aircraft to be retrofitted in each period Available budget Aircraft to be liquidated after maximum time of operation has been reached Flight operation plan (representing airlines using classes through assignment of aircraft subject to flight distances and number of seats) CO_2 emitted from flight operation							✓
(Yang, 2018)	Power generation	Production	Activity Based Costing	Maximise Profit	Lifecycle Carbon footprint costs							✓

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	ii	iii	iv	v	vi	vii
	and distribution		Mathematical Programming		Feed in tariff prices Carbon tax amount Unit costs of materials Activity based costs Total quantity of CO_2 emitted Total machine costs Total labour costs							
(Oh, et al., 2016)	Construction	Production	Mathematical Programming	Minimise CO_2 emissions	Material type Material weight Section width or diameter Section thickness Yield strength Diameter Compressive strength							✓

Reference	Industry	Lifecycle stage focus	Method employed	Objectives	Criteria considered	Challenges confronted by authors in literature						
						i	**ii**	**iii**	**iv**	**v**	**vi**	**vii**
(Xiao, et al., 2018)	Agriculture	Production, Transport	Economic Order Quantity Life Cycle Assessment	Maximise Profit	Selling price of grapes Market demand rate Replenishment costs Purchasing price CO_2 emission price Decay rate of product CO_2 emitted during transportation Energy consumed during refrigerating product	✓						

This study has highlighted that the respective factors for CO_2 management decisions requires careful consideration. However, this reality can be often underestimated when modelling CO_2 management decision problems. Balancing the commercial and environmental objectives has proven to be challenging for automotive OEMs as shown in section 3.2. However, it is possible to optimise CO_2 management decisions by simulating the empirical reality of the CO_2 management decision problem faithfully. This way the likelihood of achieving Pareto optimal outcomes can be increased. Maximising profits, minimising costs, minimising emissions, minimising lifecycle impact, selecting material type and maximising product recyclability have all been objectives for previous CO_2 management decisions as seen in Table 7.

The nature of the CO_2 management decision problem impacts whether automotive OEMs can optimise CO_2 management decisions. Automotive OEMs should be conscious that achieving the desired Pareto optimal outcome in a given CO_2 management scenario rests on how the scenario is translated during the application of the particular MCDM method employed. The interrelationships between data should be carefully analysed to capture the true reality of the CO_2 management decision problem. For example a 2000kg vehicle may have a tailpipe emission of 140g/km yet a 1600kg vehicle may have tailpipe emissions of 130g/km. The linearity between variables such as mass and emissions should not be assumed naturally when modelling the CO_2 management decision problem. Instead automotive OEMs should carefully explore and analyse the properties and values of the parameters that exist within the decision problems and their possible non-linear inter-relationships.

Automotive OEMs can simulate CO_2 management scenarios via MCDM methods to identify the optimal points where various decisions can create their desired effect and achieve Pareto optimal outcomes. In order for automotive OEMs to select between two conflicting decision options they should first assess the multiple criteria that are required to be evaluated. For example criteria such as market requirements and customer demand are significant alongside the potential financial costs associated with the various decision options as seen in section 3.3. By formulating a clear set of decision objectives, criteria and decision options, automotive OEMs can adopt a holistic view of CO_2 management decisions and thus prevent counter-productive decision.

Additionally, more decision-making methods designed for policymakers and customers were found in the study compared to approaches that were designed for automotive OEMs. Failing to prepare adequate decision support approaches tailored to manufacturers could mean that the future profits of automotive OEMs are overshadowed by CO_2 management costs. Table 3 highlighted the advantages and disadvantages of various CO_2 management decisions. Achieving Pareto optimal outcomes depends on automotive OEMs carefully analysing the cost-to-benefits associated with the various decision options. For example, it may be counterproductive to invest in CO_2 improvement technology in a particular scenario. Similarly, it may be cost prohibitive for automotive OEMs to pay a CO_2 tariff. On the other hand, making the vehicle sale and reconfiguring vehicle features could be the optimal decision in that scenario. MCDM methods can assist automotive OEMs significantly with preparing scenario-specific responses and determine the Pareto optimal CO_2 management decision in a given scenario.

Minimising CO_2 emissions is a common pursuit in global businesses across a range of industries; thus, decision-makers should integrate CO_2 emission costs alongside pursuing commercial objectives (Xiao et al., 2018). Estimates of CO_2 emissions will not suffice; hence decision-making methods need to precisely translate CO_2 cost estimates into optimal scenario-specific business decisions for automotive OEMs. Changing the decision maker's assumptions can also significantly impact the nature of scenarios and decision outcomes hence methods employed by decision-makers should allow for sensitivity analysis to be incorporated. Moreover, CO_2 emission problems typically rely on non-linear models which involve highly correlated data, where detecting the specific variables which cause variations in results can be challenging to differentiate (Burke et al., 2018). One way to overcome the complexity of correlated data is to break down the problem into smaller sub-problems to sequentially solve (Qiao et al., 2017). Mathematical programming and MOOP decision-making methods have been found to be the most commonly applied approaches in the literature and such methods enable the decision-makers to reconfigure parameters iteratively to examine overall cost implications of CO_2 legislation.

Even with data remaining constant and systematic algorithms being utilised in decision-making methods, different methods can generate dissimilar results, thus impacting decisions (Zamani-Sabzi et al., 2016). This is known as the decision-making paradox (Triantaphyllou & Mann, 1989). One criticism of decision-making methods is their failure to represent reality accurately (Kolios et al., 2016). The subjectivity of decision-makers at different stages in respective decision-making methods can be detrimental for reaching consistent decisions (Vinogradova, 2018). Subjectivity of decision-makers occurs during the criteria evaluation stage in AHP, the setting of preference thresholds and statistical functions stages in PROMETHEE and selecting distances from ideal solutions stage in TOPSIS. The subjectivity involved in all these various stages across decision-making methods causes unequal results to be generated by the respective decision-making methods.

This study has shown that automotive OEMs require a multi-objective optimisation (MOOP) decision support model, focused on the use stage of the vehicle life cycle, with precise objectives and tailored criteria to mitigate the impact of potential CO_2 tariff costs on the profits of automotive OEMs. Once the embedded CO_2 emissions costs associated with various decisions are captured, automotive OEMs can utilise a MOOP decision support model to prepare a CO_2 management decision strategy by iteratively simulating coordinated responses to emerging what-if scenarios. Through such a model, automotive OEMs can holistically examine how criteria such as vehicle fleet portfolio, customer demand, market tariffs and the financial costs associated with the options of responding to CO_2 legislation influences vehicle CO_2 performance and CO_2 tariff costs. Automotive OEMs can also evaluate the interrelated consequences of reconfiguring vehicle feature content to achieve vehicle mass reduction and CO_2 performance improvements on the profitability of automotive OEMs global vehicle sales. As a result, automotive OEMs can optimise decision-making by incorporating a set of quantified CO_2 performance parameters in order to achieve profit maximisation and CO_2 tariff cost minimisation.

Decision-makers evaluate a specific set of criteria to optimise multiple objectives for businesses. This study has shown how businesses can effectively control CO_2 emission costs whilst increasing profits by constructing models (Tsai & Jhong, 2018). Decision-makers can model scenarios to determine optimal points where emission reduction measures become cost-prohibitive and negatively impact net profits causing businesses to incur losses. To mitigate the impact of potential losses, Igarashi et al., (2016) integrated financial cost and reducing CO_2 emissions during product recycling however Nadal-Roig et al., (2018) found profits do not proportionally change in line with emission reduction. Pareto optimal outcomes can be achieved if approaches allow decision-makers to iteratively simulate objectives whilst considering criteria holistically and examining the relationships between criteria closely (Müller et al., 2018). Yang (2018) factored in CO_2 emissions costs associated with business activity by accounting for CO_2 taxes as part of modelling. Oh et al., (2016) similarly modelled scenarios which optimised building designs subject to the costs associated with CO_2 emissions. Quantifying the financial costs associated with CO_2 emissions via modelling, allows decision-makers to prepare responses to what-if scenarios which optimise commercial and environmental objectives.

Now, a decision support model designed for automotive OEMs as a response to the commercial implications of CO_2 legislation will be presented in Figure 3, followed by the conclusion. The model offers a manufacturers perspective to optimise decisions for CO_2 management.

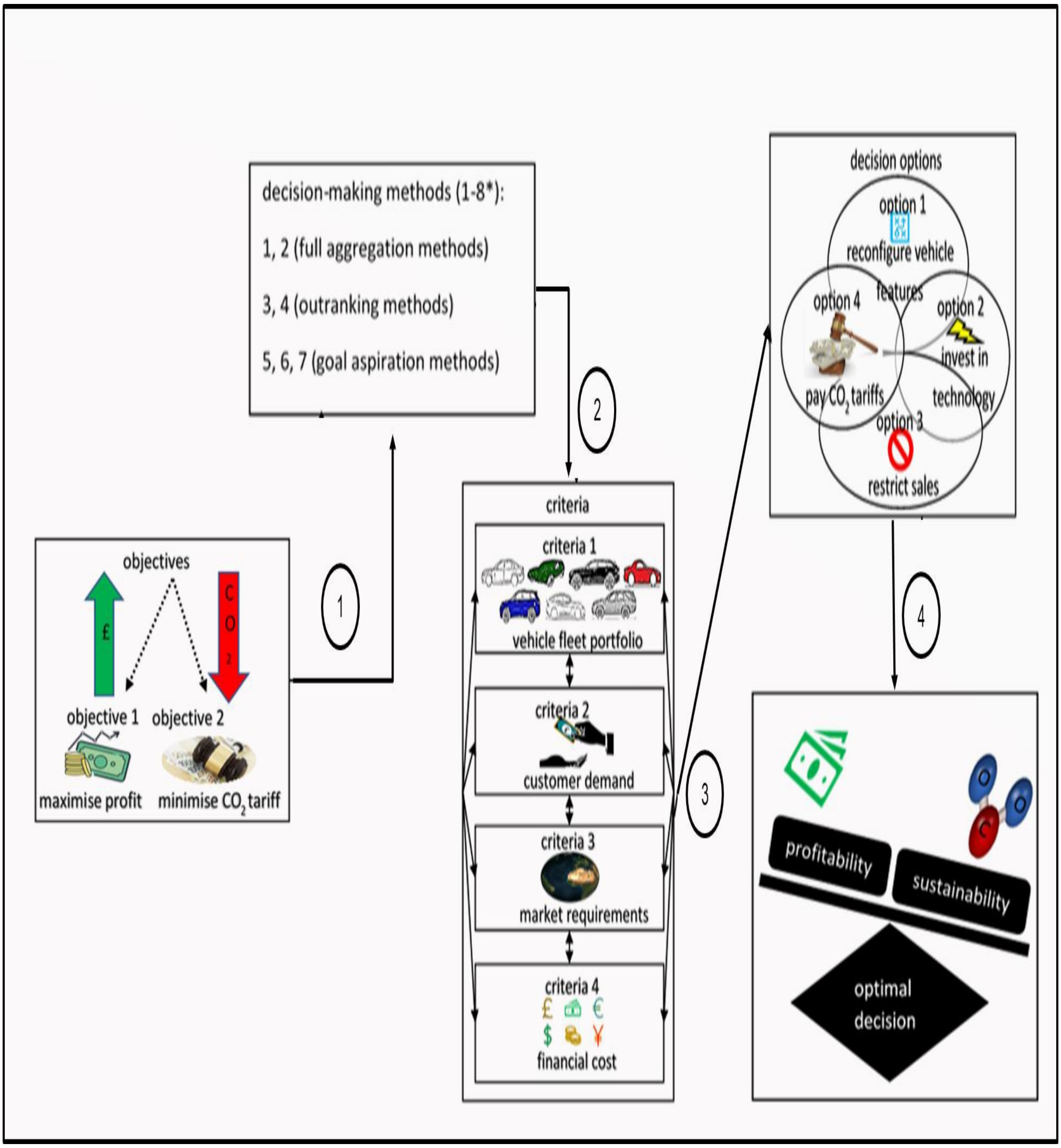

Figure 3: The proposed decision support model designed for automotive OEMs as a response to the commercial implications of CO_2 legislation

The proposed decision support model illustrated in Figure 3, was conceptualised by first assimilating the decision objectives, criteria and decision options adopted within existing approaches used to solve CO_2 management decision problems found in the literature. It is acknowledged that automotive OEMs have many other objectives to satisfy alongside maximising profits. Profits can be maximised by minimising costs in CO_2 management if automotive OEMs consider product material recyclability (Mayyas et al., 2012) to minimise product lifecycle emissions (Favi et al., 2018). Although automotive OEMs have many ways to maximise profits and minimise CO_2 emissions, the proposed model enables automotive OEMs to consider criteria such as their vehicle fleet portfolio, market requirements, customer demand and financial cost.

The decision support model considered four criteria to be evaluated by automotive OEMs for CO_2 management decisions. The key decision criteria for CO_2 management decisions focussing on the commercial implications of CO_2 legislation found in the literature were vehicle fleet portfolio (Autovista, 2019), customer demand (Sharif et al., 2019), market requirements (Ligterink et al., 2015) and financial cost (Ricardo, 2018) as seen in Table 4. However, existing approaches considered several other criteria such as investment cost in technology (Matar & Elshurafa, 2017), product material type, mass and the emissions per component produced as seen in Table 7.

Additionally, the other decision criteria considered in Section 3.4, included design configuration, fuel consumption and electricity consumption, product speed, voltage, external humidity and temperature during testing (Burke et al., 2018) plus the type of fuel used, fuel price and CO_2 reduction targets (Lee & Hashim, 2014). The possible explanation for the wide range of different criteria utilised in the literature, in comparison to the criteria adopted in the proposed decision support model, is likely due to the usage of the different terminology used across the industry to express the same criteria. For instance, investment cost fits in the financial cost criterion, whereas design configuration was covered by the vehicle fleet portfolio criterion and finally the CO_2 reduction targets were also considered within the decision support model under the market requirements criterion. Another possible explanation for the inclusion of decision criteria such as product material type and emissions per component produced, despite the proposed decision support model excluded such criteria is that, every decision problem is unique and should thus be treated accordingly. Naturally, the preferences of decision-makers vary, and so do the decision criteria to be evaluated subject to the nature of the decision problem to be solved.

Indeed, there are also ethical considerations that automotive OEMs should be aware of. Although the decision support model recognised this partially via the market requirements criterion, the decision support model did not directly facilitate ethical objectives to be fully satisfied. Safeguarding brand image was deemed important for automotive OEMs in the literature (Bampatsou & Zervas, 2011). However, the scope of this study was to mitigate the commercial implications of CO_2 legislation, and therefore the decision objectives were to maximise profits for automotive OEMs and minimise CO_2 management costs. The optimal set of decision objectives, decision criteria and decision options were formulated and found to be essential to optimising CO_2 management decisions. This study will now be concluded.

5. Conclusions

CO_2 management decision making for automotive OEMs was studied in this paper. In the process, MCDM methods were reviewed for their suitability to provide decision support in solving the CO_2 management decision problem facing automotive OEMs. Below, the main findings are listed.

- Based on the selection criteria (see section 2), 183 publications were found, whereof 144 are peer-reviewed journal articles and 40 are other types of publications
- Thirty-three percent of the publications focussed on the financial costs associated with CO_2 legislation with a further fifteen percent concentrating on the technological costs of CO_2 improvement during product development
- European CO_2 legislation was the predominant policy utilised to model CO_2 management costs in the publications found, followed by Chinese policy with American policy the least common
- The number of publications in CO_2 management decision making has increased especially during the last decade (2010-2020), with a significant rise in 2017 particularly for the automotive industry during the advent of WLTP
- With respect to MCDM methods, only two percent of the publications utilised DEA whereas ELECTRE (seven percent) compared to Goal Programming, AHP or ANP, Genetic Algorithms, PROMETHEE and TOPSIS were utilised three percent each
- A plethora of customised models, tools, methods and frameworks have been developed to specifically assist with CO_2 management decisions

The conceptual decision support model proposed in this paper enables automotive OEMs to proactively model CO_2 management scenarios to mitigate the commercial implications of CO_2 legislation. Financial cost is a key criterion considered by decision-makers when selecting decision options in response to stricter global CO_2 emissions legislation as shown in Section 3.3. While some approaches consider financial cost, alongside other criteria such as market requirements (Tsokolis et al., 2016), or optimising the vehicle fleet portfolio (Shiau et al., 2010) or even customer demand (Hoffenson and Söderberg, 2015), other approaches consider multiple criteria simultaneously as shown in section 3.4 (Michalek et al., 2006; Frischknecht and Papalambros, 2008 and Maddulapalli et al., 2012). The interrelationships between decision criteria can significantly impact the solutions generated by MCDM methods, especially if the criteria have non-linear inter-relationships. New decision-making approaches should therefore capture the significance of the non-linear interrelationships between decision criteria as illustrated in section 4.1. This way, the empirical reality facing automotive OEMs can be modelled more faithfully, thereby avoiding irrational solutions which mislead decision-makers to be generated. The subjectivity involved in various stages of decision making methods can also cause inconsistent results to be generated by MCDM methods (Kumar et al., 2014). For this reason, simulating objectives simultaneously whilst considering criteria holistically can generate superior results when solving CO_2 management decision problems as shown in Table 7.

The various MCDM methods used within existing decision support approaches had differences in their underlying theoretical perspectives as shown in section 3.5. The theoretical differences associated with MCDM methods impacted both the functional performance of each method and also the results generated by the respective methods. For instance, the methodological characteristics of the Goal Programming (GP) method are favourable for practical decisions due to the ability to relax constraints in empirical decision problems (García-Martínez et al., 2019). On the other hand, as GP is underpinned by Simons' theory of satisficing, the method can fail to produce Pareto optimal solutions. Oppositely, evolutionary algorithms such as NSGA-II perform trade-offs to produce multiple Pareto optimal solutions considerably quicker than classical decision-making methods (Tomoiagă et al., 2013) as shown in section 3.5.1.

This paper has demonstrated that automotive OEMs are increasingly concerned with the costs associated with the various decision options and criteria which can mitigate the commercial implications of CO_2 legislation. Automotive OEMs are carefully considering their decision options and evaluating decision criteria to make Pareto optimal decisions in order to achieve multiple business objectives. MCDM methods can be utilised by automotive OEMs to reconcile between interrelated decision criteria to make Pareto optimal decisions. In contrast to the binary options provided by some MCDM methods theoretically, decisions are not mutually exclusive in reality as demonstrated in section 4.1. Automotive OEMs can decide to make multiple CO_2 management decision options in parallel, subject to the scenario they are confronted with and classical decision-making methods can fail to model this reality as well.

CO_2 management decision problems are commonly solved with non-interactive and subjective methods, however, this paper has shown the inadequacies of classical MCDM methods for solving the automotive OEMs CO_2 management decision problem in Table 4. The findings of this paper suggest that interactive and objective decision making approaches such as MOOP can more precisely quantify, the commercial implications of the stricter global CO_2 emission legislation now imposed on automotive OEMs. New decision-making approaches should therefore be more data-driven, more objective and rely less on the subjectivity of the decision-maker in order to make optimal decisions in a given scenario. This way, automotive OEMs can formulate a set of coordinated decisions in a structured manner to achieve Pareto-optimal outcomes.

Automotive OEMs should not underestimate the financial impact of the commercial implications of CO_2 legislation on their future profits. The proposed decision support model allows automotive OEMs to adopt a pre-emptive response which proportionally mitigates the commercial implications of CO_2 legislation. Automotive OEMs can make optimal decisions by carefully modelling the relevant decision criteria and decision options to proactively confront the CO_2 management decision problem. By adopting such an approach, automotive OEMs can model the costs associated with CO_2 and importantly make informed trade-offs between the conflicting objectives of maximising profits and minimising environmental impact. Future work will validate the practical usefulness of the decision support model proposed in this paper. A series of semi-structured interviews, a set of computer-based experiments and questionnaires with participants as well as a case study with a global automotive OEM are all planned to build on this paper.

Acknowledgements

The authors gratefully acknowledge the support of Jaguar Land Rover Ltd. In particular, the authors would like to thank Mr Alan Fennelly, Mr Tim Brogan, Mr James Joyce, Mr James Gaade and Prof Chris Brace for their continued support.

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