

## Forecast the charging power demand for an electric vehicle

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### Content

Abstract .....	1
Motivation .....	2
Challenges.....	2
Method.....	2
Solution.....	3
Function for State of Charge .....	3
Forecasting of State of Charge – SOC.....	3
Function for Charging Power.....	4
Forecast the intraday charging power demand .....	5
Conclusion.....	5

### Abstract

*A part of the project “Smart City Rheintal” aims to enhance the share of self-consumed energy. Renewables, mostly photovoltaic, are used to cover the demand of the electric vehicle infrastructure. In order to attain this objective it is necessary to forecast the demand of the electric vehicles. Furthermore, the energy generation has to be forecasted. This forecast is already provided by an external service provider. The load curve of the electric vehicle (EV) is generated by historical charging values. The aim of this work is to develop a method to predict the energy demand of one EV. The forecast is done for the upcoming day. A tool by the company “metallogic<sup>1</sup>” is being used to achieve a reliable forecast. This tool offers a series of mathematical instruments to build up a model. The work demonstrates that a direct definition of the energy needs is not possible. Hence, a two-stage work is required. The first stage defines a model of a linear regression equation of the State of Charge (SoC) of the vehicles battery. In the second step a model for the energy forecast by using the results of the first step as an influence value is defined.*

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<sup>1</sup> <http://www.metallogic.de>

## Motivation

One of the challenges in the project “Smart City Rheintal” (SCR) is the maximization of self-consumption of renewable energy. An application is to control and shift the energy consumption of an electric vehicle (EV) fleet. To facilitate self-consumption knowledge about user behavior the behavior of the electric vehicles has to be gathered. Especially charging times – start, end, duration – , charged energy and energy consumption are essential key figures. Therefore, it is necessary to analyze the charging power of a representative EV. With the knowledge of the charging power demand it is possible to see if the forecasted energy generation will be enough to cover the energy needs of the EV for the whole intraday (not part of this work).

## Challenges

The first challenge to build up a forecasting model is to have access to valid data from a charging infrastructure (e.g. charging stations) or even from an EV itself. By now the information around EVs is not easy to access. There are personal data protection reasons and also interface and standard variances.

Further it is not easy to get a reliable function that describes the state of charge of the EV. This is a mayor challenge since we do not know when and how long the EV will be used. There are also differences in the demand behavior by EVs in the summer and winter. The other expected problems are situated in the high volatility of the charging process itself. A charging process can be interrupted at any time by the EV user. Hence, it is expected that the mathematical model will not be so easy to describe.

## Method

To find out the right forecasting function, solid time series data are needed. The local energy utility illwerke vkw in Bregenz, Austria, has cumulated such logged data from a few EVs over the last years; this is a basic condition to define a load profile.

Once the data basis is captured and formatted to a 15 minutes base, the tool “mpEnergy 3.4.1” by metalogic helps to find out a right mathematical model. The way to find out the right mathematical model is based on an empirical method proving the options the “mPEnergy” tool has in its library, since there is no straight ahead possibility to find a comfortable equation. This tool has base statistical methods like linear regression, nearest neighborhood or artificial neuronal networks. These models are available to find out the right forecasting model. Further influencing time series can be integrated into such experimental models to prove if this external information has some effects on the forecasting quality. External information can be the temperature, the day duration (in sense of daylight) or a summer winter behavior.

Once the forecasting model for the state of charge is defined, a new model must be found to forecast the energy to charge the vehicle battery. This step is also an empirical method like the one before. The aim function is thereby the charging energy and the influence function is the state of charge of the battery, which was figured out in the first step.

## Solution

Based on the EV time series data of one year and the use of a forecasting tool it is possible to build up a model to forecast the state of charge of an EV.

### *Function for State of Charge*

To forecast the state of charge of the EV's battery, the following formula, based on the scalable linear regression, was eligible to be the best method

$$\text{SOC}_{\text{new}} = \text{SOC}(-1)x + \varepsilon$$

Where:

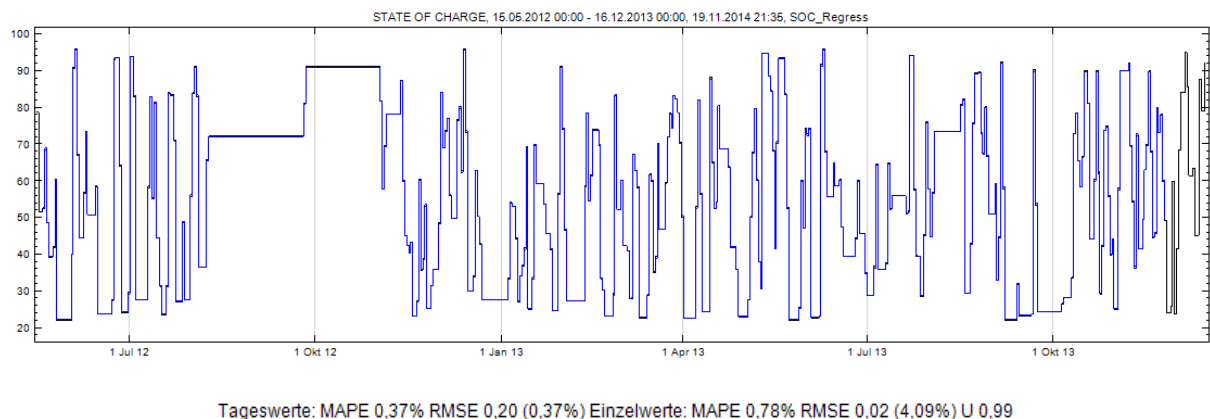
SOC\_new....the new value matrix for the state of charge

SOC(-1).....the matrix with historical value shifted back by one (-1)

$\varepsilon$ .....the error of the linear regression

### *Forecasting of State of Charge – SOC*

In Figure 1 the result of this linear regression model is displayed. The data (black curve) since April 2012 has been used to define an appropriate model. The model itself has been trained up to one week before the data ends. This provides a method to simulate the forecasting of the missing days. The results obtained can then be compared with the real data.



**Figure 1 – linear regression model for the state of charge of a car battery, real data (black curve) and mathematical model (black curve, underneath of the blue curve)**

Once the model is defined, the forecast can be done. In Figure 2, left side, it is possible to see forecasting of the state of charge of the selected EV. It is obvious that the blue and the black curve are mostly overlapping. In Figure 2, right side, it is possible to see the intraday forecasting during one day. A relative long charging time during the the night and the rapid discharge between 12:00 and 13:00 o'clock of the next day is obvious.

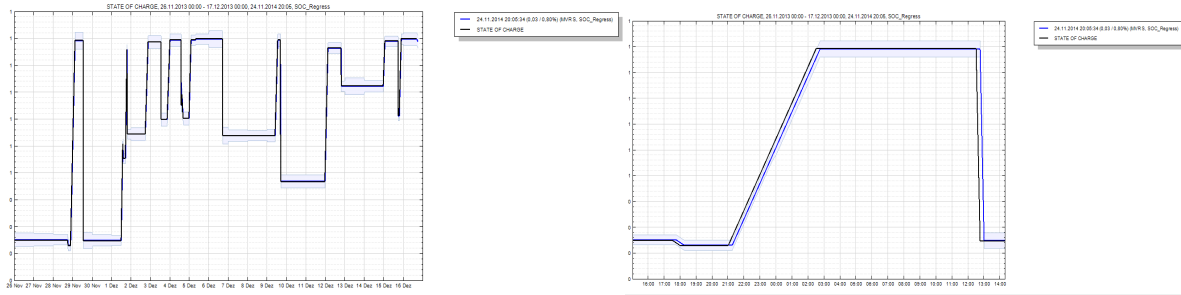


Figure 2 - SOC forecast for 10 days (left curve) and forecast during the night (right curve)

### Function for Charging Power

Once the state of charge is predicted, it is possible to define a model for the needed charging power (CP). Once again the linear regression is the base mathematical model that covers as best the curve behavior from historical charging power values. It has to be considered that there are positive and negative charging values. From the battery point of view this will represent the incoming and consumed energy. The curve profile can be seen in Figure 3. Furthermore, the training of the model is stopped a few days before the data ends. This is necessary to evaluate the quality of the forecasted curve with real data.

The right mathematical model is:

$$CP\_new = CP\_old \cdot y + SOC \cdot x + \epsilon$$

Where:

CP\_old.....historical values of the charging power

CP\_new.....the new value matrix for the needed charging power

SOC.....the matrix with forecasted value of the state of charge

$\epsilon$ .....the error of the linear regression

The linear regression base model in “mPEnergy” has a scalable option which indicates that all times series are based on a 15 minutes timescale.

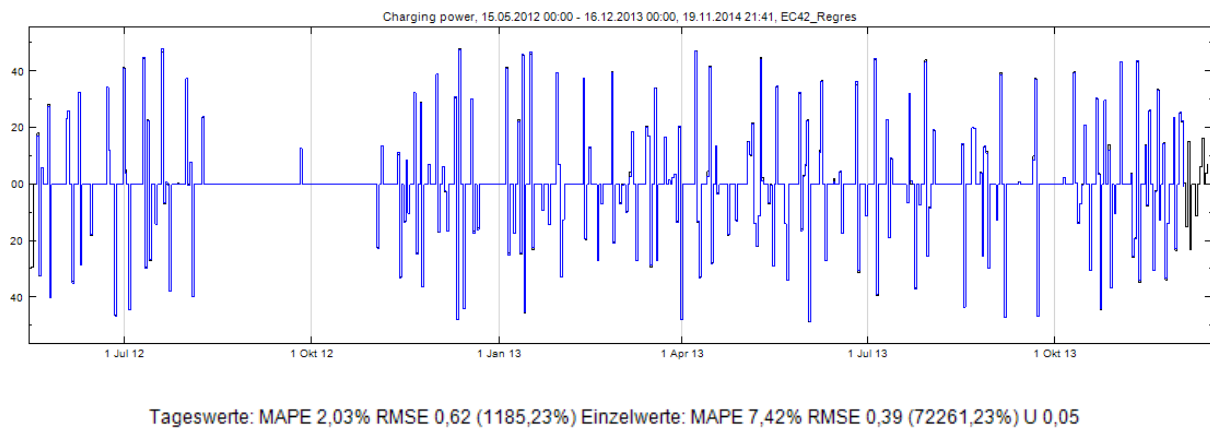
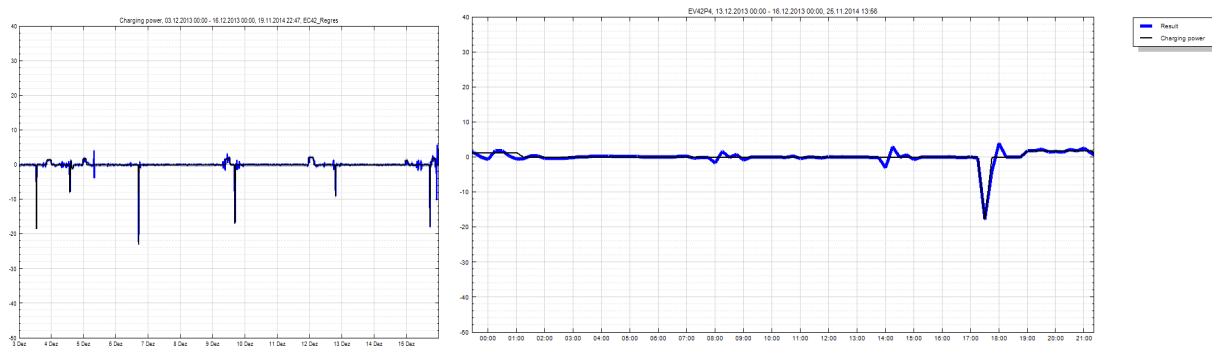


Figure 3 – Curve covering for the charging power to build up a valid model (blue curve) with historical data (blackcurve)

## ***Forecast the intraday charging power demand***

With the mathematical model for the state of charge and the defined model for the charging power, it is possible to run a forecast process. The results is displayed in Figure 4.



**Figure 4 – Forecasting the charging power. The blue curve (forecasted values) and the black curve (real values for this period) are overlapped, a good indicator for a good prediction.**

In the left curve of Figure 4, the overlapping curves are shown. The blue curve is the result of the forecasting model and the black curve is the real data captured for this period. In the right curve of Figure 4 the intraday progress is predicted. Here it is possible to see some gaps in the forecasted curve, but the energy demand can be forecasted accurately.

## **Conclusion**

The load curve of an EV can be forecasted using a two steps method. The first step is used to forecast the state of charge. The second step is forecasting the charging power using the results out of step one. An important base condition is to have enough historical values to obtain a right model. Once the models are defines, further historical values are needed from time to time to update the function. An online 15 minutes based state of charge value transmission will be desirable but is not a condition. The 15 minutes base is a very important timeline in the energy segment. Therefore all event triggered car logging data should be transformed into such 15 minutes timeline. Otherwise a model definition can be very difficult.