Applied Energy xxx (2010) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Optimal charging of electric drive vehicles in a market environment

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ARTICLE INFO

Article history:
Received 3 August 2010
Received in revised form 19 November 2010
Accepted 3 December 2010
Available online xxxx

Keywords:
Electric drive vehicles
Driving patterns
Electricity prices
Linear programming
Quadratic programming

ABSTRACT

With a potential to facilitate the integration of renewable energy into the electricity system, electric drive vehicles may offer a considerable flexibility by allowing for charging and discharging when desired. This paper takes the perspective of an aggregator that manages the electricity market participation of a vehicle fleet and presents a framework for optimizing charging and discharging of the electric drive vehicles, given the driving patterns of the fleet and the variations in market prices of electricity. When the aggregator is a price-taker the optimization can be stated in terms of linear programming whereas a quadratic programming formulation is required when he/she has market power. A Danish case study illustrates the construction of representative driving patterns through clustering of survey data from Western Denmark and the prediction of electricity price variations through regression on prices from the Nordic market. The results show that electric vehicles provide flexibility almost exclusively through charging. Moreover, the vehicles provide flexibility within the day but only limited flexibility from day to day when driving patterns are fixed.

1. Introduction

Currently, the transport sector is 95% dependent on liquid fossil fuel derived from crude oil which implies that 50% of the crude oil production is used for transportation fuels. The liquid fossil fuel consumption causes excessive atmospheric concentrations of green house gasses (GHG), in particular carbon-dioxide, with the transport sector being responsible for approximately 25% of GHG emissions related to energy, and is a major concern in the climate change debate. At the same time, crude oil reserves are concentrated in relatively few countries which presents a serious barrier to diversified energy supply and is a potent source of political conflict. For such reasons, a transition to a transport system that is compatible with a sustainable energy system is crucial [1].

Much attention has been devoted to electric drive vehicles (EDV's) as a solution to the problems of liquid fossil fuel consumption, including the potentials for ensuring security of supply and reducing carbon-dioxide emissions. In addition to this, EDV's offer a flexibility in charging and discharging that may prove highly valuable when integrating fluctuating renewable production such as wind power. In particular, the ability to charge and discharge when desired may facilitate the balancing of consumption and wind power production while the EDV's may also provide regulating and reserve power.

This paper takes the perspective of an aggregator that manages the participation of an electric vehicle fleet in the electricity market and presents a mathematical programming model for optimal charging and discharging of the electric vehicles, given the driving patterns of the fleet and the variations in electricity spot prices. The aggregator minimizes charging and discharging costs subject to a number of technical and contractual constraints. When the aggregator is a price-taker the optimization can be stated in terms of linear programming whereas a quadratic programming model is required when he/she has market power. The model is illustrated with a Danish case for which computational results are reported.

If the total electricity load of the vehicle fleet is sufficiently small, the aggregator is a price-taker. However, if the aggregator has a significant market share, he/she can affect electricity prices by changing the load through charging and discharging. Therefore, we correct electricity prices for long-term effects and describe the short-term dependency between price and demand. We do this by linear regression and use data from the Nordic electricity market.

For computational reasons, the fleet is modeled as a number of aggregate vehicles, each representing a number of vehicles with similar driving patterns. Representative driving patterns are obtained from Danish survey data by grouping the patterns according

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doi:10.1016/j.apenergy.2010.12.015

to vehicles technology and day of departure and clustering the patterns within each group.

For other contributions from the literature on EDV's, we refer to the following references. In general, business models and implementation issues for the control of EDV fleets are discussed [2] whereas the provision of grid support, regulation services and reserve power from such fleets is considered by [3,4] and the potential for reducing emissions by [5]. More closely connected to this paper are the mathematical programming models of [6–8] for analyzing the influence of future EDV fleets on the configuration of the power system. Although similar in their use of the mathematical programming approach, these models are based on social-welfare optimization for the whole power system whereas this paper takes a market-based approach for optimizing charging and discharging against market prices of electricity and from the perspective of an aggregator. To our knowledge no other papers have addressed the optimization problem of an aggregator.

The paper is structured as follows. Section 2 gives a short introduction to electric drive vehicles and different vehicle technologies. The model for optimal charging of battery electric vehicles and plug-in hybrid electric vehicles is presented in Section 3 whereas the construction of driving patterns and the prediction of electricity price variations is considered in Sections 4 and 5, respectively. Section 6 presents assumptions and data whereas Section 7 discusses computational results.

2. Electric drive vehicles

Electric drive vehicles (EDV) comprise all vehicle technologies with an electric drive train. These include battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV) and fuel cell vehicles (FCV).

Although BEV's have been on the market for several decades, the emergence of new battery technologies might finally render such vehicles competitive. At the same time, several large car manufacturers have announced the introduction of PHEV's in this and the following decade, e.g. PHEV-6 Toyota Prius that was on the market in 2009 and PHEV-40 Chevrolet Volt and Volkswagen Golf PHEV-50 that are expected on the market in 2010 [9]. Both BEV's and PHEV's have batteries that can be charged and discharged by consuming and supplying power from and to the grid, respectively, the latter also being referred to as vehicle-to-grid [2,3]. So far, FCV's have been without plug-in capabilities although this may change in the future. We will not address such vehicles as relatively many problems remain to be solved before commercialization can be realized, see [10,11].

BEV's rely solely on battery power for propulsion which is usually less expensive than the use of liquid fossil fuels. Even though most trips can be completed without depleting the batteries, substantial charging times render these vehicles less suited for long trips where recharging is necessary. Whereas BEV's are all-electric, PHEV's have an internal combustion engine which allows for longer trips. Although this engine may use hydrogen, ethanol or gas, liquid fossil fuels are the most widely used and we will therefore confine ourselves to these. PHEV driving modes include charge depleting in which the battery is used until depleted and a charge sustaining in which the engine assists the battery. For simplicity, we will only consider the charge depleting mode of PHEV's. For an extensive overview on EDV technology, see also [12].

In addition to the most widely known EDV's, the BEV's, the PHEV's and the FCV's, there are other emerging technologies for which prototypes will be expected, for example alternative fuel vehicles with compressed or liquid air fuelled engines, see [13], and hybrid electric vehicles with a free-piston engine replacing the conventional combustion engine, see [14].

3. Optimal charging

In this paper, we assume that charging and discharging of electric vehicles occur through purchases and sales in the electricity spot market. Electric vehicles may have direct access to this market, although with transaction costs and minimum trading sizes, market participation will most likely be facilitated by larger traders. This can be implemented in different ways as suggested by [2]. A first business model considers a fleet of vehicles that are parked on the same location and managed by an operator trading in the spot market. This operator also controls the availability of the vehicles for driving. A second model involves the control of dispersed vehicles by an aggregator such as an electricity retailer. However, this aggregator has no influence on the availability of the vehicles. Finally, the third business model derives from the second, except that the aggregator is an independent party, e.g. an automobile manufacturer, an automotive service organization or a manager of distributed generation. For further use of the terms fleet operator and aggregator, see also [3,4]. Here, we consider an aggregator that buys and sells electricity from and to the spot market on behalf of a number of electric vehicles owners. Due to fixed working hours, the owners are rather inflexible in terms of driving. For this reason, the aggregator has only limited influence on the availability of the vehicles and we assume the following. First, the aggregator cannot control the driving patterns of the fleet. Second, the vehicles are always plugged in when not driving so that charging and discharging can be controlled by the aggregator. We consider the case where the aggregator is a price-taker and the case where he/she has market power. If the aggregator is a price-taker, we expect charging to be planned at night-time, given the lower prices. However, if the aggregator has market power, we expect the aggregator also to plan day-time charging at higher prices in order to reduce nigh-time prices. In both cases, we aim to obtain an optimal short-term plan for charging and discharging the vehicles of the fleet, given their driving patterns and the variations in electricity spot prices. This can be accomplished through linear or quadratic programming by minimizing the costs of charging and discharging subject to a number of technical and contractual constraints.

Throughout we use the following notation. For short-term planning, the time horizon $[0,T]$ of a day, a week or a month is discretized into equidistant time intervals $[t,t+1]$ of an hour with $t = 1, \ldots, T-1$. To further facilitate computations, the fleet is partitioned into distinct types of vehicles according to driving patterns such that each vehicle type can be represented by an aggregate vehicle, see Section 4. Aggregate vehicles are indexed by $i = 1, \ldots, I$ where vehicle i represents n_i vehicles. Existing literature, e.g. [6], aggregates the batteries of the vehicles into a single battery. However, this allows the vehicles to charge much faster than is realistic. We therefore let each aggregate vehicles have its own battery. For vehicle i, the variable $l_{it} \geqslant 0$ represents the battery level at time t whereas the variables $u_{it}^{+} \geqslant 0$ and $u_{it}^{-} \geqslant 0$ represent the charging and discharging of the battery from and to the grid between times t and $t+1$ and with efficiency parameters denoted by η_i^{+} and η_i^{-}. Minimum and maximum capacity limits on the battery level are given by the parameters l_i^{min} and l_i^{max} and likewise maximum capacity limits on charges and discharges from and to the grid are given by the parameters $u^{+,max}$ and $u^{-,max}$. Charging and discharging of the battery further involve energy supply from the engine and energy consumption from driving. For vehicle i, the variable $v_{it} \geqslant 0$ represents engine supply between times t and $t+1$ whereas the maximum capacity limit on the engine is denoted by v_i^{max} and the efficiency parameter is given by γ_i. As the engine is only relevant to PHEV's, this efficiency is zero for BEV's. The parameter d_{it} denotes the driving consumption between times t and $t+1$. Finally, total charges and discharges between times t and $t+1$ is represented by the variable q_t.

The operation of the EDV's is constrained by storage balances for the batteries and capacity restrictions for both the batteries and the grid connections to and from the grid.

For the battery storage to balance, the difference in battery levels between the beginning and the end of a time period must equal charges and discharges within the period. Charges account for supply from the engine and discharges from the grid whereas discharges account for driving consumption and charges to the grid, given the respective efficiencies. Hence, the storage balance equations are given by

$$l_{it+1} = l_{it} + u^+_{it}\eta^+_i - u^-_{it} + v_{it}\gamma_i - d_{it}, \quad i = 1,\dots,I, \quad t = t,\dots,T-1,$$

where the initial battery levels l_{i0} are given.

Battery capacity constraints arise from either physical capacity restrictions or user requirements. For instance, a minimum capacity limit may be required by the users for unexpected driving or by the aggregator for reserve and regulation purposes. With such limits,

$$l^{min}_i \leqslant l_{it} \leqslant l^{max}_i, \quad i = 1,\dots,I, \quad t = 1,\dots,T.$$

Unintended end effects in the optimization such as the tendency of the battery to deplete at the end of the time horizon can be partly avoided by a long time horizon. As an alternative, at the end of the time horizon, also referred to as the set point, the battery level may be fixed to a percentage λ_1 of maximum battery capacity such that

$$l_{iT} = \lambda_1 l^{max}_i, \quad i = 1,\dots,I.$$

Similar constraints apply if the aggregator is contractually obligated to charge the vehicles in a way that guarantees a minimum battery level at a certain time every day, e.g. in the morning. Defining this minimum level as a percentage λ_2 of maximum battery capacity, the constraints are

$$l_{it_0} \geqslant \lambda_2 l^{max}_i, \quad i = 1,\dots,I,$$

where t_0 denotes the time of obligation agreed upon in the contract between the vehicle owners and the aggregator.

With capacity limits for the grid connections, the following constraints apply to charges and discharges to and from the grid

$$u^+_{it} \leqslant u^{+,max}, \quad i = 1,\dots,I, t = 1,\dots,T,$$
$$u^-_{it}\eta^-_i \leqslant u^{-,max}, \quad i = 1,\dots,I, t = 1,\dots,T.$$

Capacity limits likewise apply for engine supply. The constraints are given by

$$v_{it} \leqslant v^{max}_i, \quad i = 1,\dots,I, \quad t = 1,\dots,T.$$

It should be remarked that the constraints on the engine supply may be unnecessary as it is rarely optimal to use the engine to this extent.

When charging or discharging from and to the grid, the vehicle cannot be used for driving. This is enforced by the constraints

$$u^+_{it}d_{it} = 0, \quad i = 1,\dots,I, \quad t = 1,\dots,T,$$
$$u^-_{it}d_{it} = 0, \quad i = 1,\dots,I, \quad t = 1,\dots,T.$$

Furthermore, it is impossible to charge and discharge the vehicle at the same time. However, with the following specifications of costs and revenues this will never be optimal and hence such constraints are unnecessary.

Although not included in the model, the aggregator may be subject to regulatory policy that encourages reductions of emissions. For the formulation of carbon-dioxide constraints, see for example [15].

The objective of the aggregator is to minimize total operation costs. These include costs of battery wear when using vehicle-to-grid and costs of fuel for the engine. For vehicle i, we denote by b_i the fuel costs per unit supplied from the engine. Assessments of the fuel economy can also be found in e.g. [16]. As for fuel, we assume that the costs of battery wear are proportional to the energy discharged and we denote by a_i the battery wear cost per unit. Then, total costs of battery wear and fuel amount to

$$\sum_{t=1}^{T}\sum_{i=1}^{I} n_i(a_i u^-_{it} + b_i v_{it}),$$

where each vehicle type is weighted by the corresponding number of vehicles.

Further costs comprise the net costs of purchasing and selling electricity in the spot market when charging and discharging from and to the grid. Total purchases and sales sum to

$$q_t = \sum_{i=1}^{I} n_i(u^+_{it} - u^-_{it}), \quad t = 1,\dots,T.$$

Electricity is purchased and sold at the electricity spot price. If the electricity load of the aggregator is sufficiently small for transactions not to influence market prices, the aggregator is a price-taker. We denote by p_t the electricity spot price at time t. Then the net costs of electricity are

$$\sum_{t=1}^{T} p_t q_t. \tag{1}$$

Note that all constraints are linear. Thus, with this objective, the optimization problem is a linear program.

If, in contrast, the aggregator has a significant market share, transactions may influence market prices. Hence, he/she can affect electricity prices by changing the load through charging and discharging. We assume that the price depends linearly on the load,[2] i.e. $p(q_t) = \alpha + \beta q_t$ at time t, where $\alpha > 0$ and $\beta > 0$, see Section 5. The net costs of electricity are then

$$\sum_{t=1}^{T}(\alpha q_t + \beta q_t^2). \tag{2}$$

Now, with linear constraints and a quadratic objective, the optimization problem becomes a quadratic programming problem.[3]

For planning charging and discharging of EDV's over longer time horizons, we will resort to so-called rolling planning, see Fig. 1. Hence, we define a loop as the 36 h from 00.00 to 00.00 and from 00.00 to 12.00. When participating in the day-ahead market, every day at noon the aggregator will make a plan for every hour of the following day. This is achieved by solving the above optimization problem for 36 h, using constructed driving patterns, see Section 4, and predicted electricity prices, see Section 5. The planning horizon is extended 6 h beyond the 24 h of the following day in order to reduce the effect of a set point for the battery levels. The plan for these 6 h is discarded as a new plan is effectuated. The optimal battery levels of a loop determine initial levels of the subsequent loop. Whether optimal battery levels represents actual battery levels is determined by the quality of the driving pattern construction and electricity price prediction.

4. Constructing driving patterns

To successfully plan charging and discharging, the construction of representative driving patterns is crucial. Fortunately, short-term driving patterns are largely predictable due to fixed working

[2] With limited willingness to change driving patterns, the electricity demand curve of EDV users is vertical and hence an increase in demand only shifts the aggregate demand curve. If actually both the aggregate demand curve and the aggregate supply curve of the electricity market are linear, the market price depends linearly on the EDV demand. A linear dependence may also be seen as a first-order approximation of more complex dependencies.

[3] The objective can be shown to be strictly convex so that the problem has a unique minimizer when feasible.

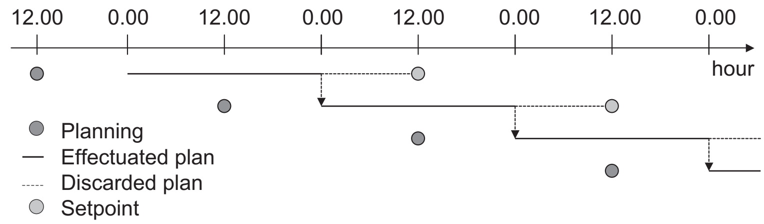

Fig. 1. Rolling planning. A loop starts at 12.00 where an optimal plan is made for 00.00–00.00 and 00.00–12.00. The plan for 00.00–12.00 is discarded when a new plan is effectuated in the following loop. All plans include optimal battery levels. The 00.00 battery levels in a loop serve as initial levels in the following loop.

hours of commuters and fixed business schedules and routes. This justifies the construction of driving patterns by clustering historical data. It is implicitly assumed that the driving patterns of electric vehicles are similar in nature to the historical driving patterns. A Danish case study illustrates with survey data on the vehicle fleet in Western Denmark (January 2006–December 2007) provided by Department of Transport, Technical University of Denmark [17]. The data covers private transport activities and includes a large number of variables such as time, location and distance.

We construct our data set by extracting the following variables from the survey and making the assumptions listed below:

- *Vehicle user*: We identify vehicle users, assuming a single user per vehicle and a single vehicle per user. This might slightly overestimate and underestimate vehicle charging, respectively.
- *Hour and day of departure*: For departures, we record the hour of the day and the day of the week and assume a constant weekly driving pattern throughout the year.
- *Driving distance*: We record the driving distance in the hour of departure and, where relevant, the subsequent hours, assuming an average speed of 70 km/h.

From this we construct a 24-h driving pattern for each vehicle user. We do not consider potential differences in driving patterns between different regions, e.g. due to different regional regulatory policies. Moreover, in spite of differences between private and business users the data does also not allow us to make such distinctions.

To facilitate computations, the vehicle fleet is partitioned into distinct types of vehicles, also referred to as aggregate vehicles, by grouping driving patterns. We group 24-h driving patterns according to:

- *Day of departure*: The driving patterns reveal commuter behavior on weekdays, with departure peaks between 6 and 9 am and return peaks between 3 and 6 pm whereas weekend days and holidays show no peaks. Thus, we distinguish between weekdays and weekend days where the latter include holidays.

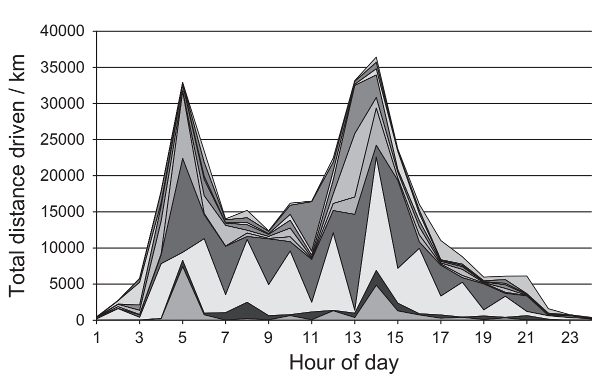

Fig. 2. Clustered driving patterns when the center is the euclidian mean of the cluster and the similarity measure is the euclidian distance.

- *Vehicle technology*: With no obvious distinction between technologies, we assume that vehicles that drive less and more than 150 km on weekdays are BEV's and PHEV's, respectively. Moreover, we assume that the weekday ratio of BEV's to PHEV's remains valid for weekend days.
- *Driving pattern*: Driving patterns are grouped by clustering, see below.

The partition is achieved by first grouping according to day of departure and vehicle technology and then clustering driving patterns within each group. Having grouped driving patterns according to day of departure and vehicle technology, there are 6039 weekday driving patterns and 2116 weekend patterns less than 150 km (corresponding to 1165 BEV's in total) as well as 415 weekday driving patterns and 146 weekend patterns more than 150 km (corresponding to 80 PHEV's in total).

For clustering, we apply the k-means algorithm [18]. Each driving pattern is represented by a 24-dimensional vector of distances. First, we cluster vectors that are similar and aim to obtain k clusters. Similarity between vectors is measured as being sufficiently close in terms of some distance. Second, we represent each cluster by a single vector. The algorithm proceeds as follows. Select k vectors as initial centers of the clusters. For each of the remaining vectors, determine the center closest in distance and assign the vector to the corresponding cluster. Update the centers and repeat assignment to clusters. We ran the clustering algorithm with different centers and similarity measures. When using the mean vector of each cluster as a center, driving takes place in most hours of a day whereas, in reality, it takes place only in some hours of the day. This can be seen in Fig. 2 where the center is the euclidian mean and the similarity measure is the euclidian distance. To overcome this problem, we instead used as a center the vector closest to remaining vectors of a cluster. Now driving takes place only in some hours of the day, as seen in Fig. 3, where the similarity measure is still the euclidian distance. In addition, it facilitates the use of a different similarity measure. This is relevant as the euclidian distance produces unrealistic driving patterns by not taking into account dependencies between subsequent hours of a day. As a similarity measure, we therefore define the distance

$$\sum_{t=1}^{T} \sum_{i,j:d_{it-1}=0 \wedge d_{jt-1}=0, d_{it}>0 \vee d_{jt}>0} |d_{it} + d_{it+1} - d_{jt} - d_{jt+1}|,$$

where $(d_{i1}, \ldots, d_{iT})$ and $(d_{j1}, \ldots, d_{jT})$ denote the vectors of driving distances for vehicles i and j, $\wedge$ and $\vee$ denote the 'and' and the 'or' operators and $|\cdot|$ denotes the absolute value. This distance is small when total driving within subsequent hours of driving is almost the same for the vehicles. The clustering algorithm was implemented in C++ and run with 8717 original and 30 representative driving patterns, respectively. Figs. 4 and 5 show the result in terms of total driving demand, including both original driving patterns and representative driving patterns obtained from clustering. As seen from the figures, in spite of a rather crude clustering reducing the number of driving patterns by 99.66%, the driving patterns are reasonably representative.

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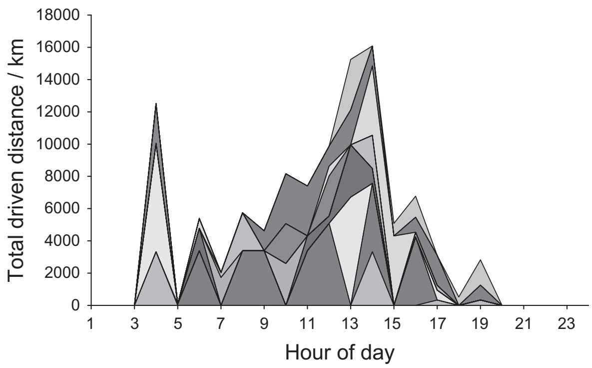

Fig. 3. Clustered driving patterns when the center is vector closest to remaining vectors of a cluster and the similarity measure is the euclidian distance.

The clustering found 20 aggregate BEV's that each represents between 28 and 1102 driving historical patterns (or 58 real vehicles on average per cluster) and 10 aggregate PHEV's that each represents between 11 and 68 driving patterns (or approximately eight real vehicles on average per cluster).

Recall that an aggregate vehicle will be weighted by the number of vehicles in the cluster it represents. Following the clustering, the representative driving patterns were therefore scaled such that when weighting by this number the total 24-h driving demand within a cluster is correct. Furthermore, weekday and weekend clusters were paired such that the number of aggregated vehicles were approximately the same. In case of a discrepancy in the number of vehicles between a pair of clusters weekend driving demand was adjusted by the ratio of weekday to weekend driving patterns such that total driving demand is still correct. The final representative driving patterns serve as input to the optimization model.

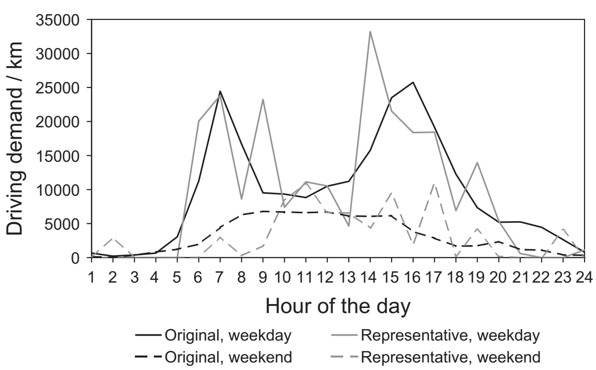

Fig. 4. BEV original and representative driving patterns for weekdays and weekend days.

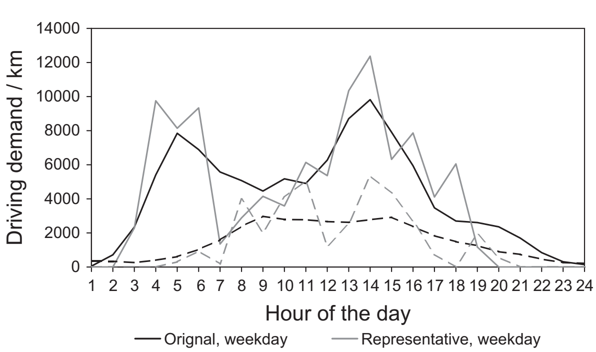

Fig. 5. PHEV original and representative driving patterns for weekdays and weekend days.

5. Predicting electricity price variations

When participating in the electricity spot market, charging and discharging should be planned in a way that takes into account market prices and their variations. For the Danish case study, the electricity spot market is the Elspot market organized by the Nordic power exchange Nord Pool. Being a day-ahead market, Elspot is used for trading hourly contracts with physical delivery the following day. All trades are settled at the market price that is determined by the balance between demand and supply bids from all market participants. By using historical observations of the area price in Western Denmark (May 2006–October 2007[4]), we will illustrate how to predict short-term variations in electricity spot prices through regression.

We regress several short-term and long-term factors on historical electricity spot prices. If the aggregator is a price-taker, this regression can be used to assess the short-term variations electricity spot prices. If the he/she has market power, we also use the regression to asses the short-term variations, but in particular, to examine the dependency between electricity spot prices and load. This serves to estimate changes in prices caused by changes in load from charging and discharging the electric vehicles. It is particularly interesting to investigate how electricity prices at night are affected by the introduction of a large fleet of electric vehicles that are often charged during night-time.

We start by running a simple multivariate regression of electricity spot prices on the main factors that influence electricity prices in the long term and the short-term. It is possible to estimate more advanced models that account for both the demand-side and the supply side of the power system. However, we will focus on the changes in electricity spot prices caused by changes in load. Furthermore, the regression mainly serves to generate representative input to the optimization model in a way that produces representative results and we do not believe that a more advanced model would have a significant impact on the results. The regression variables are

- *Forecasted electricity demand*[5] (q_{dem}): Electricity prices are determined by the equilibrium between the expected demand and supply curves that result from the bids to the day-ahead market. The data was provided by Energinet.dk [19].
- *Forecasted wind power* (q_{wind}): Being non-dispatchable wind power shifts the aggregate supply curve. Confidential data on forecasted on-shore wind power production in Western Denmark was made available by Energinet.dk [19]. The data was scaled to further account for off-shore production.
- *Hydro-power* (q_{hydro}): Hydro-power production likewise contributes on the supply side. When water reservoir levels are high prices tend to be low and vice versa. Weekly deviations of water reservoir levels from the three year weekly median were available from Nord Pool [20].
- *Coal price* (p_{coal}): Prices of coal affect the bids on the supply side of the market. Monthly futures prices for coal were provided by the European Energy Exchange [21].
- *Gas price* (p_{gas}): The above also applies to gas prices. Day-ahead gas spot prices were obtained from the APX Group [22].

[4] The time period for which all data used in the regression was available.

[5] *Although the bids placed in the spot market are based on forecasted electricity demand this data was not available and actual consumption data has been used. The error is within 3%.*

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Table 1
Regression results. For each variable, the results include *t*-statistics and *p*-values for stationarity and cointegration tests as well as long-run parameter estimates.

Variable	Unit	Stationarity		Cointe gration		Parameter	Unit	Estimate
		t-stat	*p*-value	*t*-stat	*p*-value			
Price	DKK/MWh	−25.71	0. 00			p_0	DKK/MWh	−333.10
Demand	MWh	−43.69	0.00	−22.40	0.00	β_{dem}	(DKK/MWh)/MWh	0.1174
Wind power	MWh	−21.89	0.00	−23.61	0. 00	β_{wind}	(DKK/MWh)/MWh	−0.0668
Hydro-power		−0.41	0.91	−29.47	0.00	β_{hydro}	DKK/MWh	−1. 8120
Coal price	DKK/T	2. 26	1.00	−25. 72	0. 00	β_{coal}	(DKK/MWh)/(DKK/T)	0.6475
Gas price	DKK/T	−2. 24	0.19	−28. 95	0. 00	β_{gas}	(DKK/MWh)/(DKK/MWh)	0.1282
Emission price	DKK/T	−0. 56	0.88	−29. 93	0. 00	β_{emis}	(DKK/MWh)/(DKK/T)	1.2044

- *Emission allowance price (p_{emis})*: As for coal and gas prices, prices of carbon-dioxide emission allowances affect the bids on the supply side. Prices were available from Nord Pool [20].

Hence, the regression is given by

$$p = \alpha + \beta_{dem}q_{dem} + \beta_{wind}q_{wind} + \beta_{hydro}q_{hydro} + \beta_{coal}p_{coal} + \beta_{gas}p_{gas} + \beta_{emis}p_{emis} + \epsilon,$$

where β_{dem}, β_{wind}, β_{hydro}, β_{coal}, β_{gas}, β_{emis} are regression parameters and ϵ is a random noise. Before running the regression, we tested for unit roots by using the Dickey–Fuller test [23] and found that for the variables electricity prices, electricity demand and wind power stationarity cannot be rejected, whereas this did not apply to the variables hydro-power, coal prices, gas prices and emission prices. To avoid spurious regression relationships, we therefore tested for unit roots in the residuals, both in the univariate regressions of each of the variables electricity demand, wind power, hydro-power, coal prices, gas prices and emission prices on electricity prices and in the multivariate regression. In all cases we found that cointegration cannot be rejected. Hence, we used Ordinary Least Squares to obtain long-run parameter estimates. Unit root test statistics and statistical significances for stationarity and cointegration as well as regression parameter estimates are found in Table 1 for each variable. The multivariate test showed a test statistic of −36.54 with a statistical significance of 0.00. It should be remarked that the parameter β_{dem} is larger than β_{wind}. The reason for this is that the Nordic hydro-power producers hold back production when wind power production is high in Denmark whereas the remaining Nordic demand cannot be held back when Danish demand is high. We therefore denote net load by the weighted difference $q_{dem} - q_{wind}\beta_{dem}/\beta_{wind}$ between demand and wind power levels.

To focus on short-term effects of electricity demand and wind power, we continue by correcting electricity spot prices for long-term effects of hydro-power, coal prices, gas prices and emission allowance prices. The corrected prices can be used as input to the optimization model, both in the case where the aggregator is a price-taker and in the case where he/she has market power. With an effect on prices, we proceed to assess the dependency between electricity spot prices and net load. Fig. 6 depicts the corrected price versus net load. As can be seen from the figure, the linear regression is fairly accurate for net loads between 1500 MWh and 2800 MWh. Nevertheless, electricity is a non-storable commodity and in contrast to other commodities supply and demand must balance at all times. This causes price jumps in situations of grid congestion. That is, for very high (low) demand or low (high) wind power levels, import (export) transmission limits may produce significant price increases (decreases). An appropriate model would therefore suggest a non-linear dependency between spot prices and net loads. However, with only few historical observations of price jumps, a such model cannot be estimated by regression. We will not further discuss the modeling of price jumps but assume a function of the form $p_t(q_t) = \alpha + \beta\tan(\nu q_t + \mu)$[6] to illustrate the effects of using a non-linear model. With a suitable choice of parameters α, β, ν, μ, this function is increasing and approximately linear between 1500 MWh and 2800 MWh but increases marginally for higher net loads and decreases marginally for lower net loads. The non-linear function is used to estimate the variation in electricity spot prices given the variations in net load that are due to electric vehicles.

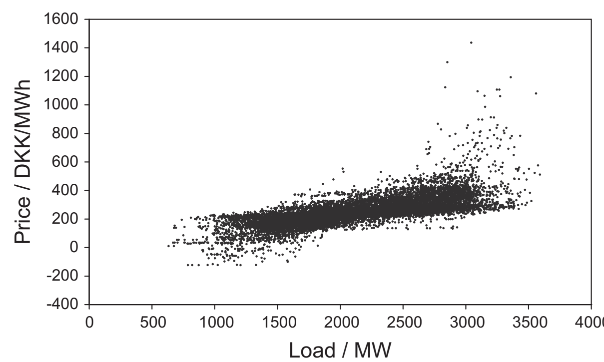

Fig. 6. Net load versus electricity spot prices. Net load is defined by the weighted difference between demand and wind power production.

We sketch a procedure for incorporating a non-linear dependency in the linear optimization problem. Let the initial points $q_t^0,\ t = 1,\dots,T$ be defined as aggregate electricity load without the integration of electric vehicles. Approximate the non-linear function by the functions $p_t(q_t) = \alpha_t + \beta_t q_t$ with the coefficients $\alpha_t = \alpha(q_t^0),\ \beta_t = \beta(q_t^0),\ t = 1,\dots,T$ by matching the derivatives at the points $q_t^0,\ t = 1,\dots,T$. Then repeat the following for $k = 1, \dots, K$ until some iteration limit K. Solve the optimization problem and obtain $q_t^k,\ t = 1,\dots,T$. Update the coefficients $\alpha_t = \alpha(q_t^k),\ \beta_t = \beta(q_t^k),\ t = 1,\dots,T$ to

$$\begin{aligned} \alpha_t(q_t^k) &= (p_t(q_t^0)q_t^k - p_t(q_t^k)q_t^0)/(q_t^k - q_t^0), \\ \beta_t(q_t^k) &= (p(q_t^k) - p(q_t^0))/(q_t^k - q_t^0). \end{aligned} \tag{3}$$

Solve the optimization problem and obtain $q_t^{k+1},\ t = 1,\dots,T$. The approach is illustrated in Fig. 7.

6. Assumptions and data

We now present assumptions and data for a Danish case study with the driving patterns and the electricity prices obtained in Sections 4 and 5 and the remaining data given below.

[6] With a slight abuse of notation, q_t now denotes the aggregate electricity demand, i.e. the sum of the aggregate electricity load without the integration of electric vehicles and the load that results from charging and discharging and is obtained from the optimization model.

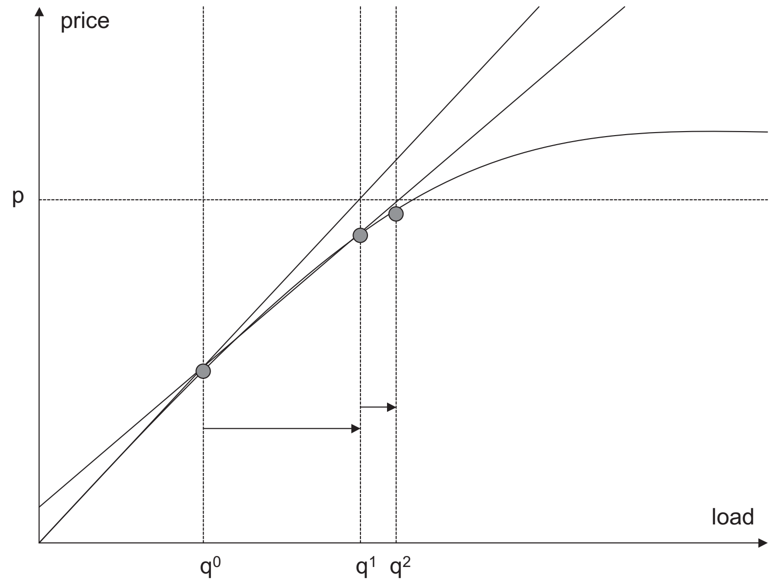

Fig. 7. An illustration of the procedure for incorporating a non-linear dependency between electricity spot prices and net load into the linear optimization problem.

It is assumed that EDV's are integrated in the current electricity system and hence the results should be interpreted ceteris paribus.

Although most likely both BEV's and PHEV's will be marketed with several battery sizes, for illustration purposes, we confine ourselves to one type of BEV and one type of PHEV. BEV's are assumed a 150 km driving range whereas PHEV's are assumed a 65 km all-electric driving range which complies with most demonstration types [24]. Driving efficiencies vary substantially in the literature. However, as in [25] we use an efficiency of 6 km/kWh for both BEV's and PHEV's which corresponds to battery sizes of 25 kWh for BEV's and 10.8 kWh for PHEV's. For both types of vehicles charging and discharging efficiencies are assumed to 90% and 93%, respectively [3], which give rise to a grid-to-grid storage efficiency of 84%. Finally, the efficiency of the engines are set to the 2015 peak efficiency of 39% or 23.4 km/l [12].

For capacity data, we use the AC-150 Gen-2 vehicle [26] that allows for 20 kW charging and discharging from and to the battery. Furthermore, we assume that EDV users have access to home and workplace charging through the current grid, in the Danish case a three-phase 16 A 230 voltage system, such that charging and discharging maximum capacities from and to the grid are 11.1 kW which is in the range of the 10–15 kW found in [3]. Minimum capacities are set to 20% of maximum capacities. The battery levels at the end of a day are assumed 70% of maximum capacity whereas the contractually agreed minimum battery levels in the morning are assumed 80%. Model runs show that varying these numbers has only minor impacts on the results.

To estimate fuel costs, we assume one liter of diesel amounts to 10 DKK including taxes and has an energy content of 10 kWh such that the resulting energy costs are 1000 DKK/MWh. The costs of vehicle-to-grid battery wear are set to 394 DKK/MWh which complies with [3].

We will obtain results for a number of scenarios differing by the size of the EDV fleet, the dependency between electricity prices and net load and the type of taxes and charges on electricity consumption and production. Each scenario will be compared to a baseline scenario.

6.1. Baseline

In the baseline scenario the fleet includes 300.000 EDV's which counts for 25% of the current fleet. Furthermore, the dependency between prices and loads is given by the functions $p(q_t) = \alpha_t + \beta_t q_t$ with α_t, β_t being constants for $t = 1, \ldots, T$. Although taxes and charges apply to vehicle owners, we assume that the fleet aggregator takes these into account when planning. We assume that current Danish taxes and charges apply. Current taxes on electricity consumption comprise fixed taxes such as electricity, emission and electricity distribution taxes, electricity savings contributions and a value added tax. Current end-user charges involve public service obligations, transmission charges and network tariffs. As a result, the end-user price of electricity is $(p_t + \rho_1 + \rho_2)\tau$ for $t = 1, \ldots, T$, where ρ_1 denotes total fixed taxes, ρ_2 total charges and τ value added tax.

6.2. Varying taxes and charges

A stronger incentive for flexible demand may be provided by replacing fixed taxes by value added taxes. This is particularly relevant for electric vehicles that are often charged during night-time when prices are low. Now the end-user price of electricity is given by $(\tau_1 p_t + \rho)\tau_2$ for $t = 1, \ldots, T$, where τ_1 and τ_2 denote value added taxes and ρ total charges. It should be noted that the value added tax that replaces the fixed tax is determined such that total taxes are unchanged for the historical consumption data during 2004–2007.

6.3. Varying fleet size

Two scenarios are based on changing the size of the EDV fleet. The scenarios are based on the extreme cases for which all vehicles are EDV's and 1% of all vehicles are EDV's, respectively.

6.4. Price-load dependencies

We first consider prices depending linearly on net load, i.e. $p(q_t) = \alpha + \beta q_t$, where α, β are constants, and second consider the procedure for incorporating a non-linear dependency between prices and net load.

7. Results and discussion

The results of the model runs for the Danish case study are summarized in Table 2 and discussed below.

Table 2
Results for the following scenarios: Baseline scenario (BSLN), baseline scenario with value added tax (VAT), with all vehicles being EDV's (100% EDV), with 1% of vehicles being EDV's (1% EDV), with linear price-load dependency (LIN) and applying the procedure for incorporating non-linear price-load dependency (NONLIN). Results include the number of EDV's (EDV), total charging (CRG), average charging price (PRC), total discharging (DISCRG), average discharging price (PRD), day-time charging (DAYCRG) and fuel consumption (FUEL).

Scenario Unit	EDV 1000	CRG GWh	PRC DKK/MWh	DISCRG GWh	PRD DKK/MWh	DAYCRG %	FUEL GWh
BSLN	300	1299	249	0.246	857	25.8	521
VAT	300	1308	250	14.1	494	24.7	540
100% EDV	1190	5154	319	0.320	878	41.7	2066
1% EDV	12	52	183	0.605	753	10.7	21
LIN	300	1314	222	12.9	910	16.9	521
NONLIN	300	1299	240	0.316	853	22.7	521

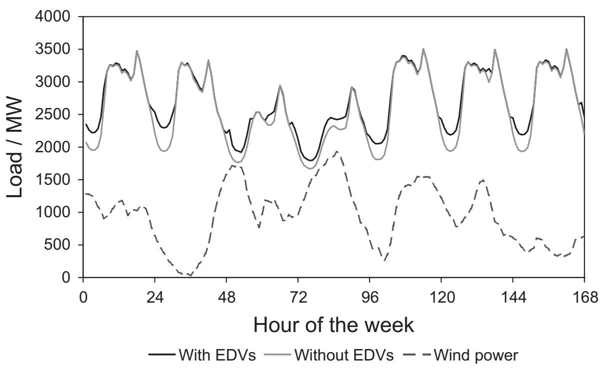

Fig. 8. Baseline scenario, selected week: electricity load including and excluding load that arises from charging EDV's along with wind power production.

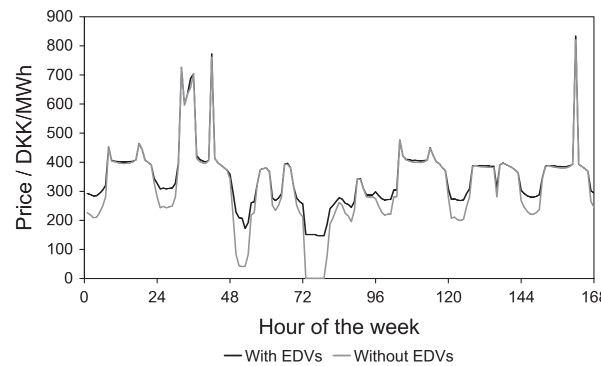

Fig. 9. Baseline scenario, selected week: electricity price including and excluding price effects that arises from charging EDV's.

7.1. Baseline

The results in Table 2 show total charges of 1299 GWh purchased at an average spot price of 249 DKK/MWh and total discharges of 246 MWh sold at an average spot price of 857 DKK/MWh. Hence, only 0.02% of charging is used for discharging, implying a very limited energy storage potential. Low discharge levels can be explained by relatively high battery wear costs and by the type of consumption taxes and end-user charges that renders charging used for discharging non-profitable. Clearly, the EDV's provide flexibility to the grid almost exclusively through charging and not as storage.

In general, charging mainly takes place at weekdays during night-time. Weekday charging accounts for 74% of total charging and is due to the nature of most working schedules. Night-time charging makes up 88% of total charging on weekdays and 61% in weekends and can be explained partly by working schedules and partly by lower prices. In spite of higher prices, day-time charging occurs when driving demand exceeds the battery capacity which shows that charging is economically more competitive than the use of the combustion engine. This is due to the differences between electricity spot prices and fuel costs (1000 DKK/MWh) and between charging efficiency (90%) and the efficiency of the engine (39%). The costs of using the engine for driving are $1000/0.39$ DKK/MWh = 2564 DKK/MWh whereas electricity prices have to be at least 2564×0.9 DKK/MWh = 2308 DKK/MWh, including taxes and charges, for charging to be this expensive. Day-time charging also occurs as a result of the aggregator trying to reduce prices during night-time. By charging mostly at night when the overall demand is low and less frequently during the day when the overall demand is high, EDV's provide flexibility to the grid within a day.

Fig. 8 shows wind power production and electricity load including and excluding charging in a selected week and Fig. 9 shows electricity prices in the same week. It is seen from the figures and also confirmed by the results for the entire period May 2006–September 2007, that the introduction of electric vehicles increases average load by approximately 100 MW (approx. 5%) and minimum load by 200 MW (approx. 10%) but does not increase maximum load. As load increases concern base-load and not peak load, additional investments in production capacity are unnecessary. As also seen from the figures, with low demand and high wind power production prices are low whereas high prices occur in situations with high demand and low wind power production. However, as charging is often high when demand is low and vice versa, charging has a stabilizing effect on aggregated load and on prices. This is also confirmed by the results for the entire period May 2006–September 2007. In particular, without electric vehicles, we experience zero-load situations 0.55% of the time, whereas with 1% and 25% electric vehicles these occur 0.48% and 0.22% of the time, respectively, which corresponds to reductions of 13% and 61%.[7] Likewise, without electric vehicles, zero-price situations occur 0.31% of the time, whereas it takes only 1% electric vehicles to prevent such situations. It should be remarked that charging is itself relatively stable. Figs. 8 and 9 show that even with high wind power production and very low prices during the third and the fourth night, charging does not increase. In fact, it is less than during the first and the second night. Hence, the EDV's show limited potential to balance variations in wind power production from day to day, with the main effect of EDV's on wind power production being restricted to increasing base-load. The lack of provided flexibility should be attributed to fixed driving patterns, insufficient battery capacities and contractual obligations.

[7] For the Danish case study zero-load situations are less interesting, as Western Denmark is connected to the rest of the Nordic region.

Please cite this article in press as: Kristoffersen TK et al. Optimal charging of electric drive vehicles in a market environment. Appl Energy (2010), doi:10.1016/j.apenergy.2010.12.015

7.2. Varying taxes and charges

In spite of an incentive for flexible demand, the results in Table 2 show moderate changes in load, the reason being that night-time charging is already attractive with fixed taxes. This is also reflected in a nearly unchanged day-time charging. Still, with value added taxes, discharge levels increase to 14 GWh sold at an average spot price of 494 DKK/MWh, implying an energy storage of 1.30%. This is facilitated by an increased use of the engine as confirmed by increased fuel consumption. With a value added tax on high prices during the day, the engine is occasionally more profitable than day-time charging.

7.3. Varying fleet size

When EDV's make up the entire fleet, charging increases roughly proportionally, in this case to 5154 GWh. However, with discharge levels of only 319 MWh, these do not increase accordingly, which is due to rather small differences between day-time and night-time prices. Day-time charging increases to 42% which however leaves day-time prices relatively low and indicates that the dependency between price and load is not sufficiently accurate. When the EDV's account for 1% charging likewise adjusts proportionally. As charging has a limited impact on prices, the differences between night-time and day-time prices are larger and discharge levels therefore actually increase. High prices during the day imply that day-time charging only amounts to 11%.

7.4. Price-load dependencies

With a linear price-load dependence, charging levels and most significantly discharging levels are unrealistically high as prices do not appropriately adjust to load changes. In particular, too much charging takes place during night-time at too low prices, a result supported by low day-time charging. More realistic results are obtained by incorporating a non-linear price-load dependence where charging and discharges stabilizes demand.

8. Conclusions

Taking the perspective of an EDV aggregator participating in the electricity spot market, this paper presents a framework for optimizing EDV charging and discharging given variations in electricity spot prices and driving patterns of the vehicle fleet. The optimization results show that low prices provide an incentive to charge at night-time although day-time charging occasionally occurs in spite of high prices. Discharging is encouraged by differences between night-time and day-time and favorable tax systems. However, if the aggregator has market power, the vehicle fleet has a stabilizing effect on prices and all incentives are reduced. It can be concluded that electric vehicles provide flexibility almost exclusively through charging. Moreover, the vehicles provide flexibility within the day but only limited flexibility from day to day when driving patterns are fixed.

Several extensions of the framework are possible. The optimization model can be extended to account for exogenously given plug-in patterns and further user restrictions. In terms of flexible demand and supply a particularly valuable extension of the model would include a balancing market and the ability of the EDV's to provide balancing power. Furthermore, in considering uncertainty of future driving patterns and electricity prices, these could alternatively be obtained from forecasting models, using either expected future values or even the distribution of future values. Along the same lines, since the electricity system is likely to change, it would be relevant to consider a potential future electricity system.

Acknowledgment

T.K. Kristoffersen acknowledges support from Carlsberg Fondet i Denmark through Project No. 2008 01 0344.

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