Using Decision Support Systems to Quantify the Costs associated with CO_2 Management - Position Paper

(Based on Presentation at ACostE's EMC meeting on 30/01/2020)

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Abstract

With global CO_2 legislation becoming increasingly stringent, businesses from various industries are incorporating the costs associated with CO_2 emissions into their decision-making. Balancing commercial and environmental objectives is challenging and thus requires a structured approach in order to accurately quantify the impacts of CO_2 legislation on the business financial margin. Using Decision Support Systems (DSS) are one the many ways of dealing with the CO_2 management decision problem. The results in this paper show that using DSS could be an effective approach to mitigate the commercial implications of CO_2 legislation.

Introduction

Cost engineers were challenged to respond to the changing landscape of modern trading by the work of Mills, (2014). Modern trading involves a wide range of risks which can be mitigated early by employing a data-driven approach (Mills, 2019). One such business risk that is constraining global businesses is the CO_2 emitted when producing, trading, transporting and recycling products (Cheung et al., 2015). Optimising CO_2 management decisions will be the focus of this paper. Although the impact of CO_2 can be traced from the point of extracting virgin materials out of the earth and across the entire supply chain right till the point of use by the end consumer, quantifying the costs associated with CO_2 management requires a systematic and proactive approach to enable informed decisions.

Although Figure 1 illustrates the development of cost engineering, Shermon (2020) stated the key challenges for cost engineers in the future are generating cost models more quickly to tolerate big-data via artificial intelligence (AI) and machine learning methods, while visually representing model outputs graphically in addition to offering a macro and a more detailed micro view all whilst importantly avoiding biased cost estimates due to subjectivity. Cost estimators have benefitted from the contributions of Da Vinci's concept of cost estimating relationships (CERs), Brunels' multi-CER series model for conducting cost-to-benefit assessments and Freimans' pioneering commercial parametric modelling system (Apgar, 2019). Isambard Kingdom Brunel believed that anything manufactured could be expressed in monetary metrics per unit of mass or size (Apgar, 2019). This paper will argue that businesses, irrespective of their industry, can express the costs associated with CO_2 management in order to mitigate the commercial implications of CO_2 legislation.

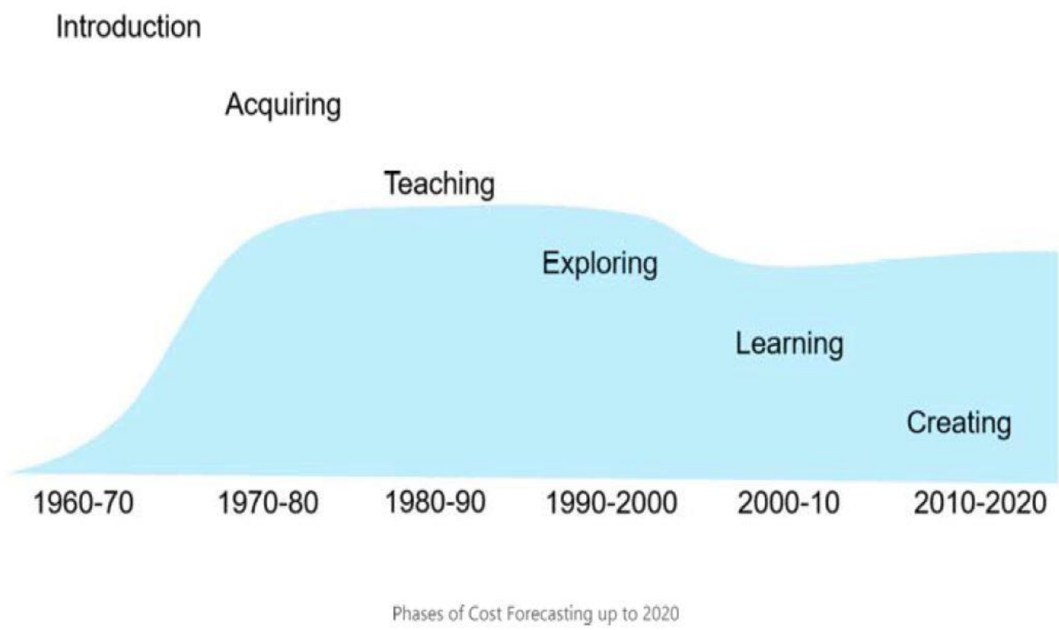

Figure 1: Phases of Cost Forecasting (Shermon, 2020)

The first section of this paper will provide some literature on the commercial implications of global CO_2 legislation across industry and then specifically the automotive industry. Secondly the potential systems, tools and techniques for optimising CO_2 management decisions will be discussed. Finally, the results of a survey conducted at the January 2020 Association of Cost Engineers (ACostE) meeting held at Bentley Motors in Crewe, UK, will be presented. The survey allowed attendees to be polled about the usefulness of employing a decision support framework for CO_2 management. Now the literature review section will follow.

Literature Review

There have been various systems designed to optimise an array of business objectives. For example Turner et al, (2019) focussed on systems for intelligent machines within factories, Newnes et al, (2015) developed a data-driven modelling approach to achieve process efficiencies in the aerospace industry, whereas Roy et al, (2011) developed a cost estimating process for the conceptual design phase in the automotive industry. A general purpose that the increasingly sophisticated systems being developed seek to address is how businesses can manage uncertainty. A great source of uncertainty for global manufacturers is global emission legislation. Designing dynamic systems for solving real-life business problems is challenging because of the embedded uncertainty and also the interrelated variables involved in the complex decision problems businesses face. Systems should therefore be built with stochastic models to reflect the uncertainty within the business reality in order to precisely model Pareto optimal points. Optimising decisions for CO_2 management can allow businesses to avoid cost-prohibitive decisions and optimise multiple business objectives.

A commercial implication that businesses are planning for currently is the European Commissions' Carbon Border Tax adjustment (CBTA). The CBTA is a tariff levied for importing products with embedded carbon emissions into the EU. Although simulating the potential what-if scenarios around CO_2 involves factoring in uncertainty, quantifying the costs associated with CO_2 can be beneficial for assessing the cost-to-benefits associated with CO_2 management decisions, particularly for steel, cement, aluminium and copper intensive industries (CRU, 2019). Businesses can proactively simulate the potential commercial implications of CO_2 legislation. However, modelling CO_2 management problems requires carefully mapping and breaking down the inter-relationships and co-dependencies that exist between variables such as products, features, parts and the respective materials of those parts.

Modelling the data flows of the variables that create CO_2 impacts more granularly will therefore be required in order to accurately translate the costs associated with CO_2 management. The data pertaining to the features and parts fitted to vehicles historically, can be used to predict the future characteristics of vehicles to be sold. Therefore, a cost estimate that predicts what may occur can be generated as also seen in inferential statistics hence why there is a strong correlation between the subject matter of cost engineering and statistics (Jones, 2018). In this paper the specific data being referred to is historical vehicle parts and features sold to customers internationally by carmakers. Vehicle features contribute to vehicle mass which impact vehicle emissions (Galindo et al., 2017). This paper focuses on modelling the mass of vehicle features to predict vehicle emissions to then generate a quantifiable CO_2 management cost estimate. This CO_2 cost estimate can then be used by carmakers to optimise CO_2 management decisions by assessing the marginal costs versus the marginal benefits associated with each respective CO_2 management decision.

Modelling vehicle emissions and CO_2 management costs at Fleet level

For a global carmaker that sells vehicle fleets in more than 170 markets as shown in Figure 2, it is necessary to model the commercial implications of CO_2 legislation at fleet level. Although policymakers set emission targets for vehicle fleets and do not account for individual vehicle emissions, there is now a need to also understand the emission performance at an individual vehicle and feature level due to the new emission testing procedure in the automotive industry known as WLTP (JATO, 2017).

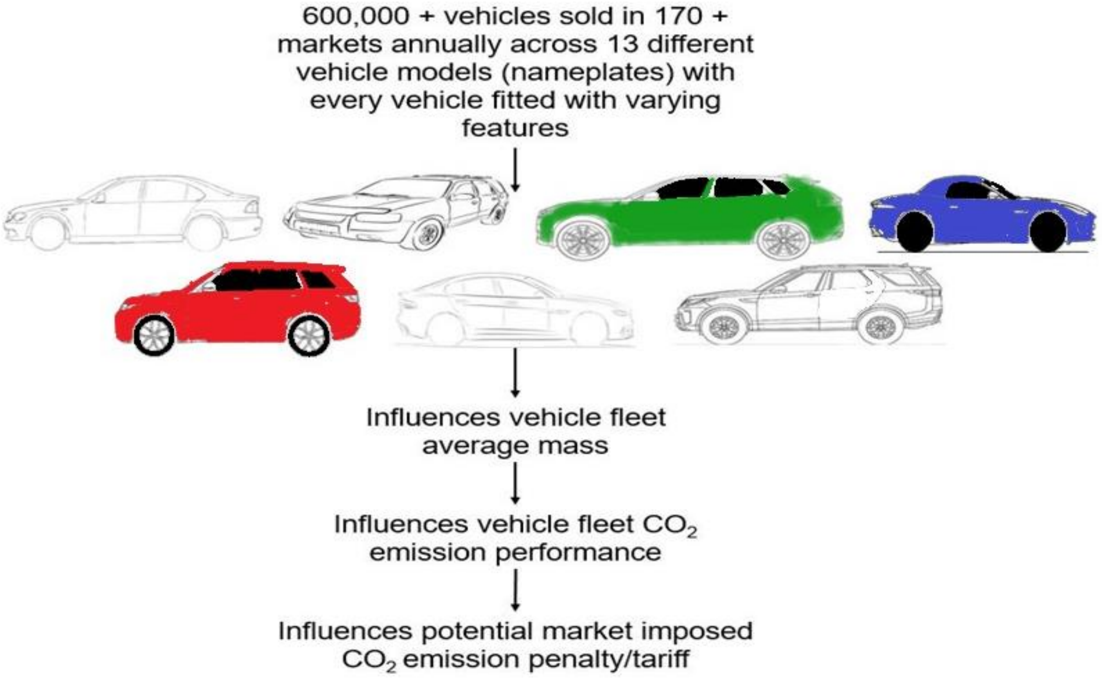

Figure 2: Modelling vehicle mass-->Vehicle Emissions --> Vehicle CO_2 management cost

Modelling vehicle emissions and CO_2 management costs at Feature level

There are approximately 2300 parts and 280 features fitted to a typical Jaguar Land Rover (JLR) vehicle also represented by a unique Vehicle Identification Number (VIN), each VIN can be configured in ≈ 350 different ways (using feature families). The parts can be classified according to their key centres of competence. Namely, the functional groups responsible for vehicle parts are: 1) Powertrain, 2) Electrical, 3) Chassis, 4) Body Interior and 5) Body Exterior. These vehicle parts combine to form vehicle features as shown in Figure 3 and conveys some of the optional vehicle features that could be reconfigured in simulations. The vehicle features can have a Boolean relationship (thus are interdependent). The vehicle features can be classified into i) standard vehicle features and ii) optional features iii) linked features e.g. part of a pack. These features have an associated mass.

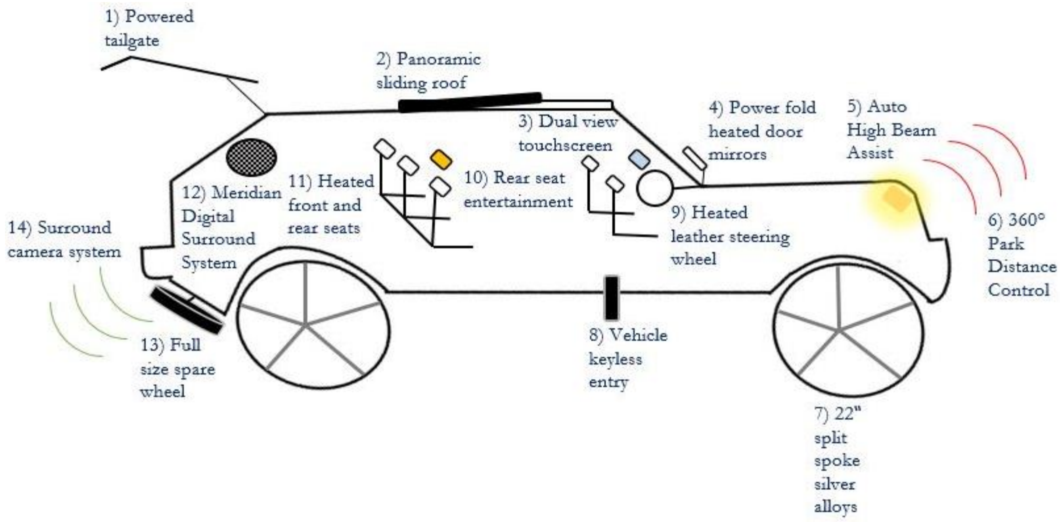

Figure 3: Modelling marginal vehicle feature mass-->Marginal vehicle Emissions--->Model CO_2 management cost

Reconfiguring vehicle features is only one of many of the possible CO_2 management strategies that carmakers could employ. Alongside vehicle feature reconfigurations PwC , (2007) produced a mind map of some of the other CO_2 management strategies available including: alternative fuel technologies, electrification technologies, internal combustion technologies and transmission technologies. Each measure has an associated benefit and a corresponding cost. Naturally carmakers aspire to pursue measures which offer the greatest marginal benefit at the least cost in line with the theory of Pareto optimality. Carmakers seek a decision making method that can enable them to optimise CO_2 management decisions. Table 1 clusters the different types of decision tools with their corresponding typical applications and limitations.

Table 1: Types of Decision Tools used for solving decision problems (Gurobi, 2018)

Decision type	Tools	Limitations	Application
Descriptive	• Data aggregation • Data mining	• Based upon historical data • Limited ability to guide decisions	• Business intelligence reporting
Predictive	• Statistical models • Simulation models	• Guessing the future? • More useful for low complexity decisions	• Estimating the output of potential what if scenarios based on a set of inputs

Prescriptive	• Optimisation models • Heuristics	• Decision maker does not always have control over variables being modelled	• Important, complex or time sensitive decisions

The proposed decision support framework relied on prescriptive decision making tools, systems and methods because the highest competitive advantage and the highest degree of business intelligence possible can be extracted from optimisation approaches as shown in Figure 4. Descriptive methods tell you what has happened historically, predictive methods merely tell you what is likely to happen in the future but prescriptive methods tell you what you should do. At this point is appropriate to make the distinction between Business Intelligence (BI) and Business Analytics. Business analytics can be defined as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport & Harris).

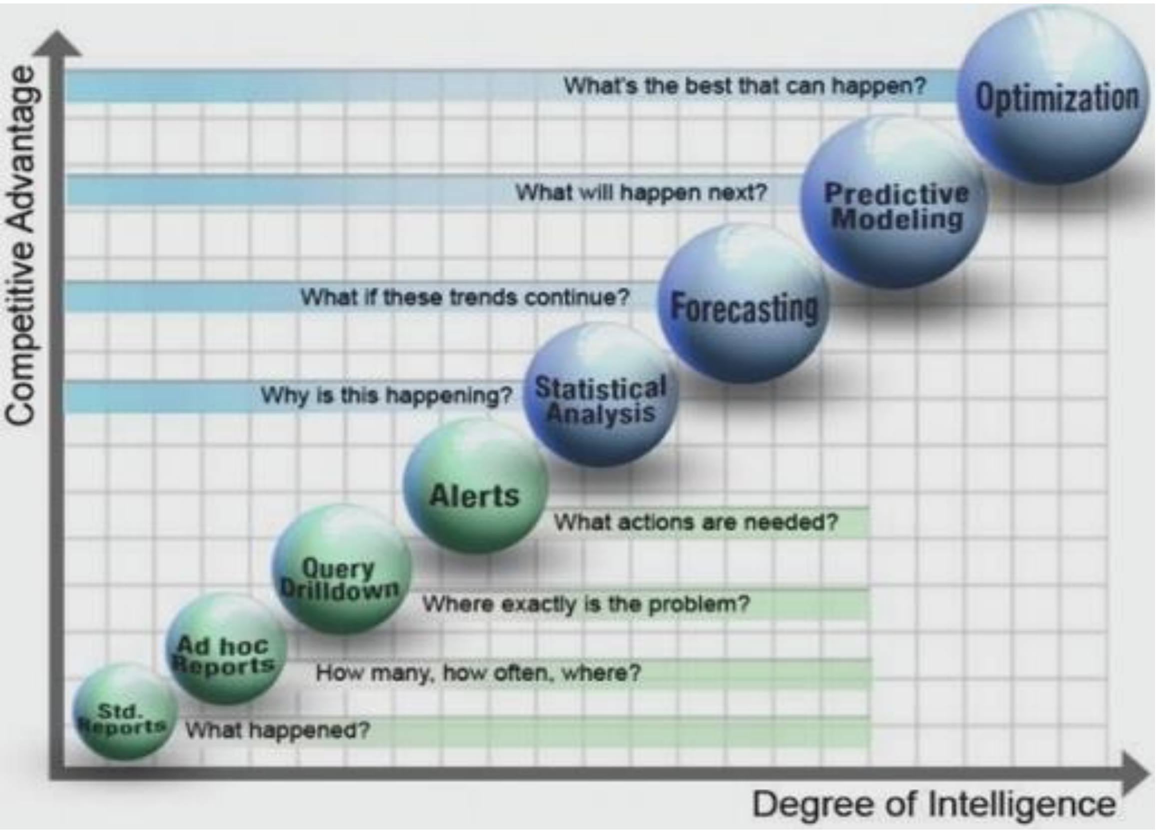

Figure 4: Producing tools, methods and techniques with the highest level of analytics capability is the most complex but also the most powerful - Optimisation methods (SAS, 2012)

The decision support framework designed for carmakers to manage the commercial implications of CO_2 legislation was demonstrated at the ACostE January 2020 meeting that took place in Bentley Motors, Crewe. The decision support framework was designed over the course of the PhD research and JLR was used as a case study. Feedback from respondents was captured via an interactive poll. The results of the poll will now follow.

Results from the Survey at the ACostE – EMC, January 2020 meeting

Thirteen respondents took part in a survey about the proposed decision support framework designed to mitigate the commercial implications of CO_2 legislation. The respondents were from industries such as Automotive, Defence, Aviation and Infrastructure. The key results from the survey have been compiled into four graphs and are illustrated in Figure 5. Some respondents did not respond fully hence there are discrepancies in the number of responses across the poll however a positive trend can be noticed with regards to the attendees perception on the requirement for businesses to mitigate the commercial implications of CO_2 legislation

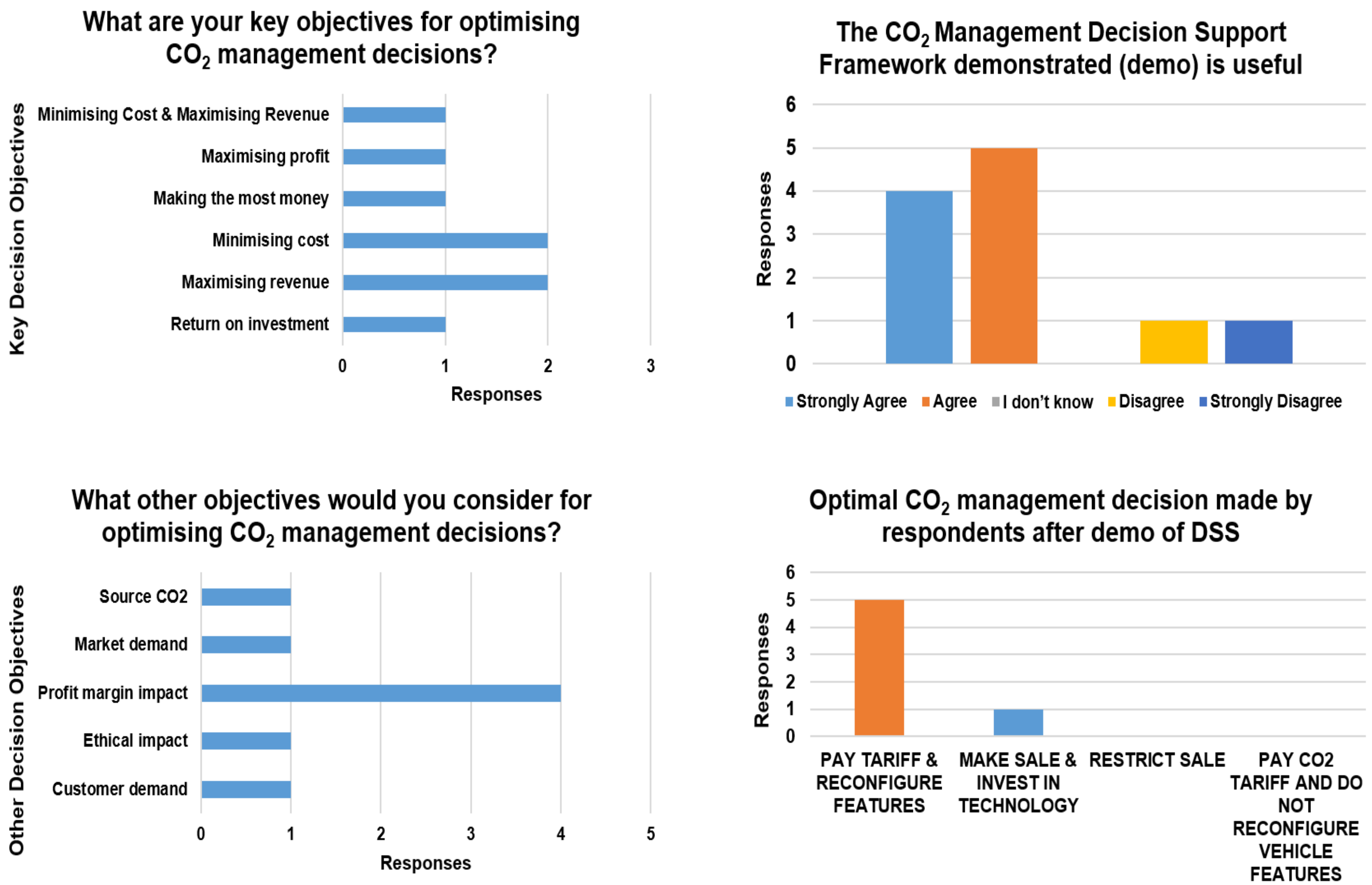

Figure 5: Results from survey at ACostE - January 2020 Meeting

The results of the survey suggest that 70% of the respondents felt that the main usefulness the decision support framework was that it was a proactive, data-driven approach and that it modelled the non-linear and interrelated decision criteria. Besides the impact of CO_2 management costs on business profits, respondents were also interested in modelling objectives such as ethical impact of CO_2 and customer demand. 82% of respondents strongly agreed or agreed that the demonstrated CO_2 management decision support framework for CO_2 management was useful. The mechanics behind the decision support framework will be published at the ACostE 2020 Summer Conference. Attendees will see the results of simulating the commercial implications of CO_2 legislation using multi-objective optimisation (MOOP) decision making methods.

Conclusion

In future research the decision support framework will be tested by participants. Participants who have experience in using decision support systems, tools and techniques will be sent an invitation to participate in completing a computer based experiment and questionnaire after the experiment. The results of the experiments and questionnaires will be published in an academic peer reviewed international journal.

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