REDUCING ENERGY DEMAND IN TRANSPORTATION – EFFECTS OF ELECTRIC VEHICLES ON CLIMATE GOALS

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ABSTRACT

The intensifying climate change comes along with the need to reduce greenhouse gas emissions significantly. The transport sector's substantial role in this context leads to the imperative to decrease the fossil energy demand in transportation considerably. The contribution of single actions to reduce energy demand in transport has mostly been modeled in linearly structured scenarios. In consequence, least models consider interactions with counteracting effects, which may occur in reality.
In a first step we examine several actions for reducing energy demand in transportation and their effects by means of a qualitative sensitivity analysis. According to this simulation, some measures shape up as worthwhile for more detailed inspections. The changeover from cars with combustion engines to electric vehicles is currently strongly supported by politics. But according to our analysis electric vehicles do not contribute significantly to reduce the total energy demand in transport. We would like to investigate this controversial correlation. Speaking for electric vehicles, there is the comparably low energy demand for the end user and the theoretical option to operate electric vehicles independently of fossil fuels. Also, due to the current electricity price, operational costs driving an electric vehicle would be much cheaper compared to a conventional car. However, this could also result in an increasing vehicle mileage. The future structure of power plants which would be necessary to meet the increasing demand of electricity is another important variable to be analyzed. In turn, these factors would counterbalance today's linear estimations regarding CO_2-emissions, electricity price and demand of fossil fuels. Since the qualitative sensitivity analysis does not account for all of those factors, we use a more detailed model for further inspections. This model contains the feedback of electricity demand, electricity price, price elasticity of mobility and the changing demand of electric mobility helps to analyze these interactions and impacts.
The obtained results of the detailed simulation give an insight into the impacts of one particular action, namely the changeover to electric vehicles. However, the meaning of this

eventual success in the overall context of climate goals needs to be observed in further steps.
This research work is a part of the interdisciplinary research project “Energy 2030” of the International Graduate School of Science and Engineering (IGSSE). In this research group, 8 researchers from 5 different faculties are modelling and simulating scenarios for energy demand in 2030. The work presented in this paper covers the key aspects of the transportation oriented part of the project “Energy 2030”.

Keywords: Energy Demand, CO_2, Electric Vehicles, Modelling, Simulation, System Analysis

PROBLEM STATEMENT

The Need to Reduce Energy Demand

The measurable and in the future reinforcing climate change entails the need to reduce greenhouse gas emissions significantly. According to the latest report of the Intergovernmental Panel on Climate Change (IPCC) it has been established that within the next 40 years the level of global CO_2 emissions has to be reduced by at least 50% compared to 2000 levels. Only this way serious and lasting damage to the environment, the economy and the society caused by climate change can be reduced or avoided [OECD / ITF 2008].
Within the OECD countries, the transport sector is the cause of 30% of all CO_2 emissions. Between 1990 and 2005 in the EU-15-states the CO_2 emissions in this sector increased by 22.9%, in the new EU countries by 45.2%. With this change the transport sector recorded the highest increases in emissions from all sectors. With 70%, the largest absolute share of the transport is contributed by road traffic [IEA 2007].
At the same time, the dependency on fossil fuels imported from abroad increases. Recent events, such as the temporary cessation of Russia’s gas supplies to Ukraine, also affect the EU resulting in domestic political tensions and dependencies. Add to this the steadily increasing economic burden associated with rising commodity prices observed. The German Institute for Economic Research expects oil prices of $ 150 per barrel by 2015 and up to $ 200 per barrel by 2018 [Hunsicker et al. 2008].
From the inevitable claim for a reduction of CO_2 emissions, the role of the important transport sector, as well as the deteriorating political and economic consequences both to businesses and for individuals, there is more than ever the need to reduce the energy demand in transport significantly.

Weak Spot of Models and Prognoses

For several decades, many attempts have been made to decrease the energy demand in transportation with technological developments, restrictions, or with measures of land use and transport planning. The contribution of single actions has mostly been estimated using different modelling approaches. Trying to find out, which action is best suited to reduce energy demand in transportation, we identify two major difficulties: First, some models are based on linearly structured scenarios and do not account for rebound effects which may occur in reality (eg VISSIM for traffic flow considerations in the microscopic field does not arrange for feedback with other packages [PTV 2004]). This can lead to simulations and prognoses which forecast more optimistic effects of a measure than the reality shows after its implementation. Second, many models, e.g. the transportation demand model VISUM or the integrated landuse and transport model UrbanSim, are well suitable to show the impact of single measures. But these models cannot display all existing measures, like emission trading systems or other regulatory measures, which makes it very difficult to compare all existing actions. . In consequence, a qualitative assessment of the effects and interactions of the various instruments for the reduction of energy demand, resulting in a prioritization on the effectiveness, in most cases has not been applied. As a result energy demand increased in the transport sector as described above, whereby the desired goals of reducing consumption in this very energy-intensive field has failed so far.

Challenge to Modelling Approaches

To understand the importance of a specific measure in the overall display, a comprehensive approach of modelling the actions to reduce energy demand in transportation needs to include all relevant interactions of system elements. System models like the STEPS model for Dortmund [Wegener 2008] show the strenght of this integrated approach. On the other side, wide-stretched models seldom have the option to focus on details which are unique to a specific action. For example the broad STEPS model contains "Infrastructure and Technology" as one overall measure.
One big aim of this research project is to examine actions to reduce energy demand in transportation regarding their effects and interactions. A special focus lies on observing the role of a possible large number of electric vehicles in Germany. Politics, media, industry and lobby groups currently have high expectations in a changeover to electric vehicles. We want to analyze its actual impact on climate goals, as well as its side effects and possible counter-productive interactions with other system elements. Actions that are in the focus of media and politics need to be illuminated from two sides. First, their role in the overall display needs to be pointed out, and second, their detailed impacts needs to be simulated. In this research work we apply this approach to study the role of a large fleet of electric vehicles.

Problem Context

This research work is a part of the interdisciplinary research project “Energy 2030” of the International Graduate School of Science and Engineering (IGSSE). In this research group 8 researchers from 5 different TUM faculties *Civil Engineering*, *Electrical Engineering*, *Business Administration*, *Life Sciences* and *Mathematics* are collaborating on integrated scenarios for energy demand in 2030. The work presented in this paper contains key aspects of the transportation oriented part of the project “Energy 2030”.

QUALITATIVE SYSTEM ANALYSIS

After analyzing a high number of models it does not become clear which of all possible measures is best suited for an effective influence on the overall system level. Thus a conceptional investigation of the most common and discussed measures to reduce energy demand in transportation is essential. Establishing a suitable model, we followed the concepts of the *Sensitivity Analysis by Frederic Vester* [Vester 2002]. With this analysis it is possible to perform qualitative assessments of complex systems. The investigated system refers to the passenger transportation in the Federal Republic of Germany, though the created Vester model is so widely held that it can be directly transferred to larger or smaller regions, such as the EU, or the province of Bavaria.

The Overall System Model

The system's target variable is the total energy demand (refer to number 1 in the illustration below). It is directly determined by six factors: *Number of trips per person* (2), *occupancy rate* (3), *modal split* (4), *number of persons travelling* (5), *trip length* (6) and *vehicle's energy demand* (7). These are the leverages of attack to five different packages of actions: *Vehicle engineering* (8), *traffic engineering* (9), *transport planning* (10), *regulatory measures* (11) and *land use planning* (12). The system also contains the variables *costs of measures* (13), *mobility* (14; here the term *mobility* is used as the opportunity to perform a trip) and *social acceptance* (15). The *price of oil* (16) affects as external disturbance. The graphical representation of the overall system model can be found in Figure 1:

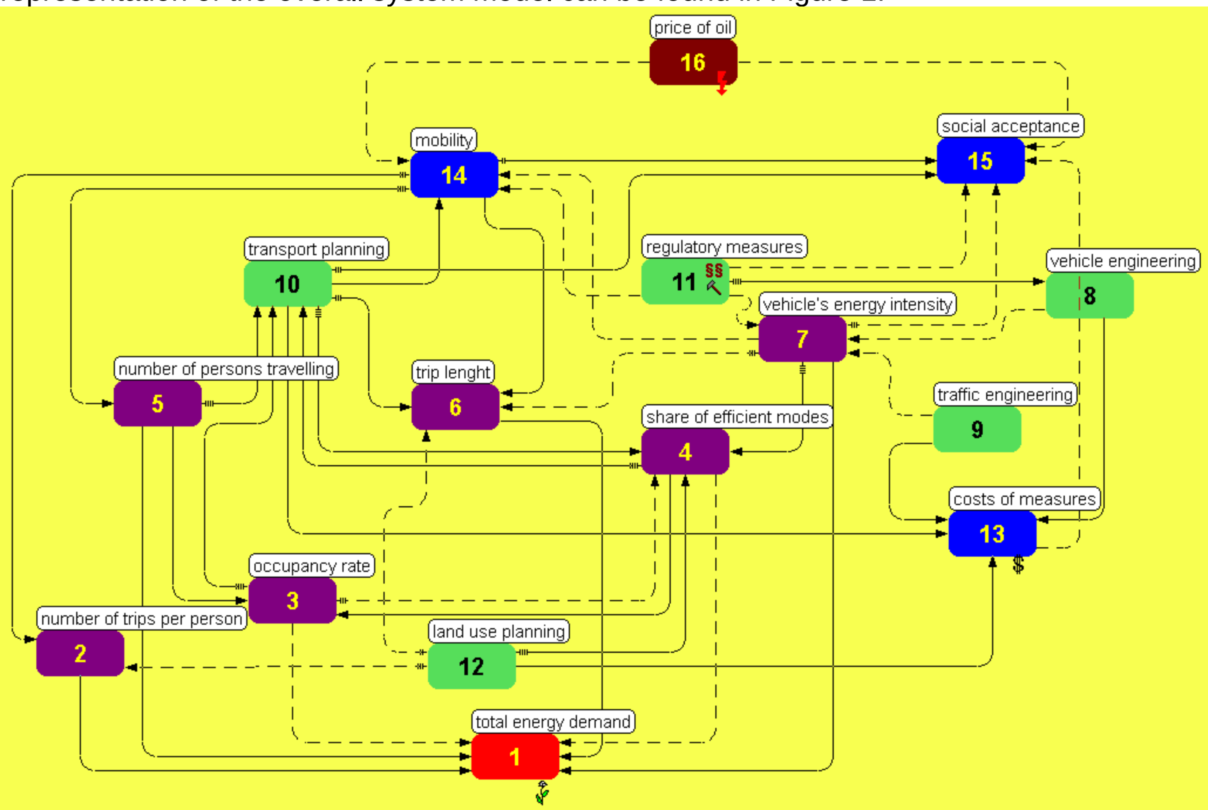

Figure 1 – Overall System Model

In this figure, a solid arrow stands for an enforcing effect of one variable to another, while a dotted arrow symbolizes a counteracting effect. Time lags in the effect are shown with small slashes in the arrow shaft. This figure already shows the high degree of mutual dependencies.

Modelling and Simulation with Table Functions

In a next step we split up the variables 8 to 12 into individual measures, being the base for five different sub-models with their own impact structures, respectively. These sub-scenarios contain their own feedback mechanisms, such as lobbying activities for regulatory measures, or demand-mix for vehicle engineering. Each interaction between two variables, that is each arrow in the illustration, is specified by a table function which qualitatively describes the impact of a change in variable 1 on variable 2. First, we define a suitable scale for each variable. This scale allows a translation from qualitative attributes, e.g. "high degree of social acceptance" into a numeric value. Any variable can take a value between 0 and 30. These values can either represent a section of a quantitative scale, or a tailored qualitative scale. This makes it possible to quantify variables which are originally of qualitative nature, such as social acceptance. Afterwards, we define an impact function for each dependency between all variables. We determine the shape of the impact function according to literature research, expert inputs or, when possible, mathematic relations. Since a variable with qualitative attributes can influence a variable that can be measured quantitatively and vice versa, the results gain mathematical inaccuracy. Therefore, all results in this model are of qualitative nature.

In a subsequent simulation possible interventions in the form of individual measures or packages over a period from 10 to 15 years can be displayed. In these, interactions with other system elements are always included automatically. The simulations' results obtained here point out in what scale an intervention's impact affects the energy consumption, cost, mobility and social acceptance.

Analyzing the Use of Electric Vehicles

We created a sub-model which underlies the variable "vehicle engineering" to compare the potential of technical progress in conventional cars and of electric vehicles. Intuitively, the changeover from cars with combustion engines to electric vehicles seems to be a very suitable action to face the climate challenges. This is based on the comparably low energy demand for the end user and the theoretical option to operate electric vehicles independently of fossil fuels. Nevertheless, electric vehicles still could not denote a breakthrough on the market. This can be explained mainly with the limited range of functions these vehicles offer (e.g. distance range, maximum speed or charging time), as well as the high purchase price. We concluded that the future electric vehicle's share strongly depends on the efforts in research and development to minimize their current disadvantages.

In two different simulations we compared the efforts in *research & development of electric vehicles* on a moderate level to a very high supporting level. The change of relevant system variables are displayed in figure 2 and figure 3.Due to the standardized scale with values from 0 to 30, these graphs only deliver qualitative results. As the values can either represent a section of a quantitative scale, or a qualitative scale they only indicate an increase or a decrease, but not the percentage changes [Vester 2002].

As shown in the graphs below, a stronger development of electric vehicles and the improving range of functions that come with it, lead to a higher share of electrified vehicles. In consequence, the vehicle fleet's energy demand sinks. In both scenarios, the development of conventional cars soon reaches a limit, which in our scale is defined as no major improvement in energy efficiency. However, we observe that one important variable does not change significantly in any scenario, namely the total energy demand in transport. This is based on two effects: First, we included a function into the model, which compensates for cheaper travel costs. This occurs for those driving an electric vehicle, since the comparably low electricity costs provide lower driving costs. The second effect is the effectively low share of electric vehicles after all.

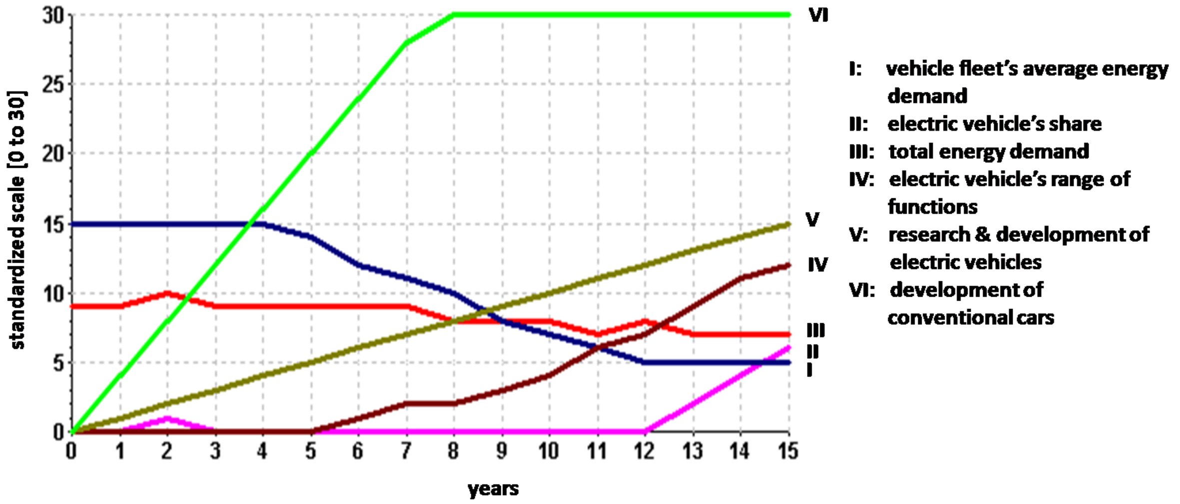

Figure 2 – Electric vehicles vs. conventional cars

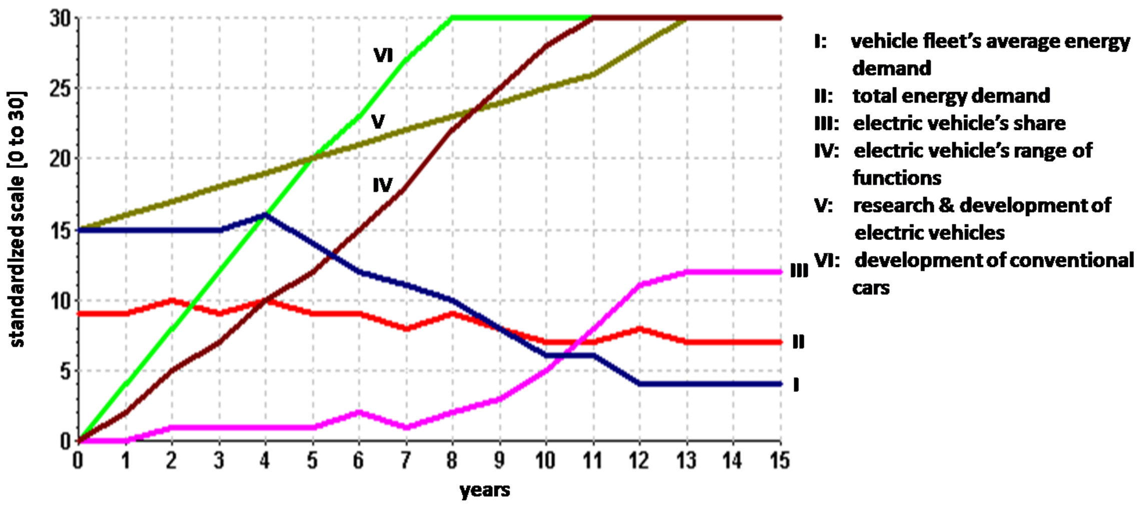

Figure 3 –Strong research & development of electric vehicles

Limits to the Qualitative Model

The results of this qualitative sensitivity analysis indicate that even a strong support of electric vehicles would not contribute significantly to reducing total energy demand in transport. At the same time, this technology is currently strongly supported by German politics, rising high expectations in media, industry and society. We would like to investigate

this controversial correlation. However, this broad model approach does not give the opportunity to verify these conclusions quantitatively. Furthermore, there are many aspects which need to be included into a more detailed inspection. The future structure of power plants which would be necessary to meet the increasing demand of electricity is an important variable to be analyzed. A change in their composition could also result in a changing price for electricity. These are variables that we assumed as being stable in the quaitative sensitivity model. In order to verify the results we obtained so far, a more detailed model and simulation is necessary.
In this paper we only discuss the simulations regarding use of electric vehicles. Further, more promising actions that we observed are mentioned in the chapter *Conclusion and Cutlook*.

ELECTRIC VEHICLES' IMPACTS - A DETAILED SIMULATION

We developed a model which contains the feedback of electricity demand, electricity price, price elasticity of mobility and the changing demand of electric mobility. It helps us to answer the following questions:

1. What is the impact of a changeover to a large number of electric vehicles regarding electricity demand?
2. What types of power plants are expected to be built to meet this new demand
3. How does this new combination of power plants affect the electricity price?
4. What influence has this new electricity price on the vehicle mileage?
5. What is a country's energy demand for private transport with a large number of electric vehicles?
6. What are the total CO_2 emissions?

The *EVICE* Model

To investigate the research questions mentioned above we created the model ***E****lectric* ***V****ehicles' **I**mpacts on **C**limate and **E**nergy Demand* ***EVICE***. Its core feature is the linkage of the model ***ifeon*** (an evolutionary model optimizing the composition of power plants according to electricity demand [Roth 2009]) with fuel price elasticity of car use. The model allows simulations up to the year 2020. A basic scheme of the ***EVICE*** model is shown in figure 4.

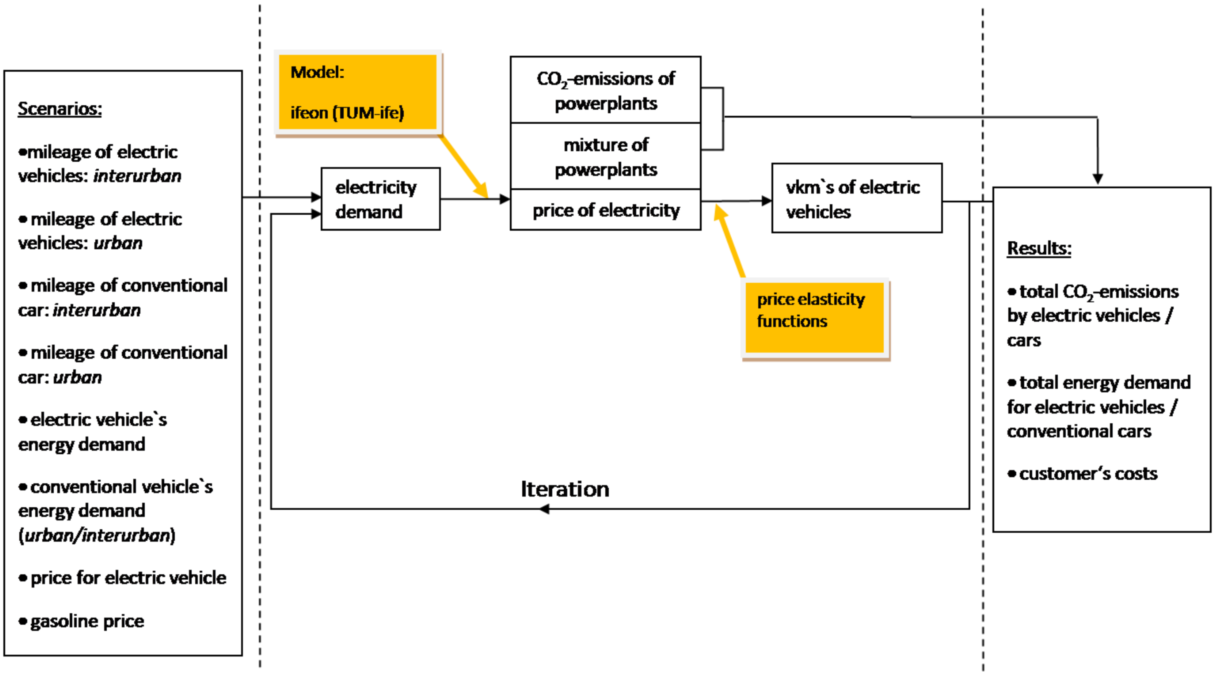

Figure 4 – Scheme of the EVICE model

First we estimate the mileage of private car traffic in Germany for the next 10 years. In different scenarios we assume different numbers of electric vehicles entering the market. These substitute conventional cars with a given share of urban / interurban use. Based on these parameters, we compute the electricity demand which is necessary to meet the energy demand for electric vehicles. We add the loads of all other electricity consumers like households and industry, based on estimations of the energy provider *eon* [Roth 2009]. Germany's total electricity demand is a main input parameter for the ***ifeon*** model. The output of this block is an economically optimized composition of power plants in Germany, respecting given constraints (e.g. phasing out of nuclear energy). The ***ifeon*** model also computes the costs to produce electricity, which is one of the two main parameters to calculate the operating costs of electric vehicles. The second parameter is the future cost of batteries, since their life time depends on the number of load cycles they are exposed to. Assuming future battery costs and lifetimes we obtain the operating costs of electric vehicles.
Since the travel costs driving an electric vehicle will differ significantly to travel costs with a conventional car, the driving performance will alter. We model this effect using different values for price elasticity in various scenarios, respectively. The new mileage of electric vehicles results in an electricity demand different to our first assumption. Feeding in the new data of electricity demand, we start an iteration of the steps as described above. After obtaining equilibrium we are able to compute final results for CO_2-emissions, energy demand, mileage and travel cost for electric vehicles and conventional cars, respectively.

Scenarios

As reference scenario, we assume no electric vehicle in Germany in the next 10 years (Scenario 0). This allows us to compare the results of different settings. In three main scenarios (Scenario 1, 2, 3) we simulate a substitution of 500,000, 1 Mio. or all 46 Mio. conventional cars in Germany by electric vehicles. Whereas the first 2 figures seem to be

realistic, the last scenario is not lifelike. The current properties of electric vehicles, especially the distance range, simply do not allow a holistic coverage of today's mobility patterns. However, scenario 3 helps to illustrate the maximum potential of electric vehicles' use.
One important input parameter is the fuel price elasticity for car use. In sub-scenarios we assume this value to be as low as -0.05 (sub-scenario A) or as high as -0.55 (sub-scenario B). These two values are assumed limits for long term changes in vehicle mileage. The numbers are based on more than 100 surveys and estimations by the INFRAS group. [FIS 2009]. A cap for the total mileage guarantees that very low operating costs do not lead to unduly high mileage. We set this restricting cap on the factor 1,5 of today's mileage. However, the results of our simulations do not reach this value.
The following chart gives an overview to the used scenarios and assumptions:

Table 1 – main scenarios

Scenario	Number of electric vehicles until 2020	Fuel price elasticity
0A	0	-0.05
0B	0	-0.55
1A	500,000	-0.05
1B	500,000	-0.55
2A	1,000,000	-0.05
2B	1,000,000	-0.55
3A	46,000,000	-0.05
3B	46,000,000	-0.55

In these 6 scenarios we assume a yearly increase of gas price by 6%. However, we also simulate scenarios with different rates. Further parameters taken into account include today's and future battery costs, average fuel consumption of Germany's car fleet, share of electric vehicles' urban / interurban use, timeslots for charging, durability of batteries, as well as additional taxes for fuel or electricity. The importance of these parameters will be discussed later.

Results and Analysis

Figure 5 shows the total energy demand in private transport (i.e. conventional cars plus electric vehicles). For conventional cars, this computes as the fuel consumption of Germany's car fleet plus the energy needed for distribution of the fuel. The electric vehicles' electricity demand is the share of the total electricity production which is needed for charging the batteries. It also includes the energy loss in the power plants and the energy needed for distribution. To facilitate the comparison, all units are displayed in Wh.
The 3 dotted lines in the upper part of the diagram represent the energy demand in scenarios 0, 1 and 2 with low fuel price elasticity. The 3 dashed lines beneath display the according variations with high fuel price elasticity. The difference of the energy demand in the year 2020 in scenario 0A (no electric vehicle) and scenario 2A (1 Mio. electric vehicles in 2020) is less than 1%. We obtain the same result in the comparison of scenario 0B and 2B. This implies that the reduction potential in energy demand due to a fleet of up to 1 Mio. electric vehicles in Germany is less than 1%.

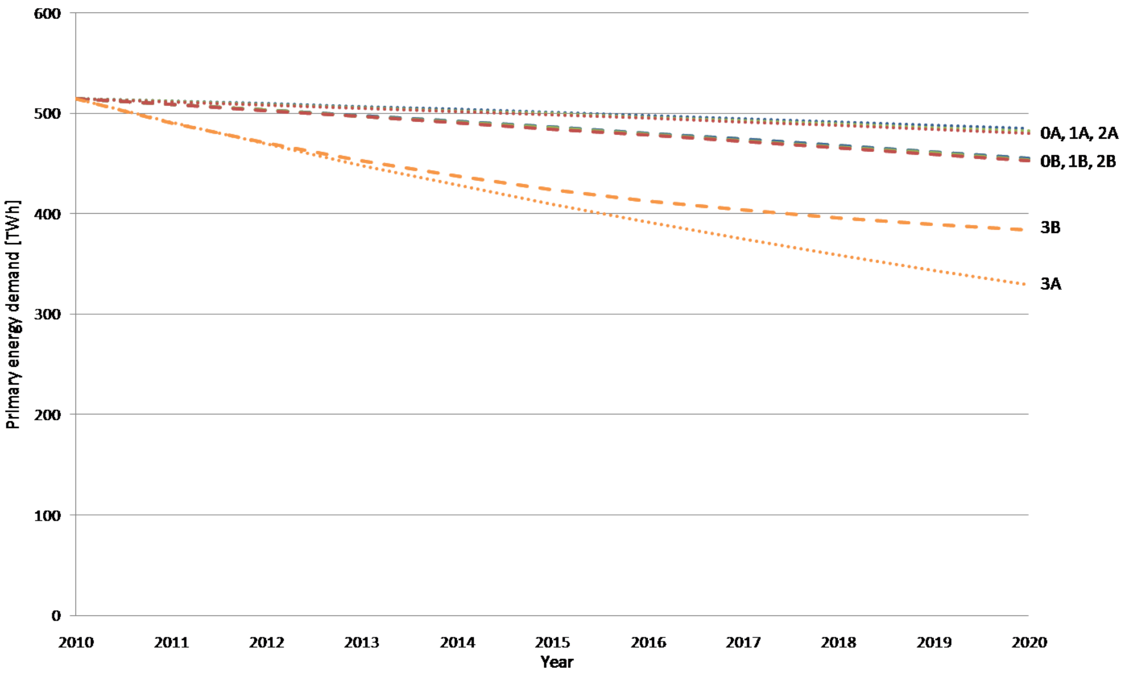

Figure 5 – total primary energy demand in private transport

Since we do not know the exact value of the behavioural change in driving (which we model with a given fuel price elasticity), the A- and B-scenarios are prescriptive limits of these results. The difference between the values of the A- and B-scenarios computes to 6%. This means that the potential reduction in energy demand in the more realistic scenarios 1 and 2 is less than the error of measurement.

Scenario 3, which represents the total substitution of conventional cars by electric vehicles until 2020, shows the maximum potential to reduce energy demand. According to this simulation, energy demand in private transport could decrease by 15% to 32%, depending on the actual fuel price elasticity. In scenario 3B the decrease of energy demand slows down continuously. This is based on the reduced travel cost which induces more traffic: the total vehicle mileage in scenario 3B is 27% higher than in scenario 0B.

Figure 6 displays the development of CO_2-emissions in the 6 different scenarios. We balance an electric vehicle's emission as a part of the power plants' emissions, according to its share of energy demand.

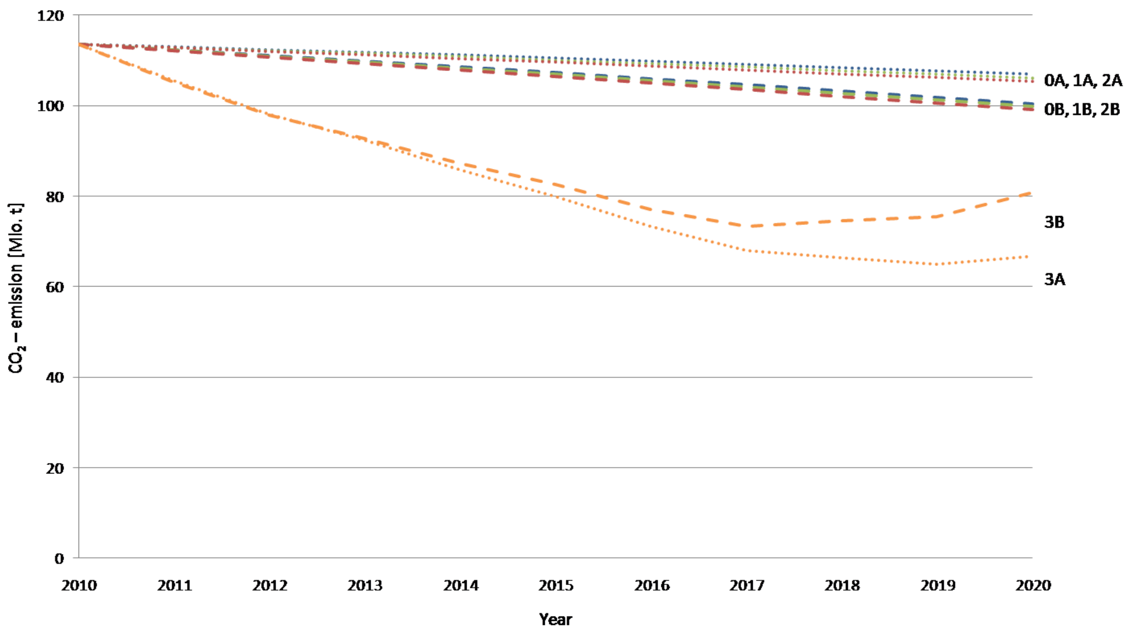

Figure 6 – total CO2-emission in private transport

The characteristics of the graphs in figure 6 are similar to the primary energy demand in figure 5, with one exception: Whereas the decrease of energy demand in scenario 3B merely decelerates, the decline of CO_2-emission in this setting stagnates in 2017 and even starts to rise again. In scenario 3A the CO_2-emission stays on a constant level after 2017. The explanation for this is object to the structure of power plants, which is necessary to meet the high electricity demand. Figure 7 illustrates the comparison of scenario 1B and 3B. Operating 46 Mio. electric vehicles in Germany, the electricity production would rise significantly. Renewable energy sources, like water or wind, cannot compensate for the additional energy demand for 2 reasons. First, these types of power plants are not economically competitive to coal or gas fuelled plants. Second, even with subsidies, a dismounting of solar, wind and water is restricted to certain constraints, which are mainly based on geographical and political circumstances as well as on land use planning. These restrictions are integrated into the ***ifeon*** model.

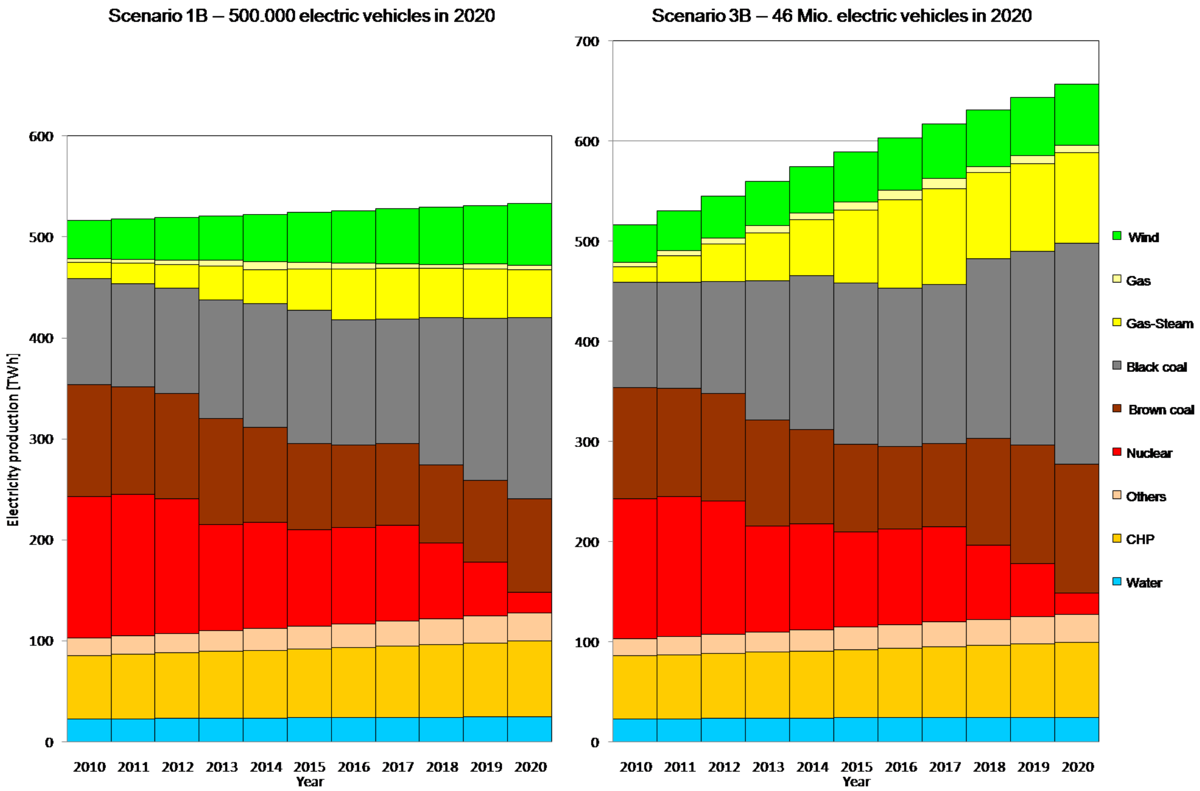

Figure 7 – composition of power plants in scenario 1B and 3B

According to figure 7, the additional electricity demand is mainly met by an increased use of black coal, brown coal and gas. These power plants lead to an increase of the average CO_2–emission of Germany's power stations. In consequence, the maximum potential to reduce CO_2-emissions with the introduction of a theoretical number of 46 Mio. electric vehicles by 2020 is between 26% and 42%, again depending on the actual behavioural change which comes along with lower transport costs.

However, the reduction of emissions according to the more realistic scenarios 1 and 2 amounts to 1,5%. Likewise the primary energy demand, this value is less than the error of measurement.

Sensitivities of unknown parameters

EVICE uses many input parameters which are afflicted with an uncertainty. These include the future fuel price, battery costs, fuel consumption of Germany's car fleet, share of electric vehicles' urban / interurban use, timeslots for charging, restrictions of CO2-emissions for Germany's power plants, durability of batteries, as well as additional taxes for fuel or electricity. In a next step we want to analyze the importance of these variables to the final result. Therefore we run several simulations, consecutively changing single parameters and calculate each parameter's sensitivity. In these simulations scenario 1B is the reference scenario. The final result which we take for comparison is the primary energy demand in private transport in 2020. We compute the sensitivities η using the mean arc elasticity function:

$$\eta_{Q,P} = \frac{\frac{Q_2 - Q_1}{(Q_2+Q_1)/2}}{\frac{P_2-P_1}{(P_2+P_1)/2}}$$

$\eta_{Q,P}$: elasticity of changing parameter
Q_1: primary energy demand in scenario 1C
Q_2: primary energy demand with parameter P_2
P_1: parameter in scenario 1C
P_2: new parameter

The higher the absolute value of *η*, the higher is the parameter's influence on the primary energy demand. The following chart displays the values of the observed sensitivities.

Table 2 – sensitivities of different parameters

Observed parameter	***η***	**P_1**	**P_2**	**Q_1 [TWh]**	**Q_2 [TWh]**
annual rise in fuel price	-22,8%	6%	3%	454	529
electricity price in 2020	-0,14%	23,6 ct/kWh	26,0 ct/kWh	454	453
fuel price elasticity	-3,65%	-55%	-5%	454	482
battery costs in 2020	-0,12%	0,80 €/100km	5,00 €/100km	454	453
urban use of electic vehicles	-0,22	70%	60%	454	454
charging time slots *	0,00%	customer	minimal load	454	454
mobility pricing for conv. cars	-6,65%	0 €/100km	3 €/100km	454	397
Conventional car fleet's gas consumption in 2020	32,0%	6,8 l/100km	7,0 l/100km	454	458
type of increase of electric vehicles *	-0,02%	linearly	exponentially	454	454
Restricted CO2 emissions for Germany's power plants *	0,02%	no	yes	454	454

* The sensitivity is computed as $(Q_1-Q_2)/Q_1$

The relevance of the annual rise in fuel price strongly depends on the fuel price elasticity for car use. In our reference scenario 1B we assumed the elasticity to be high. Therefore, in this analysis the annual rise in fuel price is one of the most decisive parameters. The results show that a lower gas price leads to a higher energy demand. This is based on the fact that the biggest share of individual traffic is posed by conventional cars. Since we linked the car use with price elasticity, a lower gas price leads to higher mileage and energy demand.
The electricity price in 2020 plays a minor role for the energy demand. We raised the price artificially and compared the results. Due to the little number of electric vehicles that we expect, the sensitivity of this parameter is less than 1%.
The fuel price elasticity for vehicle mileage itself has a sensitivity of -3,65%. With a change of this parameter, also the sensitivities of other variables would alter. We conclude that further research is necessary to study the characteristics of this parameter.
We consider the battery cost as part of the travel costs since their life time depends on the number of charging cycles and therefore on the mileage. Many industrial countries currently award highly endowed grants for research in battery technology. The probable outcomes are indistinct. The values for P_1 and P_2 are products of the expected lower and upper limits for future battery costs and the number of charging cycles [Riegel 2009]. Its importance for the overall outcome in this scenario seems to be marginal. However, a scientific breakthrough in

battery technology could lead to a strongly increasing number of electric vehicles. This feedback loop is not included in the ***EVICE*** model.

Our analysis also shows that the energy demand does not strongly depend on the urban or interurban share of the electric vehicles use. The sensitivity is -0,22%.

The charging time slot surprisingly poses a similar insignificance. In scenario 1B all batteries are charged for 4 consequent hours as soon as the driver arrives to a place where charging is possible (at home or at work) and at the same time the remaining driving range is less than 10 km. In a variation, all batteries are charged when the base load of electricity in Germany is lowest, which is between 1am and 5am. No difference in total energy demand is measurable. The only significant change due to smart charging time can be observed in scenario 3: Here a controlled charging leads to a decrease of electricity production costs of 6%. At the same time the CO_2-emissions would increase by 7%. This effect is based on the fact that controlled charging allows operating more power plants at a constant load. That way, it becomes profitable to use more power stations which are suitable for base load coverage. In Germany, these are mostly coal fuelled power plants. Hence, electricity produced with black coal would increase by 23%.

The next variable we analysed is a possible mobility pricing scheme for conventional cars. Here the sensitivity is -6,7%, which also strongly depends on the given fuel price elasticity. The value of 3 €/100km is geared to the Dutch motor vehicle tax resolved in 2009.

The biggest influence on the overall outcome has the average fuel consumption of conventional cars. It is generally expected that fuel efficiency will improve in the future. This makes it cheaper to drive, which induces additional vehicle mileage. Vice versa, if the average fuel consumption in 2020 will be a bit higher than in scenario 1B, the vehicle mileage sinks, but the higher gas consumption of cars overbalances this effect. In consequence, plus 0,2 l difference in the average fuel consumption per 100 km result in 4 TWh more energy demand. The sensitivity is 32,0%.

A further parameter to be observed is the time distribution of new electric vehicles over the next 10 years. In all scenarios described above we assumed the increase of electric vehicles to be linear. In order to see the impacts of this simplification, we compared the results to a scenario, in which the increase is exponential, summing up to the same total number of electric vehicles. No difference can be observed with this variation, the sensitivity computes to 0,02%.

A last interesting aspect is the impact of restricted CO_2-emissions of Germany's power plants. In the standard simulations, power stations need to pay a fine if they emit more CO_2 than allowed according to EU goals [Roth 2009]. This fine is in the order of estimated prices for CO_2 certificates, which currently exist in the European Union. In a variation the model forces to create the structure of power plants in that way, that their emissions have to be below the given threshold. Besides increasing production costs for electricity, no other result has changed. The sensitivity regarding energy demand is 0,02%.

Limits to the *EVICE* Model

A big drawback of ***EVICE*** is its restricted time horizon which only allows simulations up to the year 2020. Whereas in the next 10 years the use of more than 1 Mio. electric vehicles in Germany does not seem to be realistic, a larger fleet in the further future could be possible.

On the other hand, simulations until 2030 or 2050 need to rely on forecasts for this time scope of all parameters needed for this simulation. The future development of mileage, number of cars in Germany, technological innovations and behavioural change are some of the variables which come along with great uncertainties even for the next 10 years. Although a simulation for further timeframes would be interesting, the obtained results would lack of reliability.
Furthermore, ***EVICE*** works with certain simplifications. One of them is the “ceteris paribus” condition. This means that no other essential action to reduce energy demand in transportation (i.e. land use measures, regulatory measures, or transport offer) is introduced. In reality, such actions could influence parameters used for ***EVICE***, for example future car use. Similarly, a scientific breakthrough in battery technology could lead to a strongly increasing number of electric vehicles. This would influence one of the main input parameters of the model. Even though ***EVICE*** contains the most important feedback loops, certain linearity still remains. Therefore, the result we obtain from ***EVICE*** can only be used as an impact estimation and need to be fed back into the overall qualitative model.
As another simplification, we only consider energy demand and emissions based on the use of cars and electric vehicles. The energy and the CO_2 emissions that are related for production of these two vehicle types are not considered. Similarly, we assume a given infrastructure for electric vehicles and do not consider the financing of this infrastructure. Also, scenario 3 assumes a technology that is not available today. Due to the limited range of functions, especially the distance range, a holistic replacement of cars by electric vehicles is today not possible. Since all of those simplifications give an advantage to electric vehicles that does not exist in reality, the overall comparison needs to be rebalanced in favour of conventional cars.

CONCLUSION AND OUTLOOK

We set the goal to model and simulate the impacts of various actions to reduce energy demand in transportation. We detected linearity and lack of interacting feedback loops as one major weak spot of existing models. In consequence, we set up a qualitative system model according to *Frederic Vester’s Sensitivity Analysis*. In this model we can compare the impacts of several actions on system elements like energy demand, costs, mobility, or social acceptance. We created several sub-models to investigate the impacts of single measures; one of them is the use of a large number of electric vehicles for private transport.
In the qualitative model we observed that even with a considerable share of electric vehicles energy demand would not change significantly. We concluded that lower travel costs that come along with these new vehicles would lead to higher mileage. We also inferred that many parameters are missing in the qualitative model to verify the results quantitatively. Hence, a more detailed model is necessary.
We created the ***EVICE*** model in order to simulate the change of all relevant variables when using a large number of electric vehicles. This includes electricity demand, the structure of power plants, electricity price, price elasticity of car use and others. In iterations we calculated the change of each parameter and its impact on the others, until equilibrium is reached. In 3 main scenarios we analyzed the impacts of 500,000, 1 Mio. and 46 Mio. electric vehicles in Germany until 2020. We rated the price elasticity of car use as one of the

key parameters. Therefore, we ran each scenario with a high and with a low value for this variable, in order to distinguish its importance.

The simulations show, that in the scenarios with 500,000 and 1 Mio. electric vehicles, no significant change in energy demand for private transport as well as CO_2-emissions can be observed. We conclude that the main reason is the low share of these vehicle types compared to conventional cars. In the striking but unrealistic scenario with only electric vehicles and no conventional cars, we observe a reduction of energy demand between 15% and 32%, marking the limit of the maximum potential this technology offers. At the same time the results show that the electricity which would be necessary to meet the new energy demand would mostly be produced in coal fuelled power plants. Nevertheless, Germany would decrease its CO_2 emissions due to private transport by 20% - 38% compared to scenarios without electric vehicles. We emphasize the theoretical nature of this extreme scenario and refer to the insignificant improvements regarding climate goals which we observed in the more realistic scenarios.

We also analyzed the sensitivities of numerous variables used in ***EVICE***. We found that the average fuel consumption of conventional cars has the biggest influence on the total energy demand. Further important factors are the future fuel price, possible mobility pricing schemes and the actual fuel price elasticity. These findings should lead to further research. Since the use of electric vehicles will not be sufficient to reduce the energy demand in transportation significantly, the detailed study of alternative actions is of great importance. According to the qualitative system analysis at the beginning of this work, actions like carbon emission trading schemes or mobility pricing could be possible solutions. However, deeper research is needed to fully understand their impacts and side effects.

Marginal are the effects of changes in electricity price, charging time slots, the distinction of urban or interurban use of electric vehicles or the time distribution describing the increase of electric vehicles in use. The detected insignificance of future battery costs need to be questioned, since it could influence the total number of electric vehicles in Germany, and ***EVICE*** does not account for this feedback.

We find a big correlation between the results of the qualitative and the quantitative model. However, some aspects only came to surface in the simulations with ***EVICE.*** The gained knowledge needs to be fed back into the qualitative system model. Knowing the limits of potential to reduce energy demand and emissions, as well as knowing the importance of other related system elements, a change of the qualitative model's setup could be valuable. Especially the restricted time horizon we faced in ***EVICE*** could be bypassed in a qualitative system model.

In this investigation we analyzed the impacts of the using a large number of electric vehicles in Germany. In the next step of this research work we would like to point out this action's importance in the overall context of energy demand in transport.

LITERATURE

IEA (2007). CO2 Emissions from Fuel Combustion.

OECD / ITF (2008). Green House Gas Emission Strategies in the Transport Sector: Preliminary Report.

FIS (2009). Forschung-Informations-System. Elastizitäten der Kraftstoffpreise. http://www.forschungsinformationssystem.de/. 03.06.2009

Hunsicker, F.; Sommer, C. (2008). Welche Zukunft darf's denn sein?. Internationales Verkehrswesen Nr. 9, 334-335.

PTV Planning Transport Verkehr AG (2004). User's Manual, VISSIM 4.0, Karlsruhe, Germany.

Roth, H. (2009). Optimierung der Kraftwerkparkentwicklung. Lehrstuhl für Energiewirtschaft und Anwendungstechnik, TU München.

Riegel, B. (2009) Energiespeicher: Schlüsseltechnik für die Elektromobilität. Der Nahverkehr. 07/2009, pp. 28-29.

Vester, F. (2002). The art of interconnected thinking.

Wegener, M. (2008). Integrated Modeling of Land Use and Transport in Regions. Guest Lecturer in: Advanced Modelling in Integrated Land-Use and Transport Systems, TU München.