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Integrating Actor Interactions into Multi-Criteria Decision Analysis for Electric Vehicle Adoption in Germany

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ABSTRACT

A successful transition to more sustainable structures, e.g., in the energy or mobility sector, requires understanding the preferences of those who might be affected by the transition, whether positively or negatively. Multi-Criteria Decision Analysis (MCDA) is a prominent approach for assessing these preferences. We propose a method for Multi-Actor Multi-Criteria Decision Analysis that endogenously incorporates interactions between different actors using impact matrices, which reflect the feedback of rankings, a) on the characteristics of options, or b) on the weightings of criteria by actors. Using the example of demand and supply of private cars in Germany, we demonstrate that this assessment of feedback loops can have significant impact on preferences compared to single-actor MCDA and that it leads to an improved understanding of how actors influence each other. Our method systematically integrates key elements of interaction between actors into MCDA-based decision analyses without significantly increasing complexity, thereby maintaining practical applicability and interpretability compared to standard single-actor MCDA approaches.

Introduction

As pointed out by IPCC [1] and many other studies (see e.g., [2,3]), a fully successful and sustainable decarbonization of energy systems requires considering actors' attitudes towards options for actions. Multi-Criteria Decision Analysis (MCDA) is one of the most prominent approaches to identify preferred choices by ranking available options based on values of the options specific to selected criteria, the so-called characteristics, combined with the importance of the criteria from the actors' point of view. The power of MCDA in identifying preferred options for actions has been demonstrated in manifold studies (see e.g., [4–6]). Standard MCDA shows some limitations, however, when focusing on options that require the support of multiple actors [7]. Hence, approaches for Multi-Actor Multi-Criteria decision analysis (MAMCDA) have been developed. They aim at supporting the identification of the distribution of the actors' rankings of options. Further, these approaches provide information on possible discrepancies between preferred options [8]. However, MAMCDA approaches that endogenously model interlinkages among actors' decisions are currently lacking [8]. Instead, MCDAs are conducted separately for individual actors, and the resulting outcomes are subsequently used to support discussion or consensus-building processes [8,9], rather than explicitly modeling the interdependencies between actors' decisions.

In principle, current MAMCDA approaches focus on identifying options supported by all actors or on identifying discrepancies between actors and not on considering feedback of rankings on characteristics of options. The impact on attitudes is mainly included by conducting dialogue processes after assessing individual actors' attitudes separately via MCDA [8].

In the tradition of group decision-making approaches [10,11], feedback loops are partially implemented for MAMCDA, whereby information from actor-specific MCDAs is fed back to the actors, giving them the opportunity to reconsider their opinions [8]. In doing so, MAMCDA supports participatory processes and aims to support decisions on complex problems. However, while participatory processes are helpful for consensus building, they can be very costly [12]. In contrast to these approaches, our aim is not in consensual decision-making but in analyzing decisions based on MCDA that have

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been made with the involvement of several actors.

Among the most prominent approaches that explicitly consider feedback between specific factors are System Dynamics (SD) and Agent-Based Models (ABM). System Dynamics approaches focus on quantitative modeling feedback loops between elements on an aggregated level, aiming to improve understanding of the fundamentals of systems [13,14]. Special attention is paid to dynamic processes such as changes in stocks combined with flows [15,16]. Hence, SD approaches enable to identify tipping points with respect to selected factors (e.g., resource extraction) [17]. In principle, SD approaches are user-oriented, meaning that special attention is paid to visualizing developments of flows and stocks to support communication and learning processes. ABMs focus on modeling interactions of individual actors or groups of actors, taking their specific characteristics (incl. interests in and possibility for actions) into consideration [18]. They aim to assess adaptive behavior and emergent phenomena. Accordingly, they have been used, for instance, for assessing transformation processes [19], including transformation of the mobility sector [20], or flexibility options in the power sector [21]. In contrast to MAMCDA and SD, ABMs are usually less accessible to users. They provide no direct means of efficiently describing and explaining the highly complex emergent phenomena they may produce, instead largely leaving this task to the user, which makes ABM results sometimes hard to interpret. Furthermore, emergence may complicate setup, calibration, and validation of ABMs, which can impede their use in empirical applications. Moreover, compared to MAMCDA, ABMs and SD typically exhibit higher levels of abstraction with respect to broad ranges of actors' attitudes and are therefore less focused on empirical application cases.

The trade-off between modeling feedback mechanisms and maintaining a strong focus on empirical applications has previously been addressed by combining MCDA and ABM [22,23]. Beyond SD and ABM, several other approaches explicitly consider interlinkages between actors, including methods from behavioral economics (see e.g., [24]) and social sciences (e.g., cross-impact balances [25,26]). These approaches usually share key elements with SD and ABM. Consequently, SD and ABM provide useful reference points for assessing and situating MAMCDA. As a result, a gap remains between empirically grounded, actor-specific decision support and the explicit modeling of inter-actor feedback. This study closes that gap by embedding both within a unified MAMCDA framework.

In this study, we show how key elements of direct and indirect interlinkages between actors can be endogenously incorporated into an MAMCDA framework without significantly increasing complexity compared to standard single-actor MCDA, thereby fully maintaining practical applicability and interpretability of MCDA. We present a method for considering the impacts of actors' actions on a) the characteristics of options and b) directly on the attitudes of other actors. Accordingly, our approach enables, for instance, the consideration of spillovers resulting from other actors' learning effects and social norms. Hence, it allows for assessing indirect impacts on the ranking of options by other actors within a single modeling framework. Our method extends existing MAMCDA approaches, with the aim of broadening the portfolio of MCDA applications [6,27,28].

We demonstrate our approach using the German automotive sector as an example. In particular, we examine the interest of various actor groups in battery-electric vehicles, assuming that the actor groups can choose between different vehicle types. A special focus is on analyzing the effects of selected actors' actions on vehicle characteristics (e.g., costs or market shares), social interactions, or changes in social norms (see, e.g., [29,30]). Our approach continues work established by [4] as well as work on applied MAMCDA, e.g., by Macharis et al [31,32] and Hamadneh et al [33].

Our work is organized as follows: Section 2 outlines our method, and Section 3 focuses on implementation and application of the approach. We present results in Section 4 and conclude in Section 5.

Method

We extend state-of-the-art MAMCDA approaches by explicitly addressing linkages between actors, their ranking of options, and the characteristics of these options in an integrated way. We incorporate different kinds of indirect interactions, including impacts of actors' preferences on the characteristics of options (e.g., on cost or prices) and impacts on other actors' weightings of characteristics and thereby their preferences (e.g., resulting from emerging or changing social norms, see e.g., [24]). To do this, we perform an MCDA and subsequently modify its input data based on its prior results. In addition, an early termination criterion (maximum of 100 iterations) is included because equilibrium cannot always be guaranteed, given the possibility of cyclic behavior. The overall procedure is illustrated in Fig. 1.

Fig. 2 illustrates our interlinking approach focusing on the feedback loops. Arrows ① and ③ show the feedback resulting from preferring an option by actor z_1 on characteristics of option 1. Arrow ② reflects impacts of preferences on the importance of criterion 3 from actor z_2's point of view, expressed in MCDA by the corresponding weighting w_3. We include changes in weightings, which we assume also changes preferences of actors. This approach is based on the empirical observation of reactions of actors on, e.g., policy measures, technological changes, and societal interactions. However, if measures alter the characteristics of an option, the preference structure remains unchanged, although the modified characteristics may cause the relevant actors to rank the options differently.

MCDA: Basics and models

In many applications, MCDA is employed to identify preferred options for actions by ranking them based on characteristics of these options with respect to certain criteria, together with the weighting of these criteria by an actor. Among the different MCDA approaches developed [6], PROMETHEE [34,35] is one of the most prominent. PROMETHEE belongs to the family of out-ranking approaches with a pairwise comparison of characteristics of options weighted by actors as key feature [34]. PROMETHEE II provides a full ranking of all options by sorting them according to their net flows in descending order. The weighting w_k reflects the importance of the k-th criterion from an actor's point of view; weightings are non-negative numbers adding up to one over all criteria ("normalization condition"). In PROMETHEE, so-called preference functions map the differences between characteristics with respect to a criterion to an abstract degree of preference p_k, which is then weighed by the respective w_k. The overall performances of options are assessed by summing up these weighted values. In PROMETHEE II it is assumed that an actor prefers the option i with the highest net flow $\Phi_i^{\text{net}} = \Phi_i^+ - \Phi_i^-$, the difference of the domination of the other options Φ_i^+ and its domination by the other options Φ_i^-.

It holds[1]

$$\Phi_i^+ = \frac{1}{N-1}\sum_{j=1}^{N}\sum_{k=1}^{K}\left(w_k \cdot p_k\left(a_{i,k},\ a_{j,k}\right)\right) \tag{1}$$

and

$$\Phi_i^- = \frac{1}{N-1}\sum_{j=1}^{N}\sum_{k=1}^{K}\left(w_k \cdot p_k\left(a_{j,k},\ a_{i,k}\right)\right), \tag{2}$$

with

N: number of options

K: number of criteria

w_k: non-negative weighting of criterion k

[1] For more details see e.g., [36].

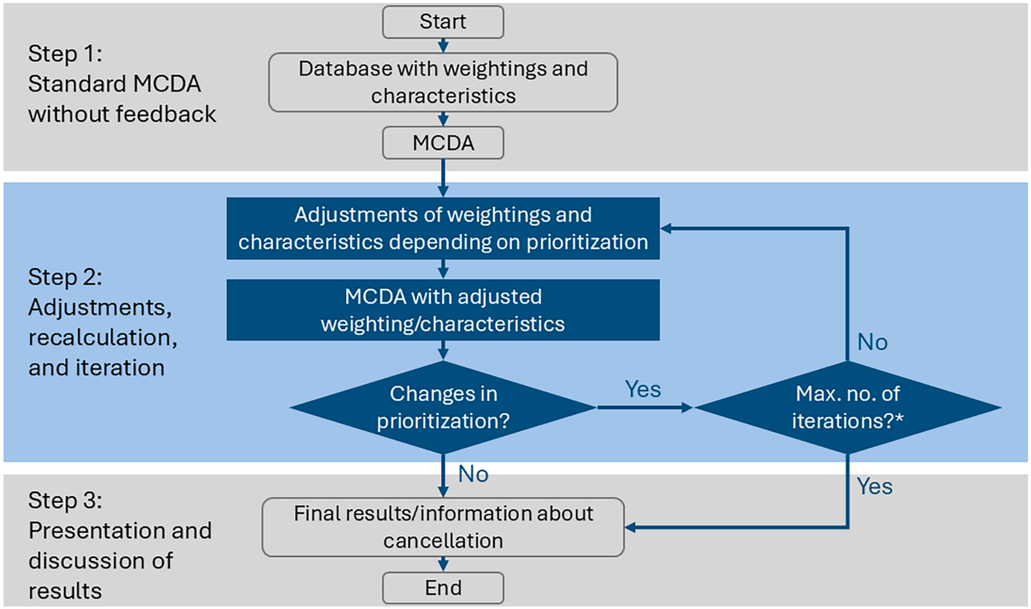

Fig. 1. MAMCDA Work-flow.

$p_k(a_{i,k},\ a_{j,k})$: degree by which $a_{i,k}$ is preferred to $a_{j,k}$
$a_{i,k}$: Characteristic k of option i with respect to criterion k

Extension to MAMCDA

Our goal is not to accurately model the entire interaction between actors, but rather to capture its essential effects on the actors' final preferences as simply as possible. This is a key distinction of our approach from ABM. To this end, we make two significant structural simplifications:

a. We refrain from seriously capturing any dynamics necessary for interaction to emerge.
b. We assume that the (pseudo-static) state regarding preferences can be split into the state without interaction and the deviation from this state due to interaction. We model the latter in discrete pseudo-time t, and because it is a deviation, we always refer to the state without interaction, which corresponds to the initial state in our approach. We model the interaction using feedback loops and simple interaction functions. We distinguish between two types of feedback:
1. Feedback of an actor's ranking of options on characteristics of options,
2. Feedback on an actor's ranking on other actors' weightings.
Our approach consists of two stages. Firstly, we extend the MCDA approach by assuming that selected characteristics of certain options will change depending on the actors' preference for a particular option. As a result, characteristics are partly endogenized. This extension allows for considering, e.g., changes in costs resulting from government decisions to promote electric mobility by introducing subsidies for such vehicles. We model such effects with a matrix-valued function f that reflects the interaction between actors' preferences for options and their characteristics. Let us denote the (i,k)-th component of f by $f_{i,k}$. The integer-valued matrix R contains all rankings of all options of all actors and depends on t, with $R_{n,y}(t)$ being the ranking of option n for actor y at t. We update the characteristic $a_{i,k}$ at (pseudo)-time t by

$$a_{i,k}(t) = a_{i,k}(0) + f_{i,k}(R(t-1)). \tag{3}$$

Assuming linear superposition of influences, we model $f_{i,k}$ by

$$f_{i,k}(R) = \sum_{y=1}^{ACT} \sum_{n=1}^{N} f_{i,k,n,y}\left(R_{n,y}(t-1)\right)$$

with ACT denoting the number of actors and $f_{i,k,n,y}$ being functions stored as tables because their input is contained within a small set of integers. These tables can be kept in a large interaction matrix. While our approach allows for arbitrary interaction functions f and therefore full flexibility, our special choice of f allows for working with interaction matrices and thus for a realization in common office software, eliminating the need for developing dedicated software.

In the second step, we endogenize weighting factors, assuming that they are partly determined by the actors' ranking of options. This approach enables us to incorporate effects resulting from, e.g., upcoming social norms and other kinds of social spillovers. We gather information on how the other actors' preferences of an option affect actor z's weightings of selected characteristics (e.g., environmental attitudes), similar as before, in a vector-valued function g with components g_k and update the weighting of characteristic k by actor z according to

$$w_k^z(t) = w_k^z(0) + g_k(\mathrm{R}(\mathrm{t}-1)). \tag{4}$$

Hereby, we assume again linear superposition of influences, which leads to another interaction matrix in the same way as before. Then, we recalculate R by applying the underlying MCDA model with the input data modified as described above. We repeat until the rankings of all actors do not change with respect to the preceding cycle in that loop, or we reach the maximal number of iterations.

Although we focus on PROMETHEE II as MCDA model for our application in this article, our approach can be based on any MCDA model. TOPSIS (*Technique of Order Preference Similarity to the Ideal Solution)* [37,38], as an example of another prominent MCDA models, is based upon finding an ideal and an anti-ideal solution. It ranks the options according to their distance from those. For details and an overview of the numerous fields of application, we refer to [38]. PROMETHEE and TOPSIS differ in terms of how they evaluate the differences between the characteristics of different options. While PROMETHEE uses a characteristic-specific preference function, TOPSIS measures the differences using a uniform distance measure (usually Euclidean distance). Like PROMETHEE, TOPSIS also requires information on the characteristics of options and the weightings of the characteristics. Hence, our

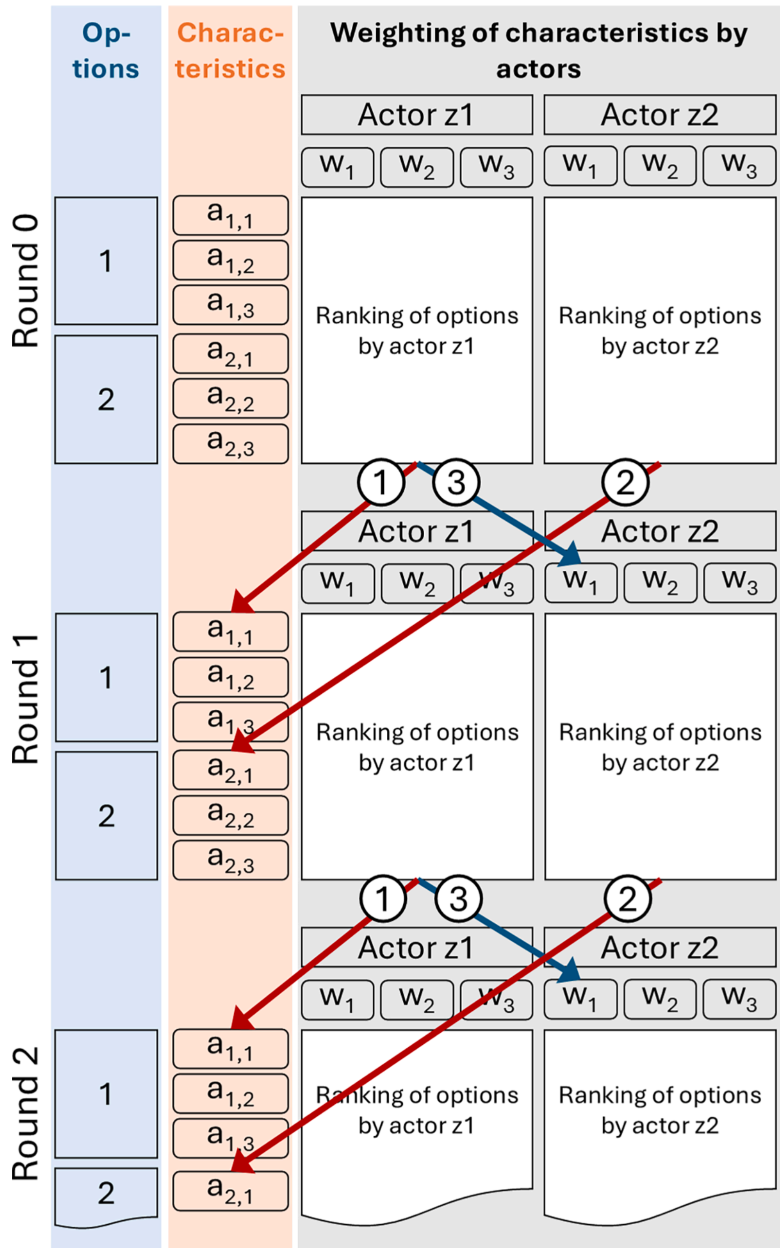

Fig. 2. Overview over the MAMCDA approach presented in this work. The arrows (1) and (3) symbolize feedback of an actor's ranking of options on characteristics of options, arrow (2) the feedback on an actor's ranking on other actors' weightings.

approach can be directly employed on these approaches and any other MCDA method using the same kind of input data. In the following sections, we focus on PROMETHEE II, pointing out any deviations from TOPSIS to PROMETHEE II in the Appendix.

Application: Transition towards battery electric vehicles in Germany

In the following, we demonstrate our approach using purchases of cars in Germany as an example. In particular, we extend analyses conducted by [4], who analyze attitudes towards cars by considering 28 types of actors and 18 types of car segments. The set of actors includes various types of private households as well as car producers. In order to include government support measures, we include "government" as an additional actor. To avoid overly large interaction matrices, we reduce the overall number of actors to 13 in our study.

Actors and their interests

Following Rhoden et al [4] and Aral [39], we assume that private car buyers are interested in price-performance ratio, price, comfort, space, family-friendliness, environmental friendliness, resale value, image/-prestige, and safety. The relevance of these factors from a household's point of view depends on financial, demographic, and spatial aspects. The corresponding weightings are derived by conducting representative discrete choice experiments (DCE) with 451 German households. The experiments were conducted in a representative manner with regard to geographic distribution, housing conditions, and other household characteristics; that is, households were selected so that the sample would reflect the national average. The DCE includes additional demographic information about the respondents. To ensure a high level of representativity and avoid overloading the number of attributes participants must evaluate in the experiment, and to limit the number of participants needed to achieve reliable results, we decided to omit aspects such as daily trip characteristics, travel needs, daily commuting purposes, trip distances, and frequencies.

According to their social situation, we cluster the households into four subgroups: HH1 represents households with low income and kids, HH2 households with high income and kids, HH3 households with low income and no kids, and HH4 households with high income and no kids. Studies conducted by, e.g., Castillo et al [40] and Celasun et al [41] emphasize that positive impacts on income result directly and indirectly from production activities. It can be expected that these impacts also support positive attitudes towards the activities and products of the respective companies among those who benefit from them, provided they are not associated with significant negative environmental impacts. Hence, the physical distance to the places where the company is located counts for attitudes towards the company and its products. To show how such effects can be integrated into MAMCDA, we also consider households that benefit from employment and income effects that are more or less directly linked to vehicle production due to their geographical proximity. Accordingly, the number of considered households increases to 8: HH5 reflects low-income households with kids living in a region with a dominant car industry, HH6 high-income households with kids located in such a region, HH7 low-income households without kids, and HH8 high-income households without kids being directly or indirectly affected by income effects linked to production activities of car manufacturers.

By using information on income distribution by households [42], information on number of households by category of households ([43, 44]) and on employment impacts of the German automotive industry [45] we determine the proportion of the total population represented by each group. Table 1 shows the identified distribution of the different household groups in Germany.

A cluster analysis is used to investigate which combination of population groups shows greater differences ("Euclidean distance") in attitudes. Clustering based on income and number of kids creates the most balanced distribution of clusters. Regarding income, we distinguish between net income below 2000 Euro/month ("low income") and above 2000 Euro/month ("high income"). Other clustering methods show much smaller differences in weightings.

Besides households, we consider vehicle producers to be relevant actors that impact the transformation of the mobility sector. Following Rhoden et al [4], we assume that vehicle producers are interested in factors such as compatibility with existing structures, market share, EBIT margins, and import dependency. To reduce complexity, we limit ourselves to car producers aiming at the mass markets and to producers of premium cars. Additionally, we differentiate between manufacturers of conventional and environmentally friendly cars. Hence, the group of vehicle producers in particular differs with respect to weightings of EBIT margins, market share, and environmental aspects. The weightings of the vehicle manufacturers are based on assessments of Rhoden et al [4].

As the third actor, we include the government, with particular interest in increasing environmental friendliness, decreasing import dependency, positive employment/income effects, and receiving tax revenues. These factors are selected based on statements in official communication, including, e.g., targets mentioned in laws and regulations. Over time, the government has continually adjusted its priorities regarding its objectives. The German debate on a future ban on new registrations of combustion-engine vehicles may serve as an example here. The assessment is further complicated by the fact that different government agencies and individual ministries assign different weightings to these criteria. This makes providing precise weightings very difficult. For the government, we assume equal weightings of the relevant factors. In a detailed sensitivity analysis, we show that households' final preference states do not depend significantly on the government's weightings, such that the precise knowledge of these weights is not essential (see Appendix 4).

Table 1
Shares of households of the overall number of households (Germany).

	Households not located in the region of vehicle producers		Households located in the region of vehicle producers	
	Low income	High income	Low income	High income
Kids	5.0 % (HH1)	21.9 % (HH2)	0.4 % (HH5)	1.6 % (HH6)
No kids	25.5 % (HH3)	42 % (HH4)	1.8 % (HH7)	3.1 % (HH8)

Sources: Own compilation based on information of income distribution by households [42], on number of households by category of households ([43,44]) and on employment impacts of the German automotive industry [45]

Table 2 shows the weightings derived from the cluster analysis of data from discrete choice experiments for the household types and from our assumptions for government and vehicle manufacturers.

The weightings are linked with uncertainties and can change over time. It is important to point out that by conducting intensive sensitivity analysis, we can investigate whether the results are robust despite these uncertainties. Furthermore, our approach determines whether and, if so, what changes in the weightings lead to changes in the ranking and thereby in the preference of options.

Options for purchasing a car and their characteristics

Car purchasers can choose from a great number of different cars. However, for showing our approach, we restrict our analysis to the three car models in each of the best-selling categories of 2023: cars with internal combustion engines (ICE), plug-in hybrids, and battery electric vehicles (BEVs). Each of these options is described using their specific characteristics based on information from publicly available sources (see table). We scale these characteristics from 1 (worst) to 5 (best) (Table 3).

Consideration of feedback loops

Our approach aims to show possibilities for integrating interlinkages between the actors' actions and characteristics of technologies in an MCDA framework. Therefore, we implemented impacts of actors' ranking of options on characteristics as well as impacts of actors' ranking on the weightings of the criteria. As MCDA model, we use PROMETHEE II using a linear preference function p_k(preference function type 5 in [35] with $p = 5$ and $q = 1$).

Impacts on characteristics

For the analysis we consider the following kinds of feedback on characteristics of cars:

A) We assume that consumer preferences are reflected in purchasing behavior and therefore influence market shares. We thus compute the value for "current market share" for a preferred car type by taking the share of the specific group of households in the overall economy into consideration. Hence, we assume that HH1 accounts 5.0 % of the market share, whereas HH2 accounts 21.9 % (see Table 1). The highest value (5) for the market share of a car type is reached if all households rank the car type first. As an additional feature, we calculate market shares for the second-ranked car types, assuming that if all households rank a car type second, the market share will be assigned a value of 2.5. Again, each household contributes its specific share to the overall sum of households on this share.

The studies of Vögele et al [49] and Mundaca et al [30] emphasize that households' purchase decisions will partly follow car purchase decisions of other household groups. We model this interlinkage

Table 2
Characteristics and their weightings.

	Households								Vehicle Manufactures				Gov.
	Households not located in the region of vehicle producers				Households located in the region of vehicle producers				Conven-Tional		Environmental-friendly		
	HH1	HH2	HH3	HH4	HH5	HH6	HH7	HH8	VM1	VM2	VM3	VM4	G
Range	0.066	0.087	0.09	0.089	0.063	0.083	0.085	0.084	0	0	0	0	0
Charging time	0.087	0.102	0.103	0.101	0.082	0.097	0.098	0.096	0	0	0	0	0
Safety	0.071	0.066	0.054	0.064	0.068	0.063	0.052	0.061	0	0	0	0	0
Comfort	0.129	0.115	0.107	0.116	0.123	0.109	0.101	0.11	0	0	0	0	0
Family-friendliness	0.082	0.086	0.085	0.082	0.078	0.082	0.081	0.078	0	0	0	0	0
Image/Prestige	0.046	0.053	0.053	0.053	0.044	0.05	0.051	0.05	0	0	0	0	0
Environ. friendliness	0.062	0.07	0.066	0.063	0.059	0.067	0.063	0.06	0	0	0.25	0.167	0.25
O&M Cost	0.061	0.072	0.075	0.068	0.058	0.068	0.071	0.065	0	0	0	0	0
Price	0.255	0.209	0.233	0.222	0.242	0.199	0.221	0.21	0.5	0	0.5	0	0
Price-performance-ratio	0.1	0.094	0.095	0.097	0.095	0.09	0.09	0.092	0	0	0	0	0
Resale value	0.04	0.045	0.039	0.046	0.038	0.043	0.037	0.044	0	0	0	0	0
Current market share	0	0	0	0	0	0	0	0	0.5	0	0	0	0
Future market share	0	0	0	0	0	0	0	0	0	0	0.25	0.167	0
Compatibility with existing structures	0	0	0	0	0	0	0	0	0	0	0	0	0
Import dependency	0	0	0	0	0	0	0	0	0	0	0	0	0.25
EBIT marge	0	0	0	0	0	0	0	0	0	0.5	0	0.333	0
Tax revenues	0	0	0	0	0	0	0	0	0	0	0	0	0.25
Employment	0	0	0	0	0.05	0.05	0.05	0.05	0	0	0	0	0.25
Revenue per car	0	0	0	0	0	0	0	0	0	0.5	0	0.333	0

Sources: Own compilation (Numbers for households based on discrete choice experiments, other data on expert judgments)

Table 3
Characteristics of car types relevant for private car purchasers.

Criteria	Source	Golf (VW) ICE	T-ROC (VW) ICE	Tiguan (VW) ICE	MODEL Y (Tesla) BEV	ID.4 (VW) BEV	ENYAQ (SKODA) BEV	C-KLASSE (MERCEDES) Hybrid	GLC (MERCEDES) Hybrid	A4 (Audi) Hybrid
Range	[46]*	5.0	5.0	5.0	1.4	1.0	1.1	4.6	5.0	5.0
Charging_time	[46]*	5.0	5.0	5.0	3.0	1.0	1.0	5.0	5.0	5.0
Safety	[46]*	4.2	4.5	4.5	3.9	4.8	4.4	4.6	4.7	4.2
Comfort	[46]*	3.5	3.4	4.0	3.4	4.1	4.2	4.2	4.1	4.0
Family-friendliness	[46]*	3.4	3.1	3.6	3.0	3.6	3.6	3.1	3.4	3.0
Image/Prestige	[46]*	5.0	5.0	5.0	3.7	2.3	1.0	5.0	5.0	5.0
Enviro. friendliness	[46]*	1.5	2.1	1.8	5.0	5.0	5.0	1.5	1.0	1.7
O&M Cost	[46]*	3.7	4.0	3.3	2.5	3.3	3.5	2.6	2.6	2.9
Price	[46]*	4.0	4.5	3.4	2.3	2.2	3.3	3.1	2.9	3.3
Price-performance-ratio	[46]*	3.6	4.0	3.9	3.1	3.7	3.8	3.3	3.3	3.4
Resale value	[46]*	1.8	1.5	2.5	3.7	4.5	3.1	1.1	1.7	1.0
Current market share	[47]	4.1	5.0	3.8	2.4	1.9	1.0	3.8	1.9	1.9
Future market share	1)	1.0	1.0	1.0	5.0	5.0	5.0	3.0	3.0	3.0
Compatibility	[4])	5.0	5.0	5.0	1.0	1.0	1.0	3.0	3.0	3.0
Import dependency	2)	5.0	5.0	5.0	1.0	3.0	3.0	5.0	5.0	5.0
EBIT marge	3)	1.8	1.8	1.8	1.3	1.0	1.0	5.0	5.0	1.8
Tax revenues	4)	4.2	3.4	4.4	1.0	1.0	1.0	4.2	4.5	5.0
Employment (D)	5)	1.0	5.0	5.0	3.0	3.0	1.0	5.0	5.0	5.0
Revenue per car	[46]*	2.0	1.5	2.6	3.7	3.8	2.7	3.0	3.1	2.7

Remarks: * Original numbers are inverted into range 1 (worst) and 5 (best) to be in line with the classification of the other numbers, 1) Own calculation based on [46], 2) production figures of cars in this segment in the last 10 years, 5) 5: production in D, 3: production in Rest of EU and 1: production in Rest of World, 3) Ebit margins of VW Group, Tesla, MB Group and Toyota [48], 4) Calculation based on gasoline and motor vehicle tax: 1 lowest tax, 5 highest tax, 6) Assigned values: 5 for production in D,: 3 for production in Rest of EU and 1 for production in Rest of World

between households assuming that preferring car types by households impacts their value according to "Image/Prestige" and we therefore increase that value by 1[2] for a car type preferred by all households and by 1/8 for a car type preferred by some, but not all groups of households.

B) In Germany, part of the charging stations was installed by vehicle producers to foster the deployment of BEVs [50]. Based on this, we assume that vehicle producers will continue to expand charging infrastructure as long as they anticipate BEVs to prevail in the future. Taking the historical activities of TESLA into consideration as rough guess [50], we assume that current vehicle-specific charging infrastructure will increase by 50% (corresponding to an increase in the corresponding characteristic by 2) if all vehicle manufacturers agree to prefer BEVs.

C) In recent years, manufacturers made considerable efforts to increase the range of their BEVs [51]. It stands to reason that they will continue their activities if they expect a prosperous future. We expect that current trends will continue, and a range of 600 km will become standard [51]. Therefore, as long as BEVs are still favored by manufacturers of environmentally friendly cars, this corresponds to an

[2] In our study we use a scale for all car characteristics reaching from 1 (worst) to 5 (best).

increase in the values assigned to the characteristic “Range” of Model Y by 2.4, ID.4 by 2.7, and ENYAQ by 2.6.
D) In the past, the German government and the car manufacturers jointly subsidized purchases of BEVs, each by giving grants up to Euro 2250 per purchase [52]. In our study, we assume that if a manufacturer favors BEVs, it will continue to subsidize them by Euro 2250.
E) We assume that in the case that the government favors BEVs, it will support expansions of the charging infrastructure (resulting in an increase in the characteristic “Charging time” by roughly 40 %). Moreover, we assume that subsidies for vehicles will return to 2023-levels (4500 Euro per purchase) [53].

Accordingly, the interaction matrices reflect the empirical observation that a stakeholder's prioritization of an option can be linked to activities that result in changes in characteristics, such as introducing supporting measures for the option, or changes in weightings, like increasing the emphasis on environmental friendliness. The calibration of the matrices and the impact of prioritization on option characteristics, as well as the impacts of the options, are based on empirical observations from the DCE. These observations also support the methodological foundation of the approach.

Impacts on weightings

An actor’s preference can also impact weightings of criteria by other actors. E.g., an increasing number of actors switching to BEVs can increase engagement in issues such as emissions reduction, use of renewable energy, and sustainable living [54]. Hence, awareness of environmentally friendly mobility and sustainable technologies will likely increase. We include this by linking the preference for car technologies to households’ weighting of “Environmental friendliness”. As a first guess, we assume that government’s preference for BEVs implies an increase in the households’ weighting of “Environmental friendliness” up to 100 % (see e.g., [55]). Another increase by 50% results from fostering BEVs by the industry. Using a sensitivity analysis, we assess the effects resulting from uncertainties regarding the exact nature of these relationships (see Annex).

Due to the straightforward modeling of interaction in our approach, it is not necessary to quantify all possible interactions between arbitrary actors in a fully populated interaction matrix. In practical use, only interactions that seem important for the specific application are necessary to be considered, leaving most entries in the interaction matrix as zero. Therefore, we refrain from modeling the influence of complete rankings on weightings and characteristics, even though the method allows this in principle, and instead consider only the influence of preferences. This contributes significantly to the simplicity and practical applicability of our method.

Results

In the first step, we consider the initial ranking of car types resulting from the assumed preferences. This initial ranking results from carefully testing different starting rankings in a sensitivity analysis, focusing on the impacts of changes in the assumed distribution of the households' subgroups. The results are consistent and show that the selected groups of actors favor different kinds of cars (Table 4). Private households might favor the VW T-ROC, whereas premium car manufacturers might prefer Mercedes' premium cars. Based on our assumptions, the government might prefer the Audi A4 as a car being produced in Germany, and rank the VW Tiguan second.

The actors’ preferences do not impact characteristics and weightings initially. Therefore, encouraging actors to alter their rankings and to initiate a process of interaction requires additional measures or changes to the framework conditions. To identify and evaluate these changes that can cause actors to re-evaluate their preferences, we take a closer look at the effects of modified car characteristics and weightings on the preference for car types. This step of the analysis is driven by the questions:

- Which combinations of characteristic levels result in favoring BEVs?
- Do these constellations fit our assumed reactions of actors to car preferences?
- Do the assumed interlinkages result in favoring BEVs? If not, which adjustments are necessary from the perspective of individual actors?

We first assess the impacts of variations in weightings on the preference of car types (Fig. 3), hereby assuming the characteristics to be fixed and certain, and concentrate on attitudes towards environmental friendliness, which impact attitudes towards other factors.

We employ a graphical approach to consider all possible scenarios with respect to weightings simultaneously. As the weightings sum up to one and are non-negative, the set of all possible weighting vectors forms the standard simplex in a K-dimensional abstract space. This is partitioned into at most N subsets by the preferred option for a particular weighting vector. For visualization, the subsets can be color-coded. However, a large K might significantly complicate visualization. Since $K = 18$ in our application, we select the values of three criteria to vary while keeping all other weightings fixed. The sum of the three variable weightings must remain constant, and their total combined with the fixed weightings must sum to one. This creates a scaled-down version of the three-dimensional standard simplex, which appears as an equilateral triangle when viewed perpendicularly. This is shown in Fig. 3. The real number in the corners of that triangle is the fixed sum of the variable weightings. These triangles are, in fact, rotated slices through the K-dimensional standard simplex. For details and a mathematical derivation, we refer to [4]. One can show that the resulting subsets are polytopes in case of PROMETHEE II, which can be computed explicitly. However, for e.g. TOPSIS, this is not true (see Appendix).

Fig. 3 also shows that considerable changes in weightings are needed for changing attitudes towards BEVs, given that the characteristics remain unchanged. Other options, like the ID.4, are not preferred at all, regardless of possible weighting changes. For other actors and other MCDA models, we get similar results (see Appendix).

In a third step, we examine the extent to which changes in vehicle characteristics relevant to feedback loops affect the preference for car types. To do so, we systematically modify selected characteristics of a chosen option and examine when a switch away from the initially preferred option (in our example: VW T-ROC) to the modified option occurs.

Fig. 4 shows that it takes a combination of significant changes in characteristics of the ID.4 to prefer it over the VW T-ROC. For HH1, decreased price alone (corresponding to an increase in characteristic for price) will not suffice for preferring BEV.

When increasing the characteristic for price by 1 (corresponding to a reduction in price of EUR 13750), the BV ID.4 is preferred only if the

Table 4
Initial ranking.

Rank	HH1 - HH4	HH5-HH8	VM 1	VM 2	VM 3	VM 4	G
1st	T-ROC (Volkswagen)	T-ROC (Volkswagen	T-ROC (Volkswagen)	GLC (Mercedes)	ENYAQ (Skoda)	C-KLASSE (Mercedes)	A4 (Audi)
2nd	Golf (Volkswagen)	Tiguan (Volkswagen)	Golf (Volkswagen)	C-KLASSE (Mercedes)	MODEL Y (Tesla)	GLC (Mercedes)	Tiguan (Volkswagen)
3rd	Tiguan (Volkswagen)	A4 (Audi)	Tiguan (Volkswagen)	MODEL Y (Tesla)	ID.4 (Volkswagen)	MODEL Y (Tesla)	C-KLASSE (Mercedes)

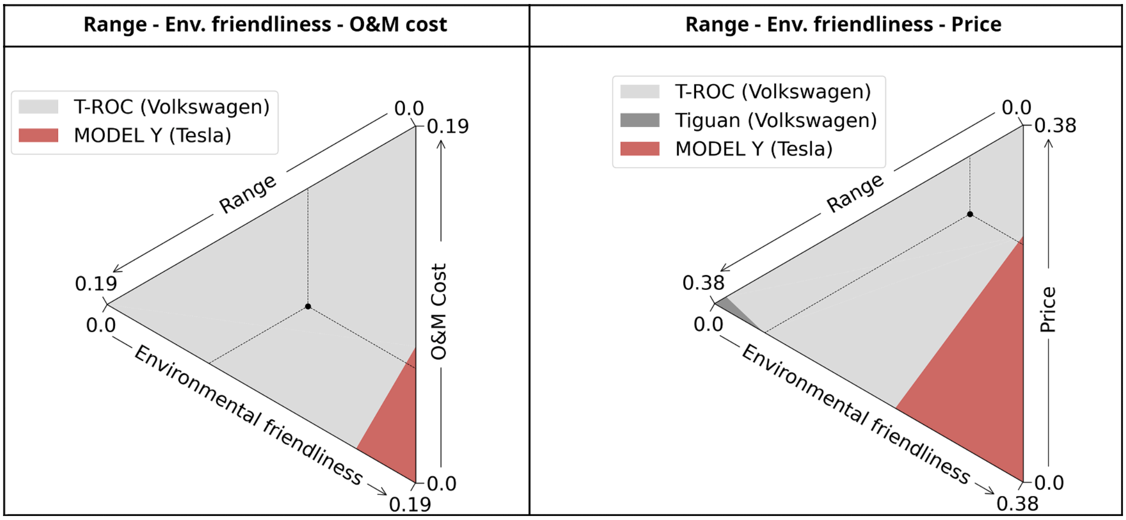

Fig. 3. Impact of selected weightings on preferred car types (Actor HH1), initial state. The assumed weightings are displayed as a black point.

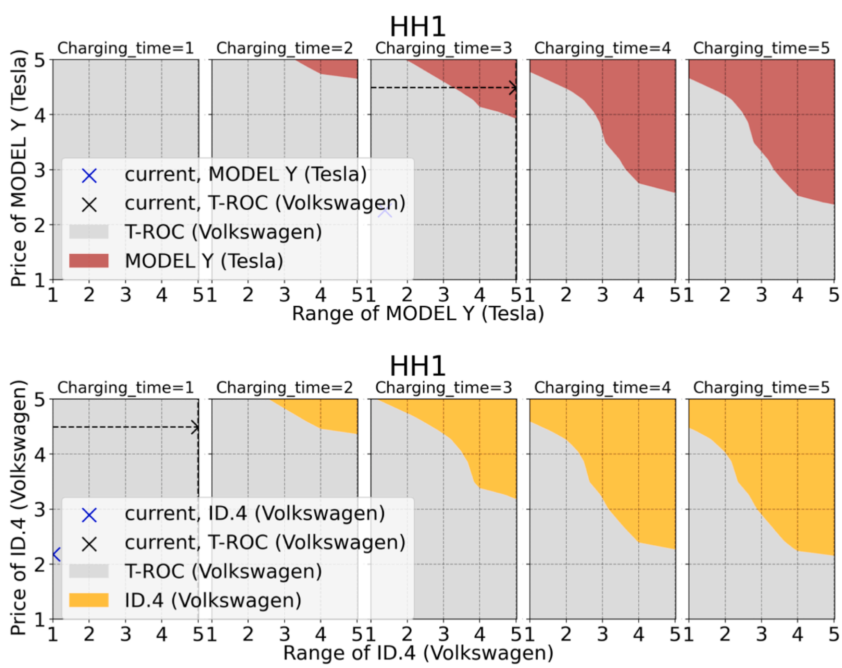

Fig. 4. Impact of variations in characteristics of the Model Y (upper figure) and ID.4 (lower figure) related to preference over VW T-ROC for ID.4 (Actor HH1).

characteristic for range increases by 2 (corresponding to an increase in range by 2*78 km), and if the charging time improves significantly. For computing these figures, we rely on an approximation of the boundaries with a numerical method developed in [56]. The corresponding results for the other households are similar (see Appendix).

As mentioned above, within our feedback framework, we assume that if all actors support the same type of car, its range will increase up to 2.7 points (corresponding to 215 km) and its price will drop by 0.5 (corresponding to Euro 6,750). The results of Fig. 4 show that these incentives and improvements will not suffice to foster e-mobility. An additional change in weighting of the criterion “Environmental friendliness” will support a shift towards BEVs and thus, e.g., support necessary decreases in price. It is essential to highlight that in the presented example, we focus on variations of relevant characteristics of one car, ignoring changes in the characteristics of other alternatives, and hence ignoring possible spillovers which might impact the ranking.

Generally, groups of actors behave according to the actions of the other groups by anticipating their resulting actions. In our calculation, we assess if this anticipated action set results in a robust equilibrium or if some group of actors still prefers another option. Since it is not certain that all actors support the same type of car, we examine their preferences in more detail. Therefore, we apply our MAMCDA approach in an inverse way: Unlike the standard approach, which begins by combining characteristics of options with a weighting of those characteristics and ends with option rankings, the inverse approach starts with existing rankings. Then, we assess whether and to what extent the state is stable or if there are factors that might lead to a change in the initial ranking. For this application, we start our inverse approach by assuming that each actor expects all other actors to prefer the same type of car, and then we check the stability of the rankings.

To illustrate this, we set the BEV VW ID.4 as the initial preferred car and display our results in Table 5, with the first row showing our preselection. The second row (Round 1) presents the preferred car type after considering the interlinkages between actors. Based on these

Table 5
Development of rankings due to feedback between actors and options.

Rank	HH1, HH2, HH5, HH6	HH3, HH4, HH7, HH8	VM 1	VM 2	VM 3	VM 4	G
Round 0							
1st	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4
Round 1							
1st	ID.4	ID.4	ID.4	GLC	ID.4	MODEL Y	ID.4
2nd	Model Y	Model Y	T-ROC	C-KLASSE	Model Y	ID.4	ENYAQ
3rd	ENYAQ	T-ROC	C-KLASSE	Model Y	ENYAQ	ENYAQ	A4
Last Round							
1st	Model Y	Model Y	Model Y	GLC	Model Y	Model Y	ID.4
2nd	ID.4	T-ROC	C-KLASSE	C-KLASSE	ID.4	ID.4	ENYAQ
3rd	T-ROC	ID.4	ID.4	Model Y	ENYAQ	ENYAQ	A4

results, the assumed feedback is not enough for all actors to ultimately prefer the ID.4. Particularly, manufacturers targeting the premium car market tend to prefer another car type. Therefore, without their support, some feedback will decrease overall preference for the ID.4, affecting how others rank the options. In response, some actors might change their preferences. After another cycle, the setting will reach a final state, shown in the last part of the table.

We perform a sensitivity analysis with respect to weightings for the final state as we did for the initial state (see Appendix A5 for the results). In the end, instead of the ID.4, Tesla's Model Y is the preferred car. The shift towards Tesla results from the lower support of the ID.4 by premium vehicle manufacturers, in particular due to their greater focus on EBIT margins. According to our assumptions, these manufacturers push sales of the Model Y.

The reached equilibrium is robust, meaning that without changes in the framework, no actor will change its priorization of options anymore.

Table 6 shows the impacts of changes in the framework. In this example, we discuss recent developments regarding attitudes toward Tesla. Recently, Tesal's image has suffered greatly for a variety of reasons. Hence, we modified the characteristic "Image" of the Model Y by reducing the score from 3.7 to 1. As a result, we see a shift from Model Y to ID.4.

Discussion

According to Scopus, there are more than 1,250 articles that address "mobility" as the main search term in combination with "MCDA" or "MCDM" (Multiple-criteria decision-making) as a refining criterion. Most of these papers focus on the preferences of households or consumers, whereas these groups are categorized differently (see, for example, [57,58]). The preferences of industries and governments are rarely addressed. Exceptions include [59] and [4]. The set of relevant characteristics includes socio-economic variables, psychological factors, mobility conditions, social influences, and technological factors [60,61]. Studies focusing on NGOs, municipal utilities, automobile manufacturers, and academia emphasize the importance of low costs, transparency of supply options, and regional aspects for e-mobility decisions, while the relevance of ecological criteria for consumers is downplayed [59].

Additionally, the number of options considered usually is limited. The 7,385 alternative vehicle options investigated in the approach of [62] can serve as an example of how to deal with a greater number of options. The extension of the number of options, as well as variations in their characteristics, is the starting point for robustness analyses (Więckowski et al., 2023). Since prioritization depends not only on the options and their characteristics, but also on the weightings reflecting households' preferences, robustness analyses should also include variations in the weightings. Thus, intensive sensitivity analyses are necessary for drawing reliable conclusions [63].

Studies such as those by Kühlert et al. (2025) assess the impact of support schemes on the diffusion of e-mobility. These papers usually focus on government subsidies, with industry measures receiving less attention or being assessed only indirectly [61,64] emphasize the importance of policy perceptions on e-mobility. In other studies, technological changes are considered an incentive for changes in the ranking of options (see e.g., [65,66]). Some studies emphasize the significance of social norms as an incentive for supporting e-mobility (see e.g., [30,60]).

Our approach allows us to consider interactions between actors, such as social norms and the introduction of supporting schemes by actors motivated by their interest in e-mobility, in an integrated manner. In its exploratory setup, it shows the potential for accounting for different feedback loops. Unlike more mathematically complex methods like SD and ABMs, the MAMCDA approach focuses more on combining relevant decision factors and rankings, as well as identifying tipping points, rather than delivering precise numerical results [67,68]. With its focus on other aspects than SD (see e.g., [69,70]) and ABM [71], MAMCDA therefore provides a readily applicable complement even for limited datasets [72].

The approach developed in this study helps understand current trends in the diffusion of electric vehicles. Specifically, it offers insights into how hesitant behavior among actors in the e-mobility sector impacts adoption. Support from vehicle manufacturers and the government could significantly accelerate the diffusion of electric vehicles. At present, however, rather cautious attitudes are evident.

Table 6
Calculations with reduced characteristics for TESLA's image.

Rank	HH1, HH2	HH3, HH4	HH5, HH6	HH7, HH8	VM 1	VM 2	VM 3	VM 4	G
Round 0									
1st	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4	ID.4
Round 1									
1st	ID.4	ID.4	ID.4	ID.4	ID.4	GLC	ID.4	MODEL Y	ID.4
2nd	MODEL Y	T-ROC	MODEL Y	T-ROC	T-ROC	C-KLASSE	MODEL Y	ID.4	ENYAQ
3rd	T-ROC	MODEL Y	T-ROC	MODEL Y	C-KLASSE	MODEL Y	ENYAQ	ENYAQ	A4
Last Round									
1st	ID.4	ID.4	ID.4						
	ID.4	ID.4	GLC	ID.4	MODEL Y	ID.4			
2nd	MODEL Y	MODEL Y	MODEL Y						
	T-ROC	T-ROC	C-KLASSE	MODEL Y	ID.4	ENYAQ			
3rd	T-ROC	T-ROC	T-ROC	Tiguan	C-KLASSE	MODEL Y	ENYAQ	ENYAQ	A4

In MAMCDA (e.g., [7]) as well as in other kinds of multi-criteria group decision-making [10,11], results of multi-criteria analysis are used within participatory processes to find solutions that fit best to a majority of actors, taking information on attitudes of other actors into consideration. In these studies, interactions between actors are assessed by taking specific contextual conditions into consideration. Thus, in principle, they are more empirically founded than in our study. However, such studies require more effort and are restricted to a selected number of actors. Hence, an approach like ours can complement the work of others (e.g., by taking the view of vehicle manufacturers into consideration), yet it does not aim to find a solution that fits best for all actors.

Our approach requires information on how actors' actions impact the features of options and their weightings. This information can be gathered from surveys and questionnaires. Additionally, data from empirical observations, including statistical data, can be used. Like other MCDA analyses, sensitivity analysis can be easily performed even with a larger number of actors and options (in our case, 13 actors combined with 9 options characterized by 19 features). In connection with Fig. 4, we conducted a sensitivity analysis with over 3700 runs. All runs are completed in a few seconds on a business laptop, demonstrating that the complexity of our method is comparable to standard MCDA in terms of computational resources. As basis for our calculations, we use the PROMETHEE software published by [73] and our custom implementation [74]. Since our extension is based on the integration of two impact matrices, the approach can easily be implemented within other MCDA frameworks.

Conclusions

Our study aims at presenting and employing an MAMCDA approach that enables feedback loops of actors' choices on characteristics of options as well as on the weighting of the characteristics endogenously. The implemented approach enables us to efficiently assess complex systems of actors, complementing extensive participatory approaches, and therefore extending existing MAMCDA.

We use the example of private cars to illustrate how our approach can be implemented. This demonstrates that considering feedback loops can lead to different results compared to analyses that neglect such effects. Implementing our approach as MCDA allows for the consideration of 'soft' factors, including the effects of and on social norms. It allows preferences and cause-and-effect relationships to be presented in a simple and comprehensible way. We demonstrate that the chosen approach can help understand diffusion processes. It allows for the identification of potential barriers to market entry and induced effects that influence the spread of technologies. The method has the advantage that individual decisions and developments are easy to trace. It should be noted that the analyses assume that the characteristics of the options are known and that no new options will be added. Using interaction matrices simplifies the analysis of feedback effects, even though there is a risk that some aspects (e.g., strategic behavior) may not be considered or may be overlooked. In this study, the matrices were derived from empirical observations. However, as they could potentially differ in the future, we conducted extensive sensitivity analyses in our study. Nevertheless, a comprehensive sensitivity analysis regarding the interaction matrix is beyond the scope of this paper and should be addressed in a follow-up study.

An extension in the empirical foundation of our approach (e.g., by considering more types of cars and broader ranges of possible realizations of characteristics) would allow us to assess the effects of subsidy policies, taking into account technological developments (e.g., increased range of electric cars).

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CRediT authorship contribution statement

Stefan Vögele: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Writing – original draft. **Matthias Grajewski:** Formal analysis, Software, Visualization, Writing – original draft. **Imke Rhoden:** Data curation, Resources, Validation, Writing – review & editing. **Jochen Linßen:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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During the preparation of this work, the authors employed DeepL Write for language editing purposes. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix

Sensitivity analyses

We provide in the main text a systematic sensitivity analysis of our approach with respect to selected input data, focusing on weightings. Here, we present selected results of our sensitivity analyses, which are put in the appendix in order to keep the presentation in the main article uncluttered.

A1 Car characteristics for all actors

We consider the initial weightings for all actors and systematically change selected entries of the initial performance matrix. As the characteristics describe the options themselves, changing their values means changing the objective properties of the options. Therefore, systematically changing key characteristics of one option gives hints on how this option must change to become the preferred one, given the current actors' prioritization expressed as weightings. We do this for an electric car, the Tesla Model Y. It turns out that all household groups prefer a conventional car over the Model Y. As the current properties of this car, indicated by a blue cross, would need to change considerably in order to become favored, we conclude that in the initial stage, the preference of the householders of the Volkswagen T-ROC over a Tesla Model Y is robust. The same analysis for the Volkswagen ID.4 instead of the Tesla Model Y leads to analogous results. The manufacturer's preference is robust with respect to the aforementioned changes, as their weighting of charging time and range is low anyway, such that these characteristics do not play an important role in their considerations.

Fig. A.1.1.

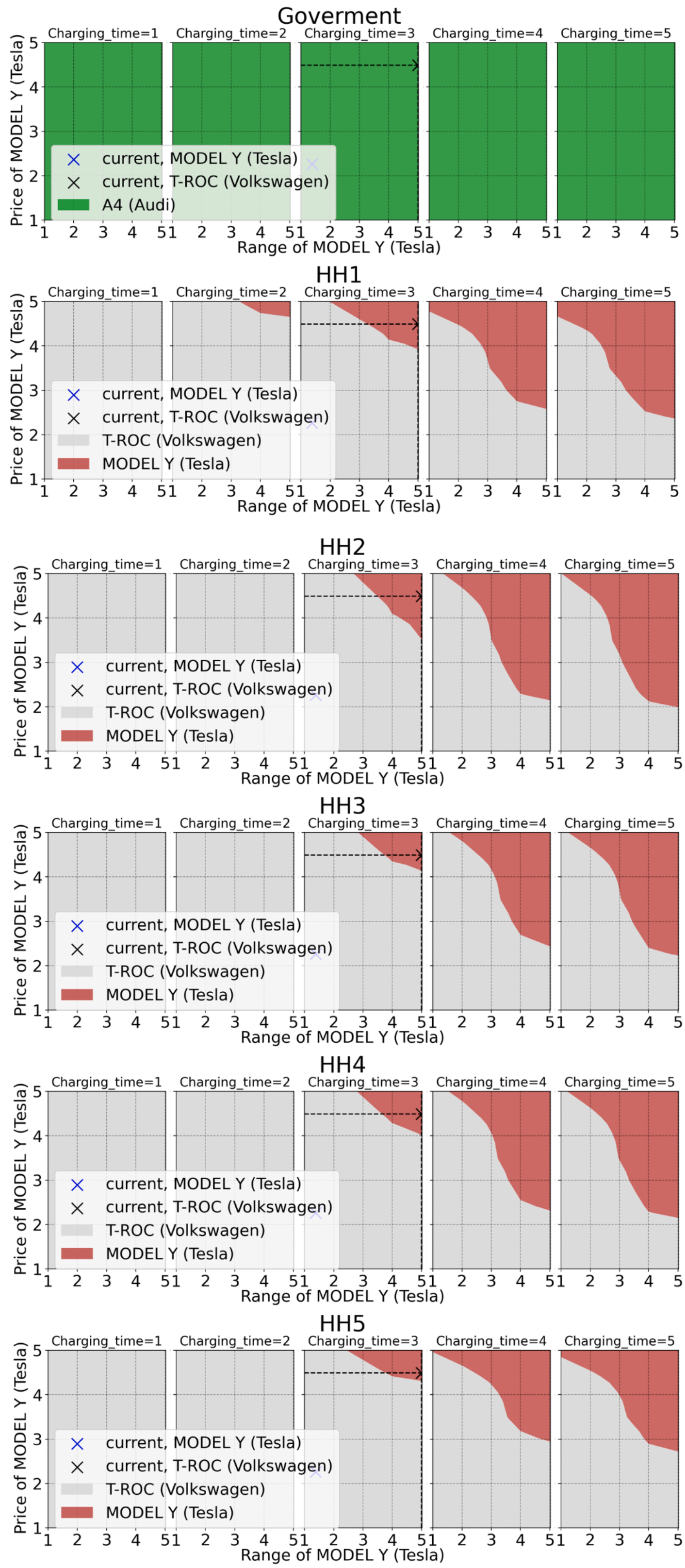

Fig. A.1.1. Impact of variations in characteristics of the Model Y (upper figures) and ID.4 (lower figures) related to preference over VW T-ROC for ID.4.

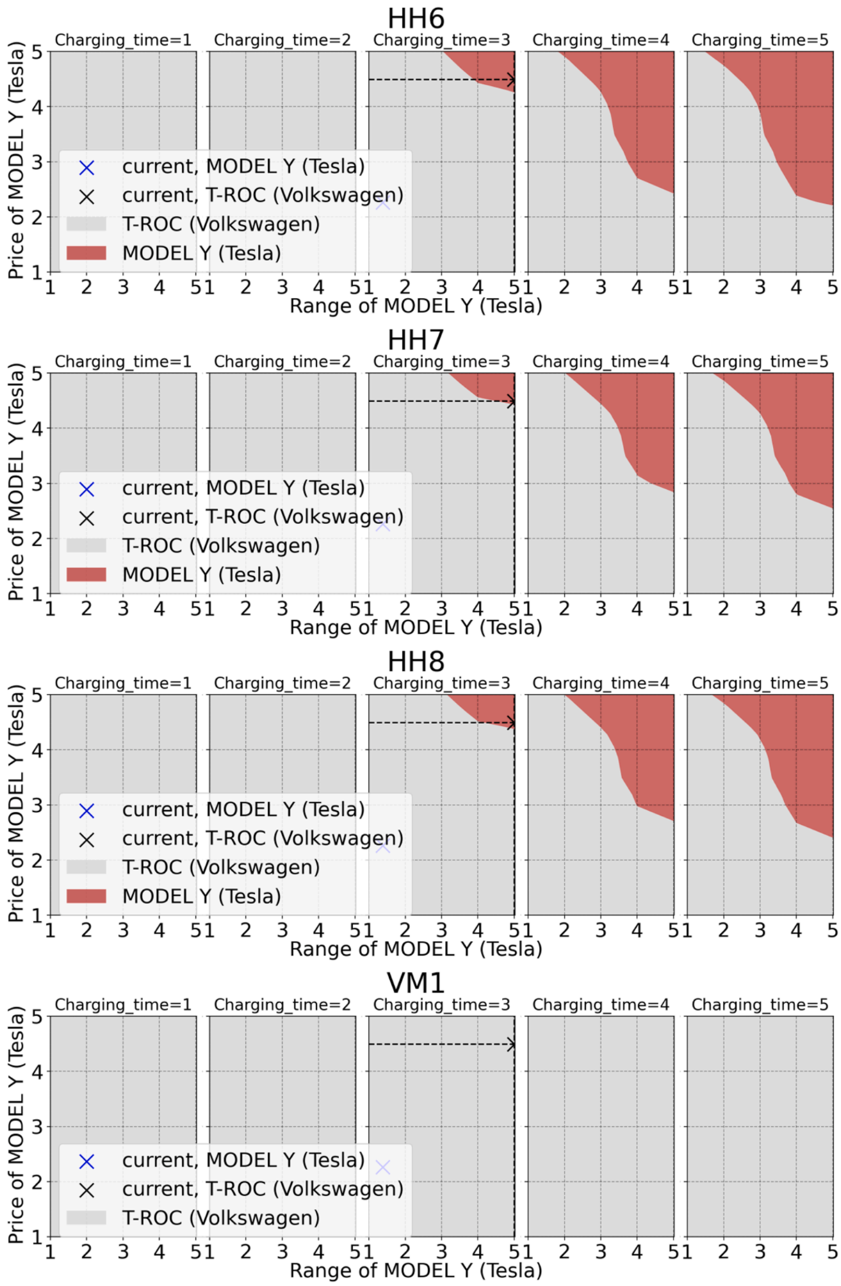

Fig. A.1.1. (*continued*).

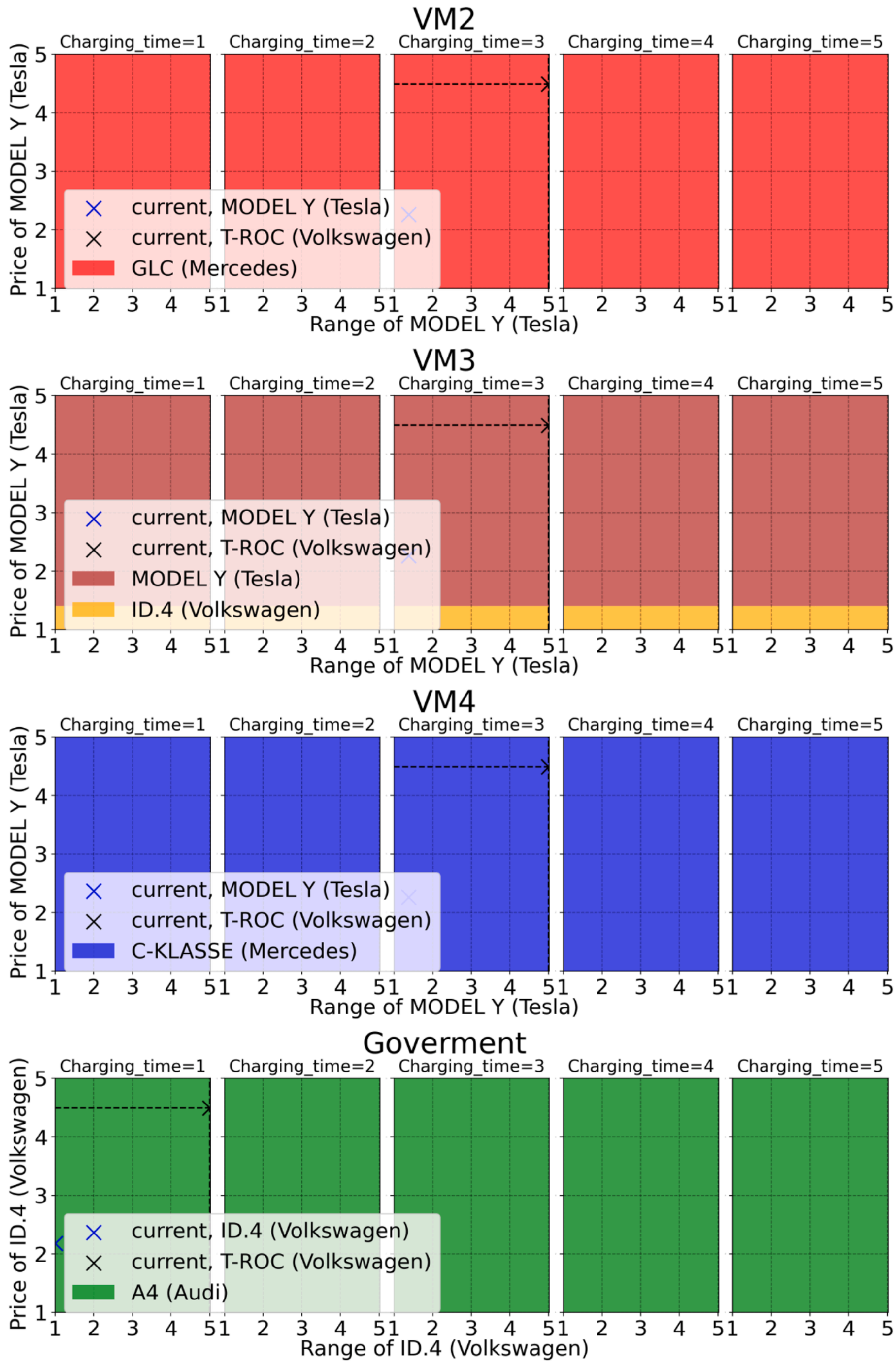

Fig. A.1.1. (*continued*).

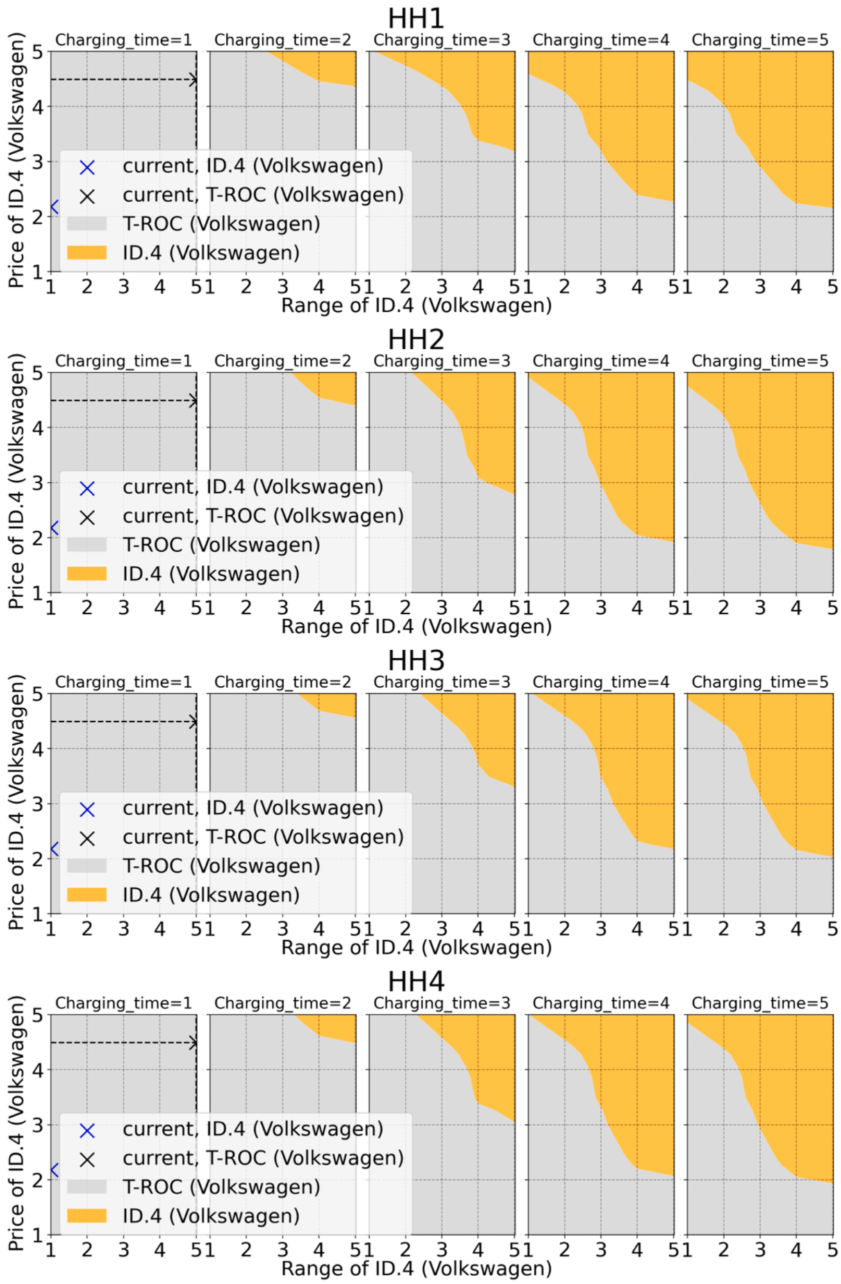

Fig. A.1.1. (*continued*).

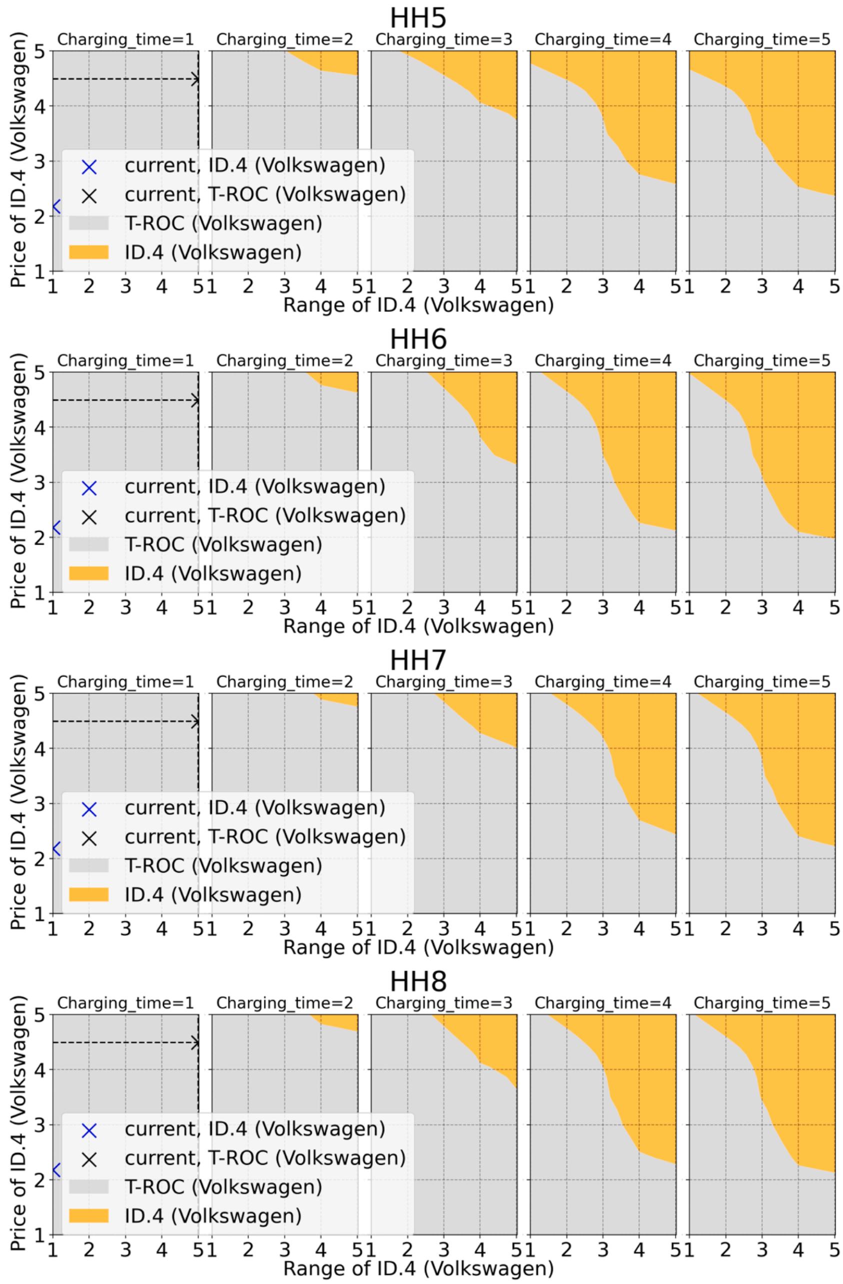

Fig. A.1.1. (*continued*).

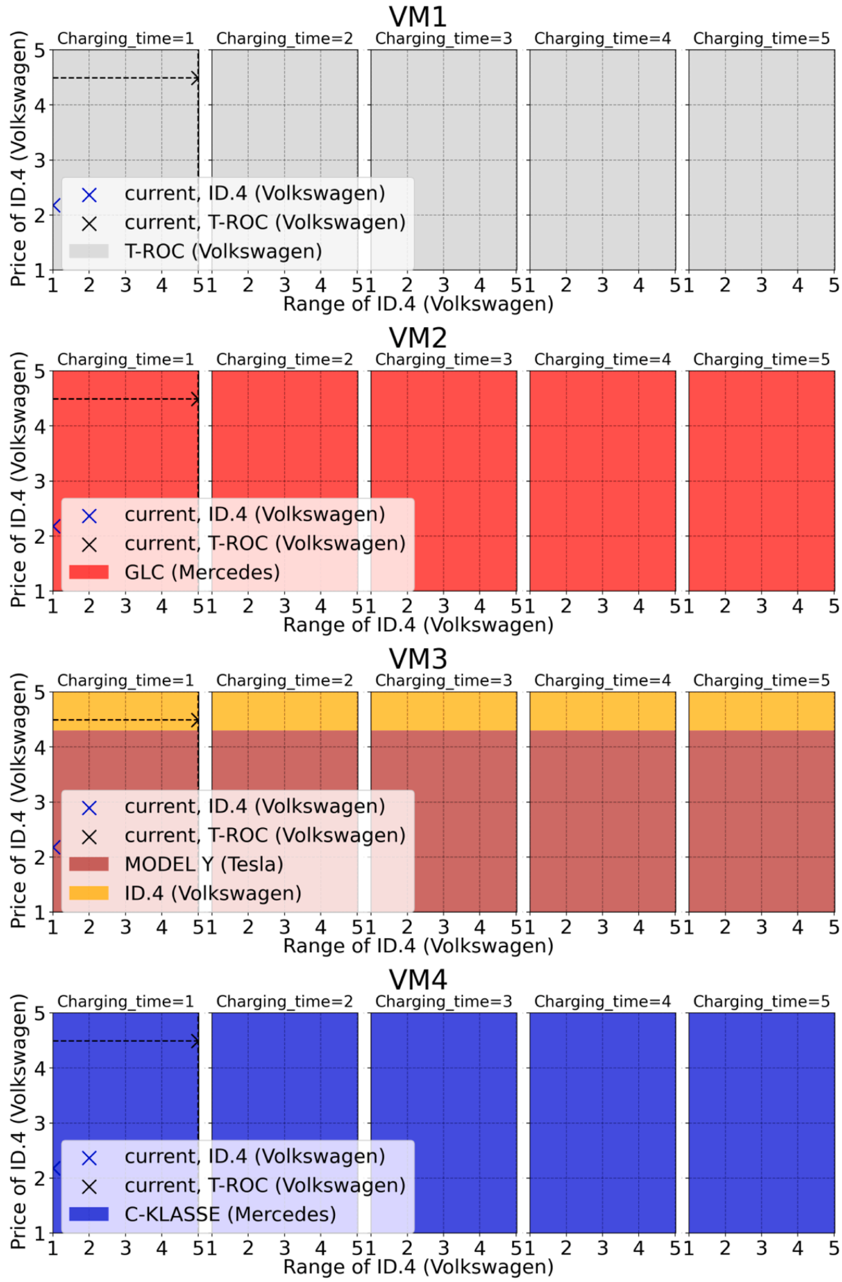

Fig. A.1.1. (*continued*).

A2: Government's weightings and choice of MCDA model (initial state)

Fig. A.2.1 demonstrates that the government's preference for the Audi A4 is robust with respect to the choice of the MCDA model and also with respect to changes in the weightings of "Environmental friendliness", "Tax revenues", and "Import dependency". Particularly, TOPSIS demonstrates more than PROMETHEE II, that by shifting weightings, a shift to the ID.4 may be possible, whereas our models rule out any change to preferring the Tesla Model Y. Shifting to the VW T-ROC seems to be rather unlikely in both models.

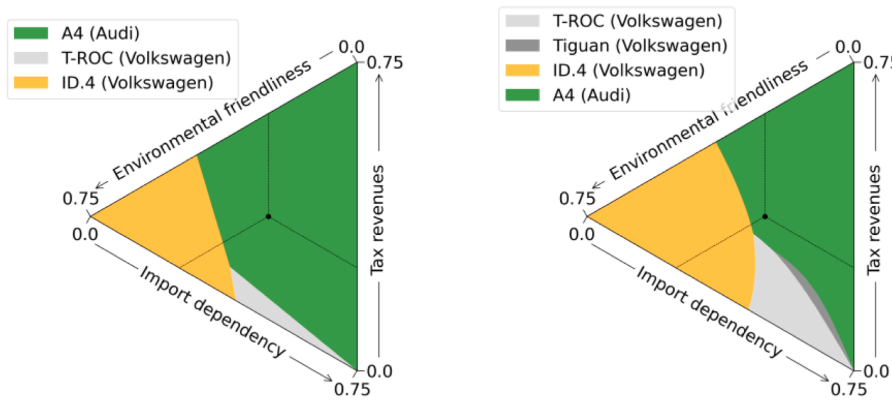

Fig. A.2.1. Impact of variations in weightings on preferred car types for actor Government, initial state (left: MCDA method PROMETHEE II with linear preference function as in the main text, right: MCDA method TOPSIS).

A3: Choice of MCDA model for the households' preferences, initial state

We repeat the sensitivity analysis with respect to weightings, which we present in Fig. 3, but for different MCDA models. We consider HH1 in the initial state. It turns out that the preferred option is the Volkswagen T-ROC, as in the main text, and that this choice is robust with respect to changes in weightings.

Fig. A.3.1., and A.3.2.

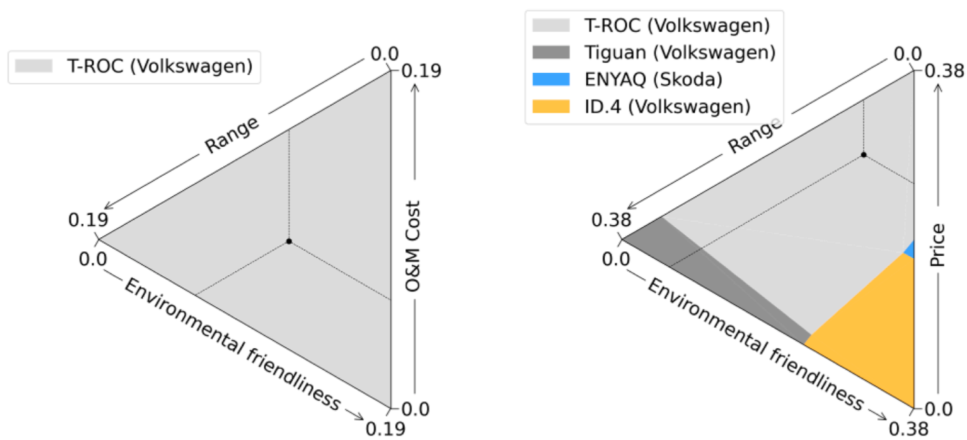

Fig. A.3.1. Figures corresponding to Fig. 3, PROMETHEE II with sigmoid preference function and c = 1.5 (preference type 6 in Brans et al [36]).

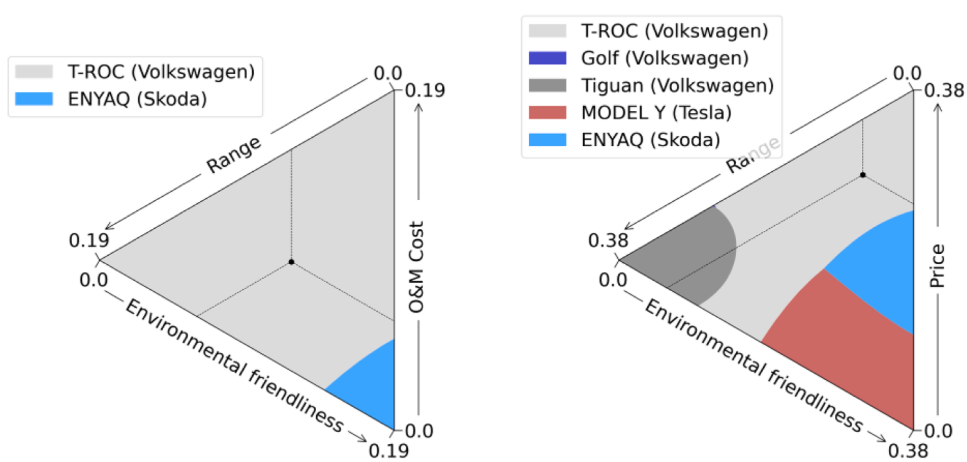

Fig. A.3.2. Figures corresponding to Fig. 3, TOPSIS.

The corresponding analyses with respect to changed characteristics (compare A1) with a different preference function for PROMETHEE II and TOPSIS as different MCDA model yield results comparable to those in A1 (see below). This indicates that our analysis is robust with respect to the MCDA model.

Fig. A.3.3., and A.3.4.

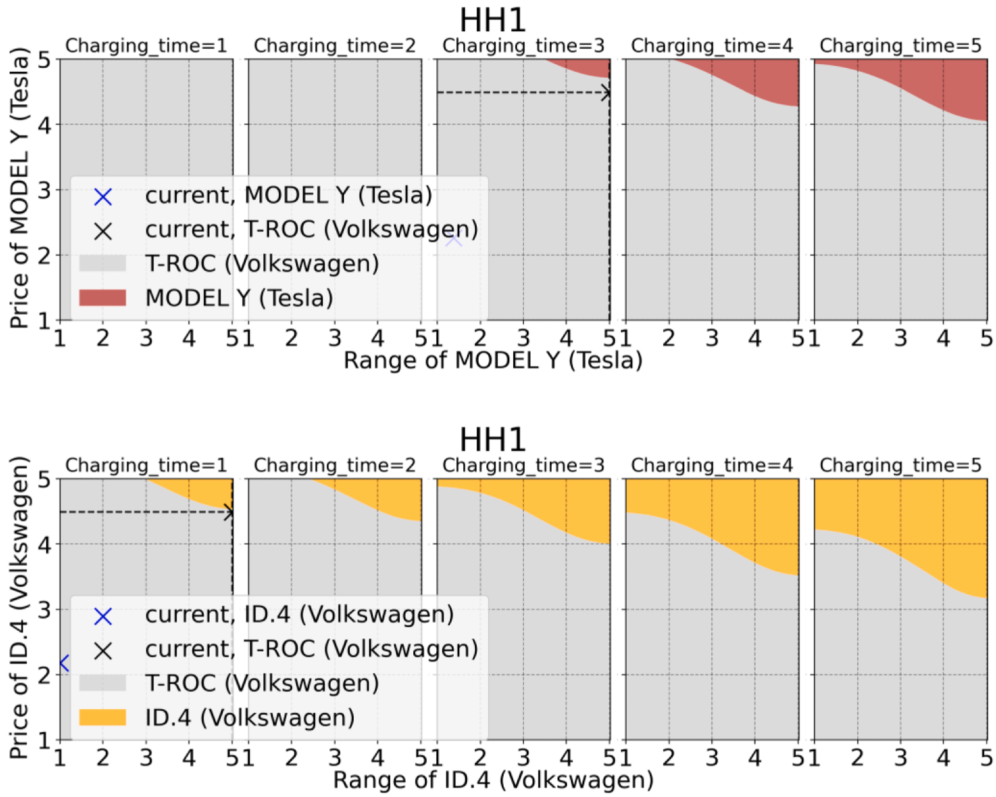

Fig. A.3.3. Figures corresponding to Fig. 4, PROMETHEE II with sigmoid preference function and c = 1.5 (preference type 6 in Brans et al [36]) instead of a linear preference function as in the main text.

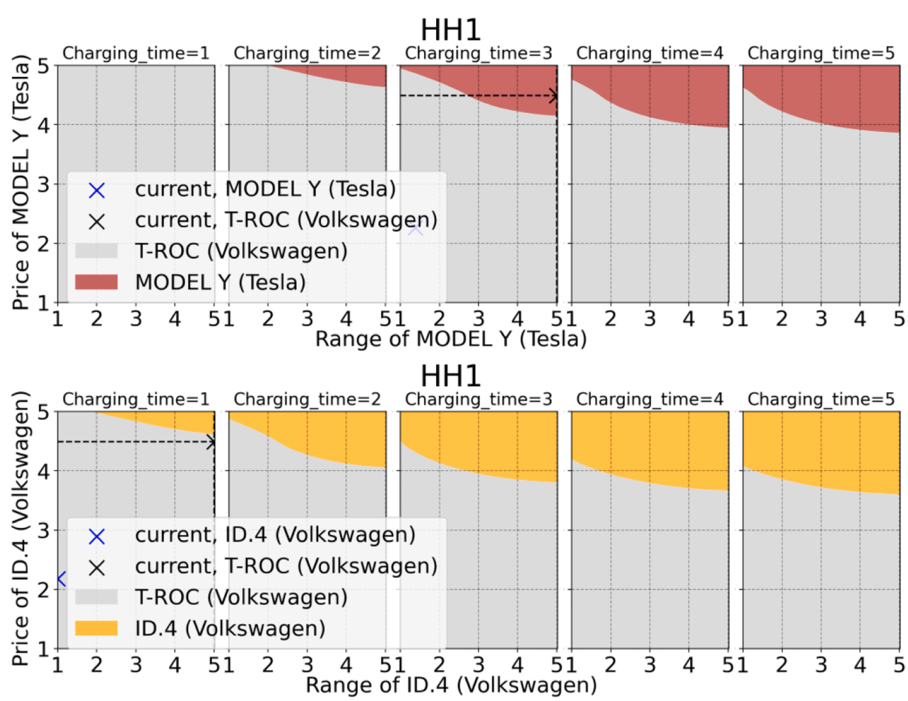

Fig. A.3.4. Figures corresponding to Fig. 4, TOPSIS instead of PROMETHEE II.

A4: Influence **on the Government's initial weighting on the households' final preferences**

Due to the lack of further information, we assume, as a first guess, that the four criteria relevant for the Government ("Environmental friendliness", "Import dependency", "Employment", "Tax revenues") are equally weighted. The sensitivity of the government's preferences with regard to the weightings of these criteria has already been examined in Appendix A2. However, as the actors interact, it is possible that the government's initial weightings may influence the households' final preferences. To investigate this, we carried out four simulations with the very same settings as in the main text, in each of which one of these four weightings was set to one and the other three to zero, in order to examine the extreme cases. The results for actor HH1 (Figs. A.4.1 and A.4.2) show that the choice of these weightings has no significant influence on the preferences of HH1. Similar conclusions apply to HH2–HH8. Therefore, precise knowledge of the weightings on the part of the government is not required. This justifies our first guess.

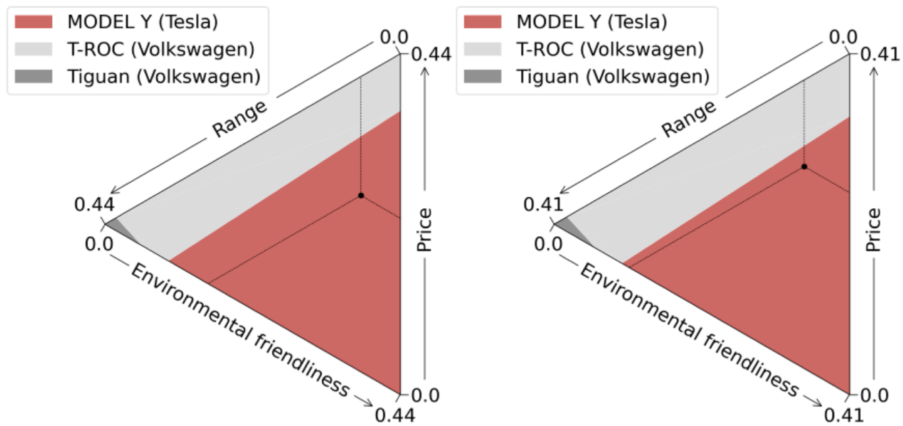

Fig. A.4.1. Final preferences for HH1, initial weight of §Environmental friendliness" set to one for actor Government (left); initial weight of import dependency set to one for actor Government (right).

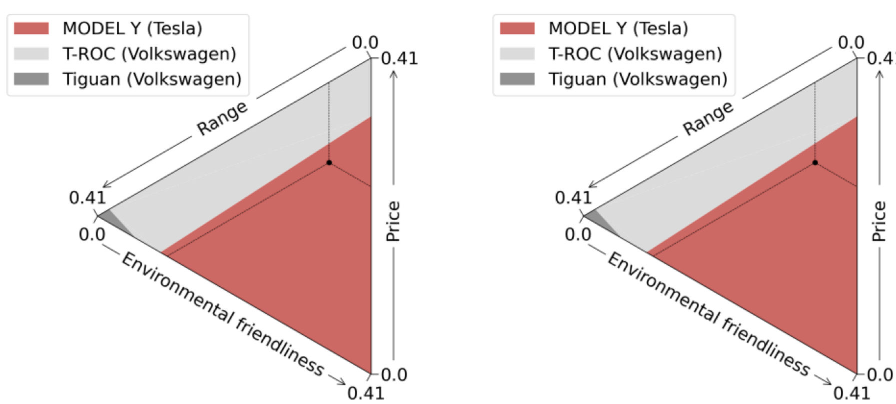

Fig. A.4.2. Final preferences for HH1, initial weight of employment set to one for actor Government (left); initial weight of tax revenues set to one for actor Government (right).

A5: Sensitivity of the Households' preferences with respect to weightings, final state

We provide in the main text a sensitivity analysis of the initial households' preferences. Here, we carry out the same analysis again, but for the final state. Here, the preference of the Model Y turns out to be robust with respect to changes in weightings. The figures for HH2 – HH8 are comparable and omitted for the sake of brevity.

Fig. A.5.1.

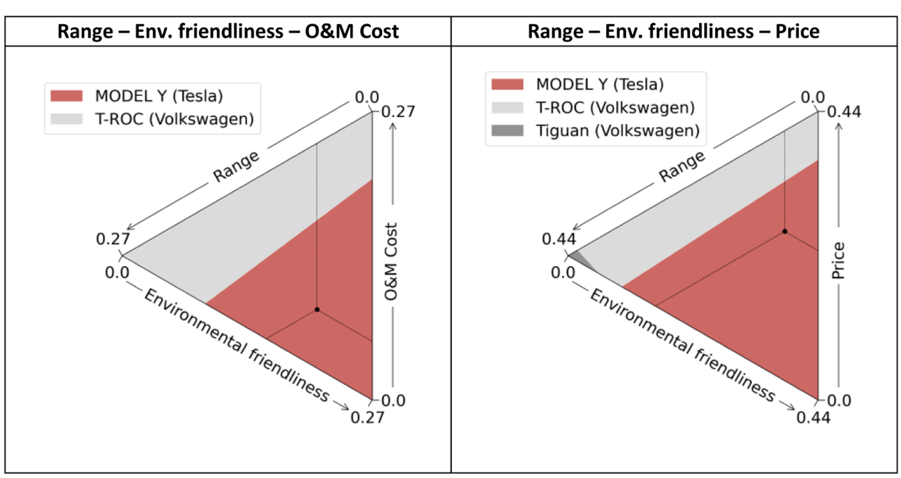

Fig. A.5.1. Impact of selected weightings on preferred car types (actor HH1), final state (compare Fig. 2 for the same analysis with respect to the initial stage).

Data availability

Data will be made available on request.

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