Electric Vehicle Charge Planning using Economic Model Predictive Control

Rasmus Halvgaard, Niels K. Poulsen
Henrik Madsen and John B. Jørgensen
Department of Informatics and Mathematical Modelling
Technical University of Denmark
Richard Petersens Plads
2800 Kgs. Lyngby, Denmark
Email:{rhal,nkp,hm,jbj}@imm.dtu.dk

Francesco Marra
and Daniel Esteban Morales Bondy
Department of Electrical Engineering
Technical University of Denmark
Elektrovej, building 325
2800 Kgs. Lyngby, Denmark
Email: {fm,bondy}@elektro.dtu.dk

***Abstract*—Economic Model Predictive Control (MPC) is very well suited for controlling smart energy systems since electricity price and demand forecasts are easily integrated in the controller. Electric vehicles (EVs) are expected to play a large role in the future Smart Grid. They are expected to provide grid services, both for peak reduction and for ancillary services, by absorbing short term variations in the electricity production. In this paper the Economic MPC minimizes the cost of electricity consumption for a single EV. Simulations show savings of 50-60% of the electricity costs compared to uncontrolled charging from load shifting based on driving pattern predictions. The future energy system in Denmark will most likely be based on renewable energy sources e.g. wind and solar power. These green energy sources introduce stochastic fluctuations in the electricity production. Therefore, energy should be consumed as soon as it is produced to avoid the need for energy storage as this is expensive, limited and introduces efficiency losses. The Economic MPC for EVs described in this paper may contribute to facilitating transition to a fossil free energy system.**

I. Introduction

Reducing CO_2 emissions and becoming independent of fossil fuels are both major economic and political drivers for switching from traditional combustion engines to electrification of the transport sector through the introduction of Electric Vehicles (EVs). To facilitate the fossil free electrification of the transport sector, the amount of renewable energy sources in the energy system must be increased significantly. By nature, renewable energy sources like wind and solar power are stochastic and introduce fluctuations in the otherwise predictable and stable power system.

In Denmark the penetration of wind power is beyond 20% and calls for either huge storage solutions or a highly flexible demand that can be controlled in order to consume power as it is produced. Electric storage is very expensive, introduces efficiency losses and is not feasible everywhere. However, the development and penetration of EVs seems inevitable, and their batteries could potentially provide a storage opportunity. The idea is that if the EVs are intelligently charged, they could become a controllable asset to the grid rather than a traditional load disturbance. They could help absorb variations in the power system and help move consumption to off-peak periods. When parked and plugged into the grid, EVs are expected to either charge intelligently or discharge, i.e. feed power back into the grid. However, handling the probabilistic load behavior of EVs present is a challenge to the balance responsible.

In the future, large fleets of EVs will be available, and could potentially provide flexible services to the grid, e.g. load shifting, balancing power, and frequency response. Another of these services could be delivery of electricity to the grid by discharging the EV battery, also known as Vehicle-to-Grid (V2G). This was first proposed by [1] and is the main reason why EVs are expected to play an important role in the future power system. The charging impact of EVs on the power grid has also been reported in the literature, e.g. [2]. Emphasis is mainly on the services EVs can provide to the electric energy system. Currently, it is not clearly understood if a centralized or decentralized strategy should be applied, and what actual services EV users require. However, it is clear that there must be an incentive for EV users to help the balance the power production and charge during off-peak periods.

Fig. 1 illustrates the Virtual Power Plant (VPP) approach for handling a fleet of EVs. In a centralized strategy, the aggregator performs the optimal charge scheduling calculations and sends out the individual charge plans to EVs. A decentralized approach could be to broadcast a price signal and let the individual EV optimize its own charging based on this price. Less communication is required at the expense of a larger computation task for the EV. In Denmark EV charging is billed with the same tariffs as for the standard domestic loads. So in this paper the price signal is the Elspot price, a Time of Use (TOU) price for the customer, taken from the Nordpool day ahead market. This price is settled every day at noon for the coming day and is thus known 12 to 36 hours in advance. The amount of wind power in the power grid is thus also reflected in this signal. Furthermore, since feed-in tariffs do not yet exist for LV grid producers vehicle-to-grid (V2G) operation will not be addressed in this study.

[3] considers a decentralized strategy where the charging costs are minimized for each EV user individually. In addition,

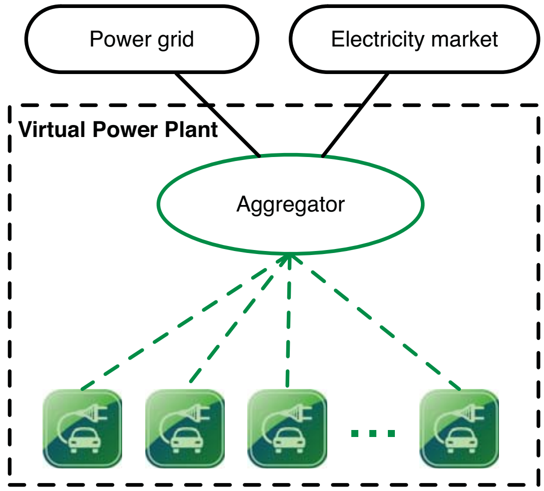

Fig. 1. Virtual Power Plant framework with EVs. The dashed green line is the price signal from the aggregator.

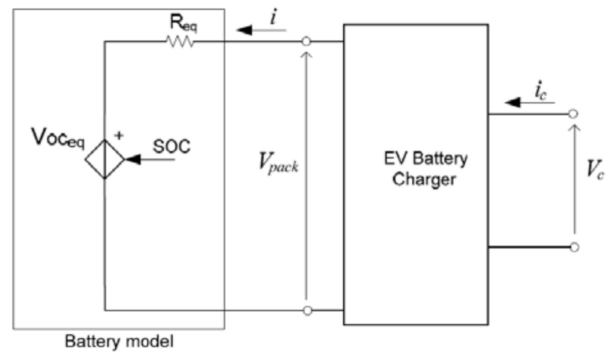

Fig. 2. Equivalent electrical circuit model of an EV battery.

a penalty on the deviation from the average EV fleet charge behavior is added to the objective function. By sending out the average optimal charging plans to all EVs, the charge strategy is negotiated by an iteration procedure that is guaranteed to converge towards a Nash equilibrium.

In practice, when charging a large fleet of EVs in periods where electricity prices are low, typically at night time, the price will in the long run start to increase in these periods reflecting new demand patterns. This price elasticity effect has been modeled for an EV demand response and a price flattening was observed [4].

An optimal charge strategy for EVs optimization of both energy cost and battery health has also been investigated [5]. The proposed battery model is based on a first principles chemical battery model and a battery degradation map was determined by simulation. This map was used to determine at what rates the battery suffers the most. Battery degradation in detail will not be taken into account in this paper but general guidelines for improving the life time will.

In [6], [7] methods for planning the individual charging schedules of a large EV fleet while respecting the constraints in the low-voltage distribution grid are proposed. Another proposed ancillary service is to minimize the load variance of the power system by queuing up charge requests [8]. In this way, uncertainty in the load and price forecasts are avoided. However, in this approach the comfort of the EV user is not taken into consideration.

In this paper, we consider several decentralized EV charging strategies based on Model Predictive Control (MPC) [9]–[11]. Minimizing the electricity costs of EV charging fits directly into an Economic MPC framework where the battery model is formulated as a linear discrete time dynamic state space model. Forecasts of the load, i.e. the driving pattern, and handling of the battery storage constraints are handled natively by the MPC. Electricity prices are assumed to be known and could be any price signal that is set by an aggregator. It could also be a price that is the deviation from the day-ahead price making sure that the load follows the plan. The MPC algorithm incorporates feedback by its moving horizon implementation. In this way, forecast errors are compensated for by the MPC algorithm.

This paper is organized as follows. Section II models an electric vehicle battery. The battery side behavior is described as well. In section III, the EV driving pattern used for simulation is defined based on real data. The Economic MPC optimization problem is formulated in IV, while different Economic MPC charge strategies are compared in Section V. Finally, section VI provides conclusions.

II. Electric Vehicle Battery Model

In this study, an EV is modeled as a flexible energy storage resource that is capable of exchanging power with the grid under a predefined charging schedule. EVs have been modeled in many different manners, depending on the detail and scope of the study in question. In this paper a model of the State of Charge (SOC) is used based on [12].

A. Battery model

A simple battery model can be composed of an electric equivalent circuit with a voltage source in series with the ohmic impedance [13], see also Fig.2. The only state variable of this model is the State of Charge (SOC) $\zeta \in [0;1]$, i.e. the normalized battery capacity at time t, that can be modeled as a simple integrator with loss

$$\dot{\zeta}(t) = \frac{V_{pack} i(t)}{Q_n} = \frac{1}{Q_n}(\eta^+ P_c^+(t) - \eta^- P_c^-(t)) \quad (1)$$

P_c is the power flowing in or out of the battery during charging or discharging; Q_n is the nominal capacity of the battery, denoted with a $+$ and $-$ respectively; η is the charger efficiency. The actual power is bounded by

$$P_{min} \le P_c \le P_{max} \quad (2)$$

The maximum power is limited by the maximum charge current. Leaving a margin for other household appliances the maximum charge power P_{max} is set to

$$P_{max} = V_c i_{max} = 230 \text{ V} \cdot 10 \text{ A} = 2.3 \text{ kW} \quad (3)$$

TABLE I
DESCRIPTION OF VARIABLES AND MODEL PARAMETERS

	Description	Value	Unit
ζ	State of Charge (SOC)	[0;1]	
V_c	Grid voltage	230	V
i_c	Charge current		A
P_c	Charge power ($P_c = V_c i_c$)		W
i_{max}	Maximum charge current	10	A
i_{min}	Minimum charge current	0	A
Δi_{min}	Minimum ramp constraint	-10	A/h
Δi_{max}	Maximum ramp constraint	10	A/h
Q_n	Nominal battery capacity	40	Ah
η	Charger efficiency	0.9	
η_{EV}	EV energy efficiency	150	Wh/km
p	Electricity price		EUR/MWh
ρ	Slack variable penalty	10^5	
T_s	Model sampling period	0.5	h
N	No. of steps in prediction horizon		

The charging power of 2.3 kW (230 V, 10 A) is chosen as the charging rate for this study, as this is the most common residential use case for EV charging in Denmark today. Considering standard household electric installations, most grid connection points only allow charging rates up to 10 A, while other appliances are running. Furthermore a small EV fleet consisting of 12% households in a generic LV grid charging at 6 pm with 2.4 kW can lead to overload of the distribution transformer [14]. The lower bound, P_{min}, could be negative and equal to $-P_{max}$ if Vehicle to Grid (V2G) is considered. Otherwise $P_{min} = 0$.

For the case study in this paper the battery chemistry is assumed to be Lithium-ion with capacity $Q_n = 24$ kWh. The SOC of the EV battery is equal to its normed capacity such that $\zeta \in [0; 1]$. The model (1) is suitable for a generic battery modeling study. In the context of EV charging management, the model has been tuned to common EV use conditions. The choice of Lithium-ion is related to market trend reports for EV batteries [15], where Li-ion batteries are expected to dominate the whole EV battery market sector with a 70-80% share by 2015.

Based on the main life time recommendations for optimal SOC management in [16] and common practice of EV manufacturer's [17] the SOC of the EV battery is limited to

$$\zeta \in [0.2; 0.9] \tag{4}$$

Other external conditions such as temperature behavior during operation are not taken into account.

B. Modeling the Charging/Discharging operation

The linear model in section II-A will be used for both simulation purposes and as the controller model. The nonlinear behavior outside the region (4) can be modeled by the open circuit voltage as

$$V_{oc_{eq}}(\zeta, Q) = V_0 - \frac{K}{1-\zeta} + a \cdot \exp\left(-\frac{Q}{\tau}\right) \tag{5}$$

- a is the exponential zone amplitude [V]
- τ is the exponential zone time constant [Ah]
- V_0 is the battery voltage constant [V]
- K is the polarization voltage [V]
- Q is the instant battery capacity [Ah] obtained from $\dot{Q} = i$, where i is the DC current during charging

The real-time EV battery voltage is $V_{pack} = V_{oc} + R_{eq} \cdot i$, where i is the current used to charge or discharge the battery. The voltage drop is considered positive during charging and negative during discharging. The resistive impedance of a lithium-iron phosphate (LFP) battery cell, a common class of Li-ion batteries, has been measured using impedance spectroscopy. A resulting intrinsic resistance of about 10 mΩ per battery cell was found from measurements [18]. The charger has been modeled as a single-phase 230V power converter. The charger operates in either Constant Current (CC) or Constant Voltage (CV) mode. During charging/discharging, the battery cell voltage is continuously monitored and maintained within a safe operational zone for the battery according to [19]. The safe voltage region of the LFP 3.3 V - 40 Ah battery cell is $[2.8; 4.0]$ V, which entails the SOC window 20-90%. The EV battery is only in discharging mode when driving.

C. State Space Model

The EV battery model in section II-A can be formulated as a discrete time state space model that fits into the MPC framework.

$$x_{k+1} = Ax_k + Bu_k + Ed_k \tag{6a}$$

$$z_k = Cx_k \tag{6b}$$

where $k \in \{0, 1, ..., N\}$. Defining the manipulable u, disturbance d and output z. The EV charge control signal is equal to the charging power $u = P_c^+$ while the only state is the SOC, also equal to the output $x = z = \zeta$. The demand d_k, i.e. battery usage from driving, is modeled as a disturbance to the battery SOC according to the description in section III. The state space matrices for the SISO model (6) are

$$A = 1 \qquad B = \frac{\eta}{Q_n} T_s \qquad C = 1 \qquad E = -T_s \tag{7}$$

This result follows from discretization of the state space matrices obtained from (1). Note that the efficiency and capacity is not in E but will be included in the signal d_k. u is kept constant between samples.

III. DRIVING PATTERNS

In order to estimate the driving pattern of the average EV driver, survey data from [20] including a group of observed commuters in Denmark was investigated. In Fig. 3 the total number of parked cars with 5 minute resolution for different weekdays, i.e. cars that could potentially charge if connected to the grid, have been plotted. The amount of trips is also shown as a function of time. The morning and afternoon peaks at 7:30 am and 4:00 pm are both clearly visible. Based on the presented data, an EV commuter driving pattern scenario was defined for simulation purposes such that

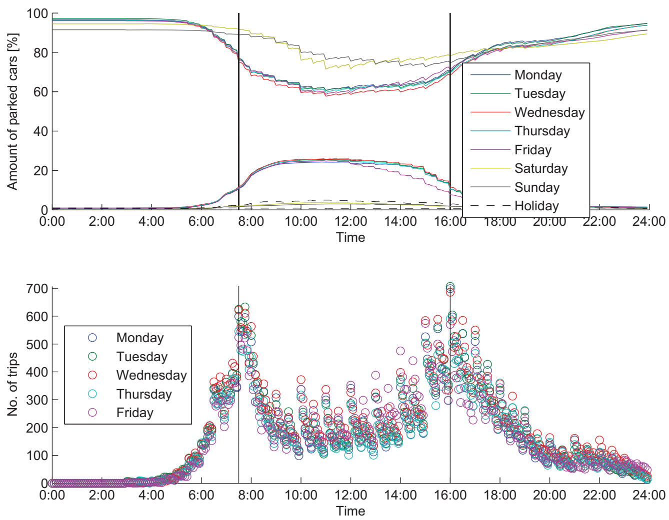

Fig. 3. The lower plot shows the no. of trips for difference weekdays. The upper plot shows the availability, i.e. the amount of parked cars at home (upper) and at work (lower).

- The average driving distance to work is $d_w = 18.92$ km
- The average driving time to work is $t_w = 22.6$ min
- Two trips of length $d_w + 5$ km and $d_w + 10$ km, and duration $t_w + 10$ min and $t_w + 20$ min
- The start time of the two daily trips is at 7:00 am and 4:00 pm

We assume that the EV is connected and able to charge whenever it is not driving. Furthermore, the estimated energy efficiency for typical EVs are $\eta_{EV} \in [120; 180]$ Wh/km [20]. As a compromise we use a fixed average value of $\eta_{EV} = 150$ Wh/km in simulations.

In the simulations in section V, the actual demand d_k when driving is constant for each trip and is equal to the average energy used for every trip. The actual demand depends on the driving behavior, i.e. the acceleration of the EV. When integrated the simulated demand will give exactly the amount of energy used at the end of the trip.

The minimum charge time is dependent on the sampling period and, since the price signal is available every hour, this should be the largest sampling period. In this way a decision whether to charge or not can be placed at all available price levels. This paper is a feasibility study intended to demonstrate Economic MPC. Therefore all simulations use $T_s = 30$ min. In practice, we would recommend significantly shorter sample times.

IV. Economic Model Predictive Control

In this paper Economic MPC will be applied for EV charge scheduling. Economic MPC for intelligent energy systems has previously been proposed in [21], [22]. MPC will minimize the electricity costs of charging a single EV based on predictions of the electricity price and the expected driving pattern over the prediction horizon of N samples. The objective function to be minimized is ϕ and the linear MPC can be formulated as

$$
\begin{aligned}
\text{minimize} \quad & \phi = \sum_{k=0}^{N-1} p_k u_k + \rho w_k && && \text{(8a)}\\
\text{subject to} \quad & x_{k+1} = Ax_k + Bu_k + Ed_k && k \in \mathcal{N} && \text{(8b)}\\
& z_k = Cx_k && k \in \mathcal{N} && \text{(8c)}\\
& u_{\min} \leq u_k \leq u_{\max,k} && k \in \mathcal{N} && \text{(8d)}\\
& \Delta u_{\min} \leq \Delta u_k \leq \Delta u_{\max} && k \in \mathcal{N} && \text{(8e)}\\
& z_k \geq z_{\min,k} - w_k && k \in \mathcal{N} && \text{(8f)}\\
& z_k \leq z_{\max} + w_k && k \in \mathcal{N} && \text{(8g)}\\
& w_k \geq 0 && k \in \mathcal{N} && \text{(8h)}
\end{aligned}
$$

where $\mathcal{N} \in \{0, 1, \ldots, N\}$ and N is the prediction horizon. The output $z = \zeta$ is constrained by the battery capacity limits, but the constraints in this problem are softened, i.e. the SOC is allowed to lie outside the band of operation defined by (4). This constraint violation is defined by the slack variable w_k that is heavily penalized by the slack variable penalty ρ. Also note that the lower bound on the output, $z_{min,k}$, is time varying and represents a safety margin to absorb prediction errors. It can thus be set according to what degree of flexibility is needed for the individual EV user. When operation decreases so does flexibility, and the possibility of shifting consumption and saving money is reduced. However, in this paper we use $z_{min,k} \geq 0.2$ (see section II-A). p is the electricity price and u is the input equal to the charge power P_c. The EV is not able to charge when disconnected from the grid, i.e. when driving, resulting in a time varying input constraint

$$
u_{max,k} = \begin{cases} P_{max} & \text{for } d_k = 0 \\ 0 & \text{otherwise} \end{cases}
$$

Likewise, $u_{min,k}$, could be time varying and negative if V2G is considered. $\Delta u_k = u_k - u_{k-1}$ is the discrete time rate of movement input constraint. The input charge current can change very quickly compared to the time horizons considered, so these rate limits can be set very high, e.g. $\Delta u_{min} \geq u_{min}$ and $\Delta u_{max} \geq u_{max}$, and can in theory be neglected. However, when a stochastic model is used they help to smoothen out the charging and adds robustness against forecast errors.

The optimal EV charging plan within the prediction horizon is the solution to (8) and is denoted $U^* = \{u_k^*\}_{k=0}^{N-1}$. This charging plan is calculated at every time step k and represents a decision plan, stating when to charge and how much power should be used. It is optimal in terms of economy, and is the cheapest solution based on the predictions and model assumptions available at time $k = 0$. The first decision of the plan, u_0^*, is implemented, i.e. a certain amount of power is delivered to the battery at the present time step $k = 0$. This process is repeated at every time step and constitutes the principle of a model predictive controller also known as receding horizon control.

V. Simulation

Fig. 4 and 5 show the closed loop MPC charge plan simulated over one week. Based on the perfect forecasts of the electricity el-spot price and the demand, i.e. the driving pattern, the controller charges just the right amount of energy prior to each trip. The first simulation uses a prediction horizon of $N = 24$ h, while the latter uses $N = 48$ h. The advantage of using a 48 h horizon is clearly seen; this controller is able to pick the cheapest charging period seen over a larger time window. For example, if energy is expensive on Friday morning, it is cheaper to fill up the battery on Thursday morning in order to cover the next two days' consumption. Knowing more about prices and demand in advance, allows for a better charging plan and ultimately more money can be saved. However, forecasts will always contain uncertainty, so a balance must be found between long prediction horizons, i.e. more computation time, and how much money can be saved. Even if a perfect forecast is used, the increase in savings is very small when the prediction horizon is increased. This is due to the nature of the day ahead price and the limited capacity of the battery, i.e. charging all energy needs during the summer to cover the whole winter period is not possible. The battery capacity thus limits the amount of energy that can be shifted using a large number of EVs.

The Economic MPC strategy can be compared to other strategies like uncontrolled charging, also referred to as *dumb charging*, where the EV starts charging whenever it is plugged in. This can easily be simulated with the MPC controller by setting the soft lower output bound to $\{z_{\min}\}_{k=0}^{N} = \{z_{\max}\}_{k=0}^{N}$. It is observed from Fig. 6 that the EV charges to full capacity after every trip and unfortunately charging takes place in the most expensive periods.

Another optimal charge strategy could be a fixed cost strategy where the electricity price remains the same throughout the entire interval. The response using this strategy is seen on Fig. 7. Obviously the controller does ensure charging takes place in the cheap periods, since it is cheap during the entire interval. It does, however, minimize the energy consumption and charges just enough energy for each trip just before the EV leaves. A third strategy could be to take advantage of the deterministic part of electricity price and use a simple timer to delay the dumb charging to periods where the electricity price is usually low. However, a charging scenario that is reactive to a price signal is desired in the decentralized approach.

Comparing the simulation results, it is found that using MPC with fixed costs saves around 39% of the costs compared to dumb charging. If Economic MPC with the varying prices is considered, savings increase to almost 60%. Using the longer prediction horizon another 0.5% is gained. The computation time for solving the individual open loop problems are within micro seconds.

The proposed Economic MPC was also simulated for a period of one year with the real day ahead price from 2010, and the results were compared to dumb charging. For the dumb charging simulation the total energy consumption was found to be 2.6 MWh. The annual energy consumption obtained from simulation is very close to the estimates for an average household in Denmark [23]. The Economic MPC saves an annual 47% of the electricity costs associated with the Elspot price.

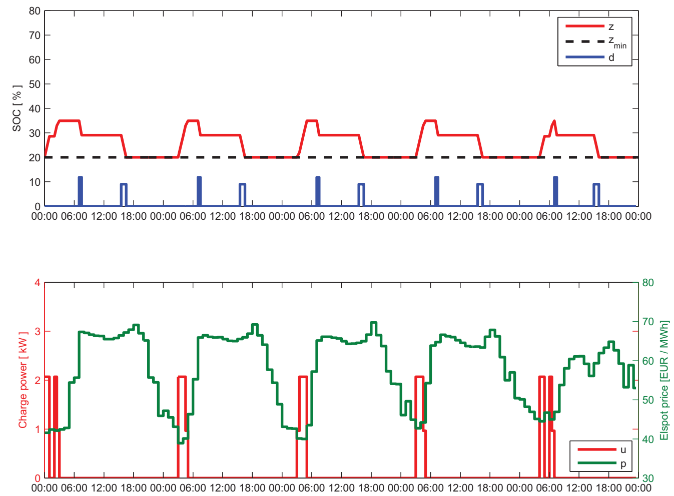

Fig. 4. Optimal charging of EV for five days using Economic MPC with prediction horizon $N = 24$ h. The upper plot shows the SOC ζ and the driving pattern or demand d_k. The lower plot shows the electricity price variation and the charge power.

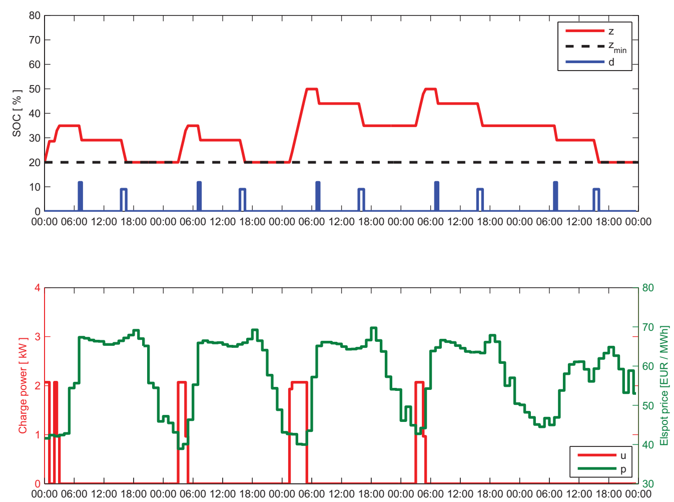

Fig. 5. Economic MPC charging with $N = 48$ h.

VI. Conclusion

Economic MPC was introduced as a method for charging EVs in Smart Grid using varying prices. A suitable EV battery model was derived to be used in the optimization of EV charge scheduling in a Smart Grid. Realistic commuter driving patterns were analyzed from real data and used in simulations along with electricity prices taken from the day-ahead market. A comparison of different charging strategies were compared clearly showing the potential of using Economic MPC to shift the load in a cost efficient way. Perfect forecasts were used in the simulations. Future work will address the inherent stochastics of the driving pattern and electricity prices.

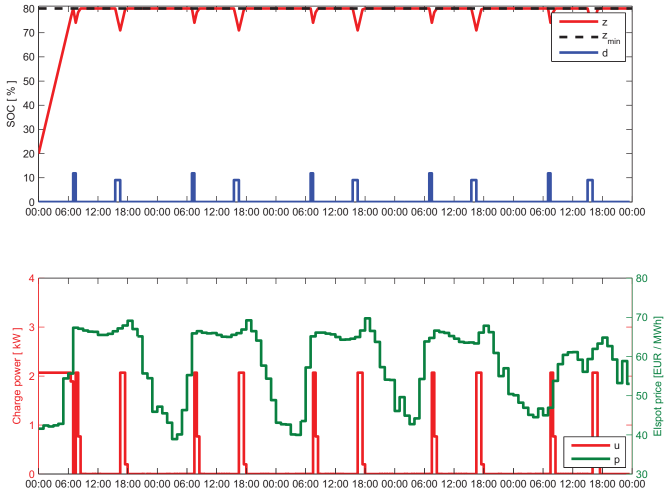

Fig. 6. Uncontrolled *dumb* charging. $\{z_{\min}\}_{k=0}^{N} = \{z_{\max}\}_{k=0}^{N}$

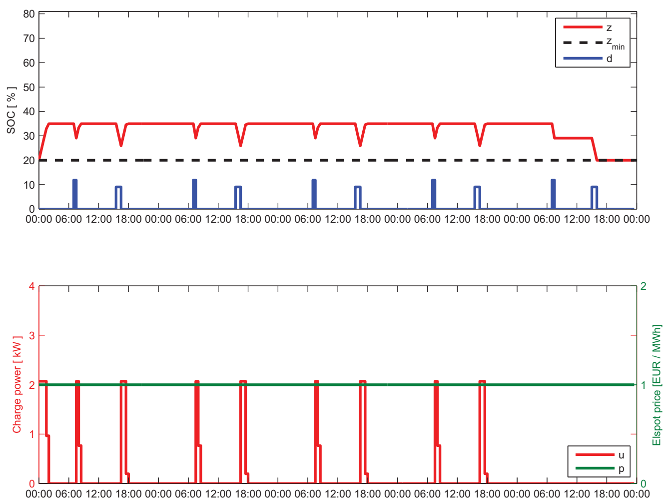

Fig. 7. MPC fixed unity price charging with $N = 24$ h.

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