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MULTI-CRITERIA ANALYSIS OF DRIVER PREFERENCE FOR NEW VEHICLE TECHNOLOGIES TO IDENTIFY ROBUST ALTERNATIVES

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Abstract

A large number of vehicle technologies are being researched and developed to improve personal transportation. This study compares surveyed and observed preferences for various vehicle criteria to examine how attractive future technologies may be to consumers. Observed preferences are used to distinguish between technologies that appeal to different market segments, and to validate a multi-criteria decision analysis algorithm. Applying this algorithm, bio-diesel and fuel cell vehicles are identified as being robust over a wide range of Swiss primary energy and technology cost assumptions. A focused examination of battery technology cost identifies a threshold value of $52/kWh as being important for Li Ion technology to be widely adopted in electric vehicles.

Introduction

People rarely make decisions in a rigorous way, using all of their preferences to weigh all of their options. This is not to say that consumers lack the intelligence, or the desire to make the best decision possible, but rather that they most often lack the time and information to approach decision making using scientifically validated tools such as Bayesian decision tree models or linear least-cost optimizations. Many good theories have been proposed to explain how human decision making works[1], and some authors have even applied this analysis to automotive design decisions [2]. The common element of many models of human decision making is that a choice must be made between alternatives using the most information that can be cognitively processed within a given (usually short) amount of time. What this work attempts to do is not to analyze how people make decisions per se, but to show how applying simple Multi-Criteria Decision Analysis (MCDA) tools can assist the decision maker while reducing the amount of time required to reach a decision. Several fuel, hybridization, and vehicle technologies that are robust over a wide range of stakeholder preferences are identified using these tools.

Heuristic Vehicle Design and Multi-criteria Analysis Methods

The transportation technology field is undergoing a renaissance. Over the past decade, powertrain electrification has radically changed how the future of personal mobility is viewed. It is now commonly assumed that tomorrow's cars will contain a significant degree of electrification, either by internal combustion or fuel cell hybrids, or be fully electric battery vehicles. To study the impact of combining the various technology options that are currently being researched and developed, a heuristic approach was developed. This method combines the technologies listed in Table 1 from the bottom-up using rules from first principles and from engineering practice. This is the exact opposite of the top-down approach manufacturers use to design new vehicles, where criteria targets (acceleration performance, cost, etc.) drive technology choices. Heuristic vehicle design uses extensive combination of technology options to find individual vehicle criteria. The advantage of this bottom-up approach is that a wide variety of technologies may be automatically combined, simulated, and analyzed, leading to an understanding not only of individual technology costs and benefits, but also of how interactions between different technology options (or choices) can affect the results for different stakeholder criteria. Several previous studies have examined large sets of future vehicle options, but remained limited in the number of unique combinations of vehicles technologies that they examined [3], [4].

Table 1: Technology options considered in the heuristic design activities

Option Bin	**Category**	**Options**				
Classes	Exog.	3	compact sedan	sedan	pickup truck	
Markets	Exog.	2	passenger	sport		
Engines	Exog.	4	otto	diesel	fuel cell	electric motor
Emissions control	Dep. Endog.	2	selective catalytic red.		particulate filter (open/closed)	
Hybridisation	Exog.	5	none	mild	plug-in series	parallel
Body Structures	Exog.	4	steel	HS steel	aluminium	composite
Transportation Fuel	Endog.	7	gasoline natural gas	diesel hydrogen	bio-diesel electricity	ethanol (E-85)
Primary Energy	Dep. Endog.	4	conventional	biomass	renewable/nuclear (non-biomass)	
Displacements (L)	Endog.	12	1.2 1.3 1.5 1.7 1.9 2.2 2.5 2.7 2.9 3.2 3.5 3.7 3.9			
Engine Efficiency	Dep. Endog.	3	none	turbo	assisted turbo	
Fuel Cell Powers (kW)	Endog.	3	80 90 100			
Electric Path Power (kW)	Endog.	10	3 30 40 50 60 70 80 90 100 110			
Secondary Energy Storage Chemistry	Endog.	2	NiMH	Li-ion		
Secondary Energy Charge/Average Energy (Ah/kWh)	Dep. Endog.	10	0.5 / 0.18 4.5 / 1.7 10 / 3.8 20 / 7.5 30 / 11.3 40 / 15 50/18.8 60 / 22.5 70 / 26.3 80 / 30			
Total:		5.81E+08				

The complete combination of all the technology options of interest for this study would result in simulating over 500 million vehicles, which would be both challenging to implement and in many cases not useful. Heuristics allow the design set to be reduced by eliminating impossible combinations and selectively combining technologies according to engineering practice.

The vehicle sets discussed in this paper are divided into the North American market (248 vehicles, NAM), and the European/Swiss market (2235 vehicles, CHM). Technology performance is strongly dependent on assumptions made regarding cost, environmental burdens, etc. Figure 1 shows how some key input assumptions vary over the six Swiss scenarios, arranged from least to most favorable for alternative technologies, from volume production of alternative drivetrains by 2010 with high fuel prices and non-renewable primary energy sources (Swiss2010v_high_non) to volume production by 2035 with low fuel prices and renewable primary. These cost and emissions values are scaled relative to the maximum value for each input assumption. A more comprehensive list of these input assumptions can be found in Appendix A1, together with references used to arrive at these assumptions.

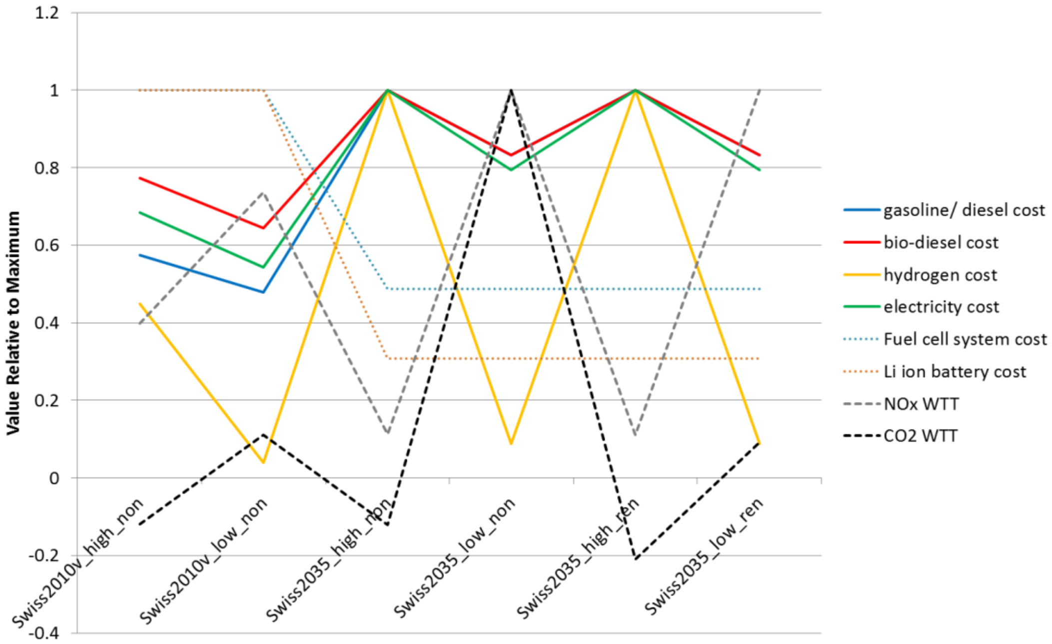

Figure 1: Relationships between cost (fuel and technology) and emissions for six Swiss scenarios

Once a virtual vehicle set is composed using heuristics and the input assumptions have been defined, the designs are simulated using deterministic dynamic programming to ensure fair comparison of the various hybrid architectures. For more details on this approach, please see [5], [6]. Results for some representative vehicles in the US market (NAM) and the Swiss market (CHM) can be found in Appendix A2 and A3 respectively.

To evaluate how future car designs rank based on customer preferences for various cost, performance, environment and utility criteria, a multi-criteria decision analysis (MCDA) was performed. The algorithm selected is called the 'Pair-wise Outperformance Alternative' (POA) method. This method was developed by PSI in collaboration with IIASA for evaluating discrete alternatives for electricity generation in the EU NEEDS project [7]. The POA approach to MCDA is characterised by equations 1 through 4, where technologies *i* and *j* are described by the criteria indicator vector *r*, and ranked according to the stakeholder weighting vector *w* which is the numerical representation of how much value a stakeholder places on each criteria. The relative performance of the two technologies is scaled by the function β to improve algorithm performance in differentiating between winners. This ranking is performed for each technology in the design set.

$$dc_{ijk} = w_k \cdot (r_{ik} - r_{jk}) \cdot \beta(r_{ik}) , \quad (1)$$

$$dc_{jik} = w_k \cdot (r_{jk} - r_{ik}) \cdot \beta(r_{jk}) , \quad (2)$$

$$\beta(x) = \alpha^{-x} (\alpha = 10; 0 \le x \le 1) , \quad (3)$$

$$d_{ij} = \sum_{k=1}^{n} (dc_{ijk} - dc_{jik}). \quad (4)$$

If $d_{ij} > 0$ then vehicle design *i* is preferred to alternative *j*. This algorithm requires that indicator values be normalized, and the method used in this work is to divide each technology's performance for an indicator by the best performer for that indicator as shown in Equation 6 (left side where best value is largest). This method of normalization tends to reduce the impact of criteria where the indicator values are closely clustered without much spread or outliers in the results.

The MCDA approach was then extended from examining single stakeholder rankings to the broader question 'What performance level must transportation technology attain to be accepted by a broad set of stakeholders?' This question is at the root of many policy decisions, and was answered by generating a complete set of preference profiles, with all combinations of either a high or low preference for each of 8 different cost, environment, performance, and utility criteria. The full set of 256 preference profiles (i.e. 2^8 “stakeholders”) were then used with the POA algorithm to rank the vehicle designs, and the top three cars for each profile were given scores according to the Olympic podium scores used by the New York Times [8], that is, 4, 2 and 1 points for the first, second and third cars, respectively. This process is shown schematically below in Figure 2.

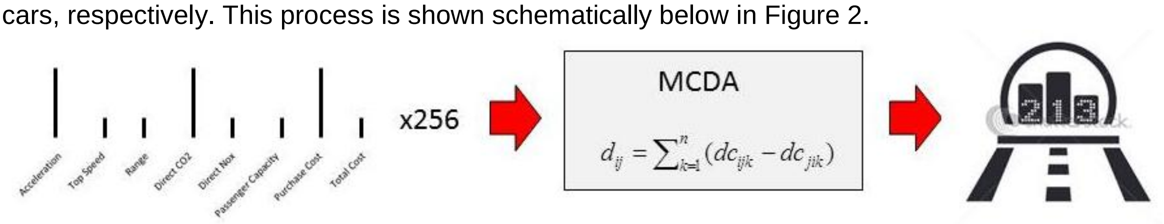

Figure 2: Combinatorial approach to selecting a broad range of stakeholders

The scores across all 256 stakeholder profiles were summed for each design to obtain a measure of how robustly the vehicle performed over the possible all preference profiles, according to Equation 5.

$$Score_{tech} = \sum_{i=1..N} (4 \cdot gold_i + 2 \cdot silver_i + bronze_i) \qquad (5)$$

It should be noted that in reality not all the possible profiles are equally probably and therefore this method is not strictly representative of the general public, but experiments with more realistic preference distributions did not show much variation from the results obtained with this more simplistic (and hence more streamlined) approach.

Results and Discussion

In order to validate the performance of the MCDA algorithm against real market data, Swiss passenger vehicle sales data was analyzed to find average criteria preferences for different customer groups. These preferences were then used to see if the MCDA analysis would select vehicle designs similar to actual Swiss vehicle sales. Sales data from Auto-Schweiz [9] and corresponding performance data for the first half of 2010 was gathered for the 30 most often-sold vehicles in Switzerland (approximately 14% of the total vehicle sales). This data was sorted into three different groups of vehicle consumers based on the criteria shown in Figure 3 using k-means clustering by minimizing Euclidean distance in n-space [10].

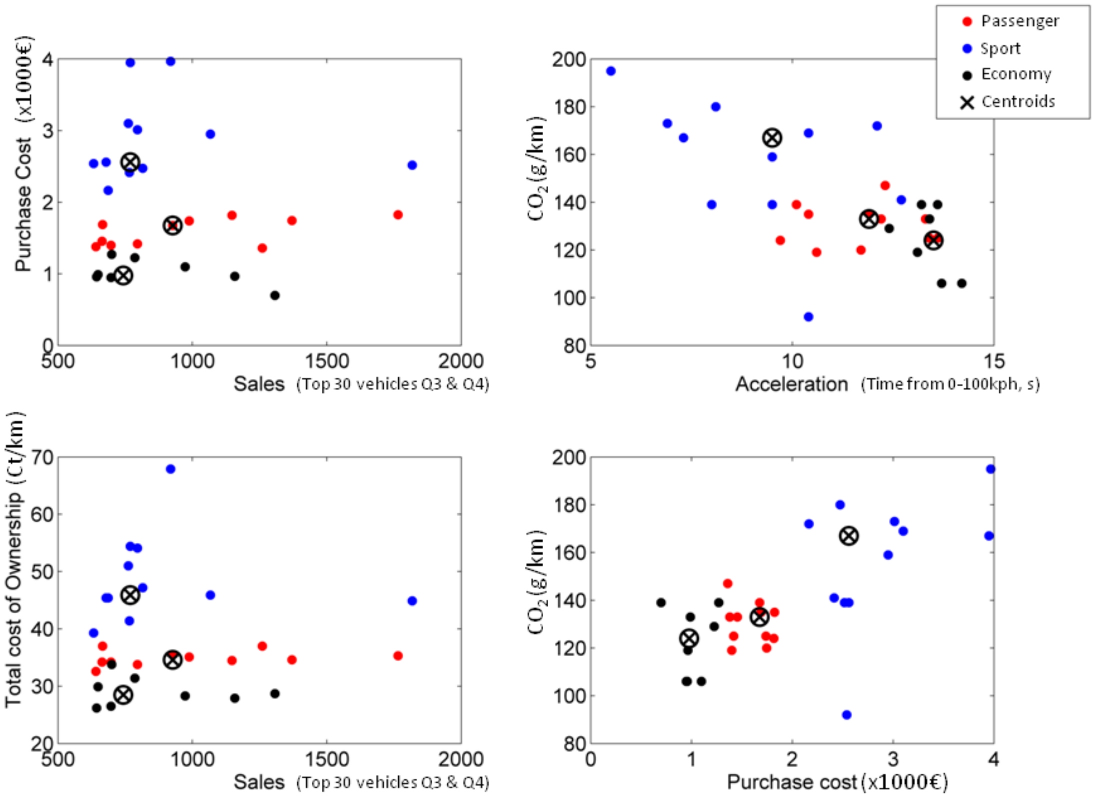

Figure 3: Clustering observed preferences based on the Swiss vehicle sales during the first half of 2010 using the k-means analysis results to find three distinct groups of vehicle buyers. Cluster 1 groups Passenger sedans, Cluster 2 Sport cars, and Cluster 3 Economy vehicles.

The Swiss vehicle sales data can be effectively grouped into categories of buyers who preferred mid-sized passenger vehicles (Cluster 1), small, sporty vehicles (Cluster 2), and small economy vehicles (Cluster 3). An interesting comparison between these observed preferences in the Swiss market and the results of three stakeholder surveys (of which roughly half of the 115 respondents were in the EU, and half were in the US) can be seen in Figure 4. For more details about the surveys and their results please see [11].

In order to derive consumer preference for each clustered group from sales data, the centroids (means) of each cluster were sales-weighted and then assumed to represent the purchasing preference. These values were then normalized by the range between the best and worst performers for each criterion as shown in Equation 7 (left side where best value is largest). Normalizing between the best and worst values may increase differentiation based on criteria where the spread across the criteria is small. This was not how the MCDA algorithm inputs are normalized, and the different approaches were used to reconcile the fact that consumers cannot choose a vehicle that is not available. The observed preferences diverge significantly from the stakeholders' surveyed preferences, although the 'expert' survey respondents from industry tended to match the observed preferences more closely. These results are preliminary, because the data set is relatively small.

(6)

(7)

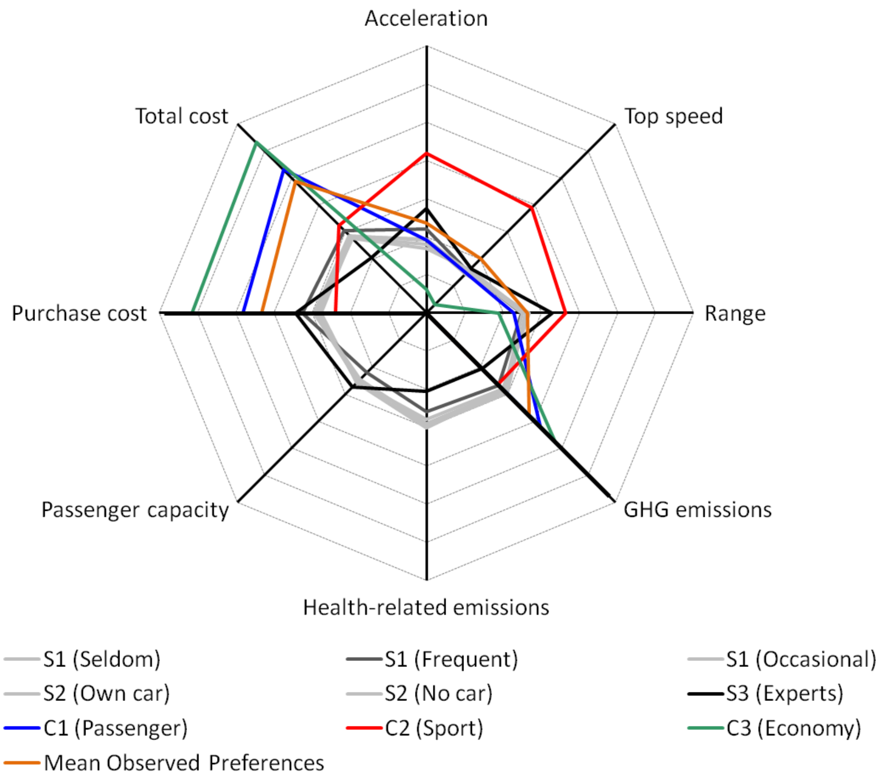

Figure 4: Survey responses from three stakeholder surveys for eight criteria of interest. Note that no sales data was found for passenger capacity and specific NOx emissions.

The observed preferences for the three groups over the eight criteria in Figure 4 were used as inputs to the MCDA algorithm to test our hypothesis that vehicles with characteristics similar to those purchased by the group members should result. The mean characteristics of the vehicles in the aggregated groups as well as the individual characteristics of top vehicles selected after MCDA was performed on two different vehicle sets shown in Table 2. The base set for this MCDA were the NAM virtual vehicles, which included CNG, E85, and H_2 as fuels, but none of these options were selected by stakeholders based on the observed Swiss preferences. Comparing the 'Data' to the first MCDA result (which is a set only consisting of ICE gasoline vehicles to better represent the dominant technology in the analyzed data) the large displacement vehicle technology available is selected by the C2 (sport) group, which reflects their higher preference for fast and powerful vehicles. The coloured cells show very clearly how for four out of six criteria, the order between the MCDA results and the vehicles purchased by the observed preference groups is the same, even though the absolute values of the criteria differs (because of the different characteristics of the virtual vehicle sets). The most notable difference occurs in the 'all vehicles' MCDA, where the passenger customers actually select vehicles with higher acceleration performance. This is directly related to the fact that the mild hybrid bio-diesel vehicles exhibit very good economy performance, which then drove this selection.

Table 2: Comparing clustered (averaged) according to market segment to MCDA results for the top vehicle choice obtained using derived observed preferences

	Hybrid	Fuel (G-gasoline, D-diesel)	Displace-ment (L)	Electric Power (kW)	Battery charge (Ah)	Accel-eration 0-100 kph (s)	Top speed (kph)	Range (km)	CO_2 (g/km)	NO_x (g/km)	Capacity (m3)	Purchase Cost (€)	Total Cost (ct/km)
Data: Swiss Vehicle Sales, Q3&Q4 2010													
Passenger (C1)	-	G	1.4	-	-	11.9	177	789	133	n/a	n/a	16750	35
Sport (C2)	-	G/D	1.8	-	-	9.5	202	906	167	n/a	n/a	25600	46
Economy (C3)	-	G	1.2	-	-	13.5	160	778	124	n/a	n/a	9770	29
All	-	G/D	1.4	-	-	11.2	184	820	138	n/a	n/a	19102	38
MCDA: Only ICE gasoline vehicles													
Passenger (C1)	-	G	1.9	-	-	6.7	253	642	151	0.3	2.4	15965	24
Sport (C2)	-	G	2.9	-	-	6.2	269	719	288	0.2	1.7	26882	32
Economy (C3)	-	G	1.9	-	-	10.0	217	917	110	0.2	2.4	15309	21
MCDA: All vehicles													
Passenger (C1)	Mild	Bio-Diesel	2.7	3	4.5	6.7	255	716	138	0.2	2.5	16959	24
Sport (C2)	Parallel	G	1.5	60	60	7.6	268	1197	175	0.2	1.7	37007	38
Economy (C3)	Mild	Bio-Diesel	1.7	3	4.5	10.0	219	1008	102	0.2	2.5	16303	22

High Mid Low

In order to examine how sensitive our MCDA results are to input assumptions, the same stakeholder weights (C1, C2, and C3) were used as inputs together with the CHM vehicle sets for another series of MCDA runs. When examining the following results, it is important to remember that they use a much larger set of vehicles than the previously discussed results, and also refer specifically to the Swiss energy landscape (with low carbon primary energy from renewables and nuclear). The results of the sensitivity analysis are shown in Figure 5, which clearly shows how bio-diesel non-hybrids and fuel cell hybrid vehicles are robust over most stakeholder preferences, for the Swiss input scenarios. For clarity, these figures only show the top two technologies (Rank 1 and Rank 2) that were selected. The C2 (Sport) group selects parallel hybrids over the non-hybrids selected by the other two groups because of their increased power and hence acceleration performance. It is interesting how little dramatically changing environmental and cost criteria over the various scenarios changes the selected vehicles. This suggests that bio-diesel and hydrogen are very robust technologies in the face of uncertain future technology and fuel price and up-stream emissions in Switzerland. This does not mean that these technologies are necessarily robust across a wide range of stakeholder preferences, however, because the observed stakeholder preferences are still relatively similar for all three groups.

Fuel Cost	Swiss2010v	Swiss2010v	Swiss2035	Swiss2035	Swiss2035	Swiss2035	
H_2	9€/kg	0.8€/kg	20€/kg	1.8€/kg	20€/kg	1.8€/kg	C1
Fossil	1.5€/L	1.1€/L	2.5€/L	1.9€/L	2.5€/L	1.9€/L	C2
Well-to-pump emissions (kg CO_2/kg fuel)							
H_2	1.2 kg/kg	1.2 kg/kg	11.1 kg/kg	11.1 kg/kg	1.0 kg/kg	1.0 kg/kg	
B-100	-1.3 kg/kg	-1.3 kg/kg	-1.4 kg/kg	-1.4 kg/kg	-2.3 kg/kg	-2.3 kg/kg	C3
Elec.	0.121 kg/kWh	0.121 kg/kWh	0.134 kg/kWh	0.134 kg/kWh	0.093 kg/kWh	0.093 kg/kWh	

Figure 5: Fuel cell hybrids and bio-diesel non-hybrids are robust for six Swiss scenarios

A more focused analysis on the effect that the battery cost assumption has on the type of vehicle selected by a broad range of stakeholders generated according to the method described in Figure 2 was performed. Two advanced and one baseline vehicle with the characteristics shown in Table 3 were selected from the NAM vehicle set.

Table 3: Assumed vehicle performance characteristics for the 'set of three' consisting of an all-electric vehicle, a fuel cell vehicle, and an internal combustion engine vehicle.

	Battery size (Ah)	Battery energy (kWh)	Vehicle mass (kg)	Consumption (L/100km eq.)	Acceleration (s) 0-100kph	Top Speed (kph)	Range (km)	Direct CO2 (g/km)	Direct NOx (g/km)	Passenger Capacity (m^3)	Purchase Cost ($)	Total Cost ($)	W/Wh	Battery cost ($/kWh)
EV	160.0	65.6	1762	2.1	11.3	272.3	257.5	0.0	0.0	2.3	42930.8	48594.5	2.4	127.0
FCV	40.0	16.4	1500	4.4	9.6	272.3	444.5	0.0	0.0	2.5	41943.2	45188.7	7.3	372.2
ICE	na	na	1082	8.5	8.5	255.2	589.8	201.6	0.1	2.5	10692.5	21537.9	na	na

The battery cost was gradually reduced and a new MCDA was performed until the all-electric vehicle (EV) achieved a higher score than the baseline ICE vehicle as shown in Figure 6. The score was calculated by awarding four points to each technology that was selected first by a stakeholder, two points for a second rank selection, and one point for a third rank. The result shows that if the goal of wide-spread adoption of EV's is to be achieved, the cost of Li battery pack technology must reach \$52/kWh. It is important to note that all-electric vehicles may find useful niche adoption with much higher specific battery cost, but this experiment was performed to investigate the broader adoption target. It is also interesting that the fuel cell vehicle was selected from the start as being preferred to the ICE vehicle, suggesting that this technology may find widespread adoption should the technology costs assumed in the NAM case be achieved.

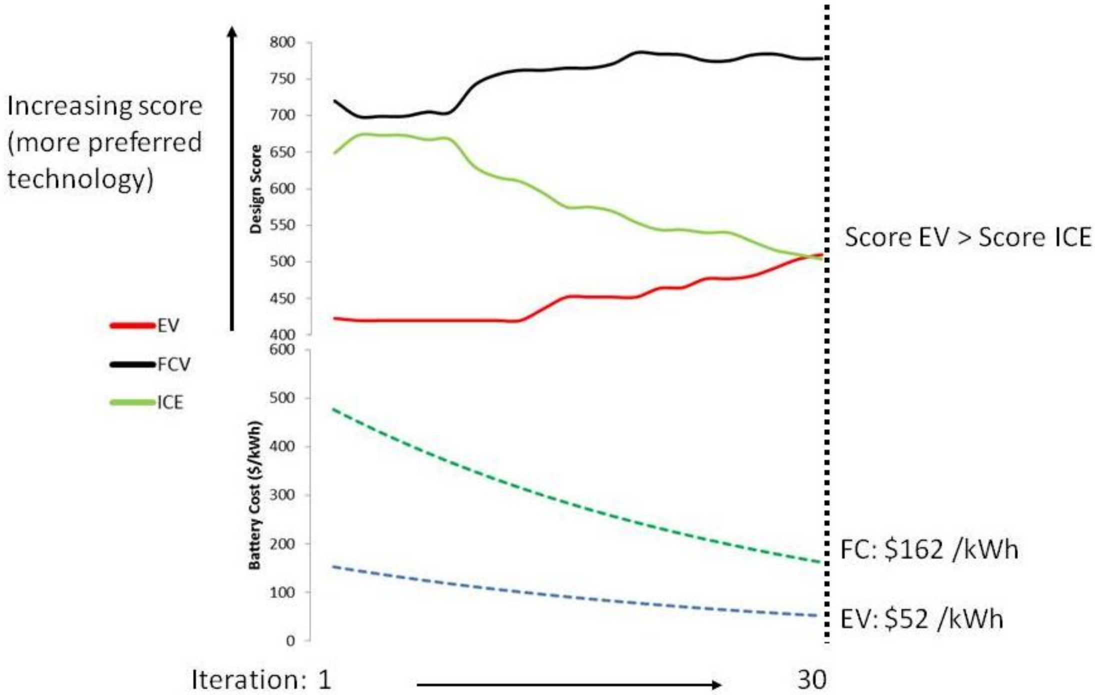

Figure 6: For a broad range of stakeholders to accept battery electric vehicle technology, Lithium Ion pack costs have to achieve $52/kWh.

Conclusions

Several methods were applied to examine the impact that stakeholder preferences for eight different characteristics have on preferred technology. The main conclusions of this work are that:

1. Observed preferences diverge significantly from stated preferences for vehicle consumers, while the manufacturers estimations of consumer preference fall closer to observations,
2. Multi-criteria decision analysis using the 'POA' algorithm is able to accurately select vehicles which correspond to stakeholder preference,
3. Bio-diesel and hydrogen fuelled non-hybrid, parallel and fuel cell hybrids are robust over a broad range of Swiss technology assumptions,
4. Battery technology must undergo a dramatic reduction in cost before electric vehicles are attractive to a broad set of stakeholders, but could find niche adoption with much higher battery cost.

Various methodologies have been presented here which can be applied to help make better individual or group decisions about transportation energy technology. Please visit www.multicriteria-analysis.com for more details on how these results were generated, and for the opportunity to evaluate your own personal preferences.

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Appendix

A1: Input Assumptions for each Swiss Scenario based on [12-14]

	Swiss2010v_high_non	Swiss2010v_low_non	Swiss2035_high_non	Swiss2035_low_non	Swiss2035_high_ren	Swiss2035_low_ren
Fuel Cost						
gasoline (CHF/L)	1.27	1.06	1.84	2.21	1.84	2.21
diesel (CHF/L)	1.35	1.12	1.96	2.35	1.96	2.35
E-85 (CHF/L)	1.44	1.20	1.44	1.73	1.44	1.73
B-100 (CHF/L)	1.82	1.52	1.96	2.35	1.96	2.35
hydrogen (CHF/kg)	9.00	0.79	1.77	20.00	1.77	20.00
CNG (CHF/kg)	1.88	1.48	3.34	4.25	3.34	4.25
electricity (CHF/kWh)	0.18	0.15	0.21	0.27	0.21	0.27
Powertrain Cost						
Fuel Cell System (CHF/kW)	92	92	45	45	45	45
Li Ion Battery Cost ($/kWh)*	224	224	69	69	69	69
ICE Cost (CHF/L)	645	645	451	451	451	451
Well-to-Tank Emissions (g/kg)	bio-diesel	hydrogen	bio-diesel	hydrogen	bio-diesel	hydrogen
VOC	3.82	1.40	3.59	1.28	3.59	1.28
CO	0.91	3.33	0.12	3.08	0.12	3.08
Nox	2.17	4.01	0.61	5.44	0.60	5.44
PM10	0.34	4.79	0.20	3.80	0.20	3.80
PM2.5	0.18	1.88	0.07	2.05	0.07	2.05
CH4	2.27	0.00	2.18	25.96	0.00	2.40
N2O	2.99	0.00	3.00	0.15	1.36	0.00
CO2 (w/ C in VOC & CO)	-1316.91	1230.00	-1338.84	11036.03	-2307.16	1020.00

*Note: costs are scaled by W/Wh. These values are for high-power packs

A2: Vehicles reprepresentative of the North American Market (NAM) which was the basis for the multi-criteria analysis of the real world vehicle sales.

Hybrid	Fuel (G-gasoline, D-diesel)	Displace-ment (L)	Electric Power (kW)	Battery charge (Ah)	Accel-eration 0-100 kph (s)	Top speed (kph)	Range (km)	CO_2 (g/km)	NO_x (g/km)	Capacity (m3)	Purchase Cost (CHF)	Total Cost (CHF)
None	G	1.9	-	-	9.2	224	846	221	0.19	2.16	28268	46073
None	D	1.7	-	-	10.4	216	1041	206	0.16	2.21	27414	42155
None	Biodiesel	1.7	-	-	10.4	216	947	108	0.19	2.21	27414	42580
None	H2 450 bar	1.9	-	-	9.2	224	239	239	0.17	2.16	28268	47194
Mild	G	1.9	3	4.5	9.2	225	887	211	0.19	2.26	28765	46114
Mild	D	1.7	3	4.5	10.4	217	1088	197	0.15	2.26	27911	42363
Series	G	1.1	60	60	11.5	236	1565	171	0.17	2.17	38559	53604
Series	D	1.1	60	60	11.7	236	1754	171	0.15	2.17	37837	51283
Parallel	G	1.0	60	60	8.4	249	1071	195	0.18	2.17	37699	54514
Parallel	D	1.0	60	60	10.3	233	1328	180	0.15	2.17	36648	50832
EV	Electricity	-	130	120	7.3	244	180	173	0.21	2.07	46663	59182
FCV	H2 450 bar	30 kW	60	60	13.9	189	461	179	0.13	2.17	39562	55984

A3: Vehicles reprepresentative of the Swiss Market (CHM) which was the basis for the multi-criteria analysis sensitivity analysis.

Hybrid	Fuel (G-gasoline, D-diesel)	Displace-ment (L)	Electric Power (kW)	Battery charge (Ah)	Accel-eration 0-100 kph (s)	Top speed (kph)	Range (km)	CO_2 (g/km)	NO_x (g/km)	Capacity (m3)	Purchase Cost (CHF)	Total Cost (CHF)
None	G	1.9	-	-	10.2	219	807	235	0.26	2.11	18327	32064
None	D	1.7	-	-	11.6	211	995	199	0.20	2.47	20181	32885
None	Biodiesel	1.7	-	-	11.6	211	905	104	0.21	2.47	20181	36447
None	H2 450 bar	1.9	-	-	10.2	219	228	31	0.09	2.11	18327	39587
Mild	G	1.9	3	4.5	10.2	222	890	215	0.24	2.53	19469	32503
Mild	D	1.7	3	4.5	11.6	214	991	97	0.20	2.53	21322	36736
Series	G	1.1	60	40	13.0	232	1572	154	0.17	2.43	29174	40256
Series	D	1.1	60	40	13.3	232	1748	143	0.16	2.43	31208	42114
Parallel	G	1.3	60	40	10.0	239	1067	190	0.21	2.43	28360	40947
Parallel	D	1.0	60	40	11.6	229	1335	160	0.17	2.43	30124	41831
EV	Electricity	-	170	160	6.2	263	266	61	0.21	2.12	48761	60199
FCV	H2 450 bar	30 kW	100	40	7.7	220	594	25	0.05	2.43	34840	48405