ebalanceplus

Description of prediction models and algorithm specification

Deliverable D3.5

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Technical References

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PP = Restricted to other programme participants (including the Commission Services)
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Summary

Summary of Deliverable

The ebalance-plus aims to increase energy flexibility of distribution grids, predict available flexibility, increase distribution grid resilience and design and test new ancillary models to promote new markets based on energy flexibility. In particular, Task 3.5 has the objective to develop and integrate multiple prediction models to exploit the available flexible resources at building and grid level. The structure of this document is the following:

Section INTRODUCTION provides an overview of the deliverable and how it is related with the other work packages.

Section PHOTOVOLTAIC PREDICTION MODULE describes the data required for the algorithm to work as well as the structure of the model.

Section ELECTRICITY CONSUMPTION PREDICTION MODULE explains the data required by the model to generate accurate forecasts and describes the different parts of the module.

Section REGULATION POWER PRICE PREDICTION MODULE describes the inputs and outputs, as well as the algorithm developed for the forecast.

Section EV FLEXIBILITY PREDICTION MODULE summarizes how the electric vehicles can be used to generate energy flexibility.

Section 6. ENERGY EXCHANGE PREDICTION MODULE summarizes the works towards the energy exchange prediction module initially resulting from the e-balance project.

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Abbreviatures and acronyms

RES	Renewable Energy Sources
EV	Electric Vehicle
PV	Photovoltaic
NWP	Numerical Weather Prediction
ECMWF	European Centre for Medium-Range Weather Forecasts
NCEP	National Centers for Environmental Prediction
nMAE	Normalized Mean Absolute Error

Nomenclature

Cr	-	Allowed charging rate [h^{-1}]
Ct	-	Time until charging deadline [h]
E	-	Energy [kWh]
Flex	-	Flexibility [kWh^2]

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1 INTRODUCTION

The increase of renewable energy sources (RES) in the electricity mix brings new challenges in the electric systems due to the volatility of wind and solar power plants. The changing energy consumption is now combined with the fluctuating energy generation produced by the technologies reliant on the weather. Therefore, power grids must be flexible enough to adapt to new circumstances and keep the system stable by matching power generation and consumption.

The ebalance-plus is a project with the objective to increase energy flexibility of distribution grids, predict available flexibility, increase distribution grid resilience and design and test new ancillary models to promote new markets based on energy flexibility. To be more precise, the objectives of Task 3.5 are to develop and integrate prediction models at building level, grid level, electric vehicle (EV) prediction, storage prediction, distributed energy resources prediction and available flexibility. In this task, methods for forecasting future flexibility of various assets are developed, they can be controlled/managed like EV, storage, etc. Furthermore, forecasts for rooftop photovoltaics (PVs) as well as electricity consumption to be used for control of load of the demo cases.

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2 PHOTOVOLTAIC PREDICTION MODULE

The photovoltaic forecasting module is a self-learning and self-calibrating system based on a combination of physical and advanced machine learning models. This module is designed to predict the energy produced by the photovoltaic panels at the building level for the different demo sites from one to 48 hours ahead.

The description of the PV prediction module is detailed in two different sections. Section 2.1 Inputs and outputs describes the necessary inputs required to generate accurate predictions and, also, the expected outcomes from the model. Section 2.2 Description of the algorithm explains the basis of the model and how it works.

2.1 Inputs and outputs of the PV-prediction module

The PV forecasting algorithm considers multiple inputs that can be divided into two categories: demo-site data and weather data.

The demo-site data includes the physical characteristics of each specific facility which defines, among others, the location of the photovoltaic panels, their rated power, and the layout of the PV panels (orientation and tilt). This information will establish the basis for the physical model, which estimates the solar resources for the area and the potential production according to the weather.

It is necessary to train over the historical data, which includes the time series of power production and the availability of the plant (capacity available, schedules of maintenance, etc.) to learn from each specific installation and generate more accurate predictions. These power observations will have a resolution of 15 minutes (one observation recorded every quarter of an hour).

On the other hand, the forecasting algorithm also requires information about the weather, which is provided by the Numerical Weather Predictions (NWPs) from different meteorological institutes such as the European Centre for Medium-Range Weather Forecasts (ECMWF), National Centres for Environmental Prediction (NCEP), etc. These NWPs are mathematical models based on the current state of the atmosphere that predict the weather conditions, including variables like temperature, wind speed and direction, irradiance, humidity, and precipitations.

Finally, once the model is trained using the previous inputs, it will generate a power production forecast every hour adapted to each installation with a resolution of 15 minutes and horizon of 48 hours ahead.

The inputs and outputs of the PV-prediction module are summarized in *Tables* Table 1 and Table 2.

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Table 1. Inputs for the PV-prediction module.

Inputs	Description
Location	Latitude and longitude of the PV installation
Capacity	Panel and inverter capacity of the PV installation
Layout design	Orientation and tilt of the PV panels
Power measurements	Historical and real-time power measurements of the PV system with a resolution of 15 minutes
Availability schedules	Planning and maintenance schedules indicating the available capacity of the PV system
NWP models	Numeric Weather Predictions provided by multiple institutions

Table 2. Outputs of the PV-prediction module.

Outputs	Description
PV power prediction	Forecast of the PV power production for the following 1 to 48 hours ahead

2.2 Description of the PV-prediction module

The photovoltaic prediction module consists of two main models. The first one is called the NWP-based prediction model, which uses the historical data together with the NWPs to generate predictions of the PV production for each demo case. This first module generates the forecasts covering the whole horizon: from one to 48 hours ahead.

The NWP-based model combines the data provided by the demo cases and the NWPs, generating as many models as weather forecast providers are included in the setup. This can be seen in Figure 2.1.

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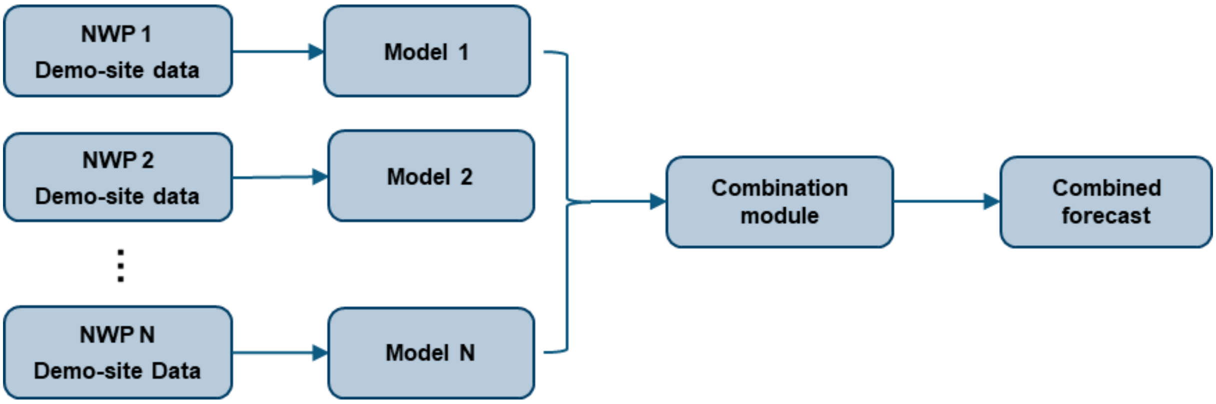

Figure 2.1. NWP-based prediction model.

The NWPs are usually predictions that follow different methodologies and contain different information. Therefore, as demonstrated in multiple studies, a good way to improve the forecast accuracy is to include a combination module [1], [2], [3]. This module analyses the accuracy of each individual model and the correlations among them, assigning weights to generate a combined forecast with lower error. An example of this can be seen in Figure 2.2.

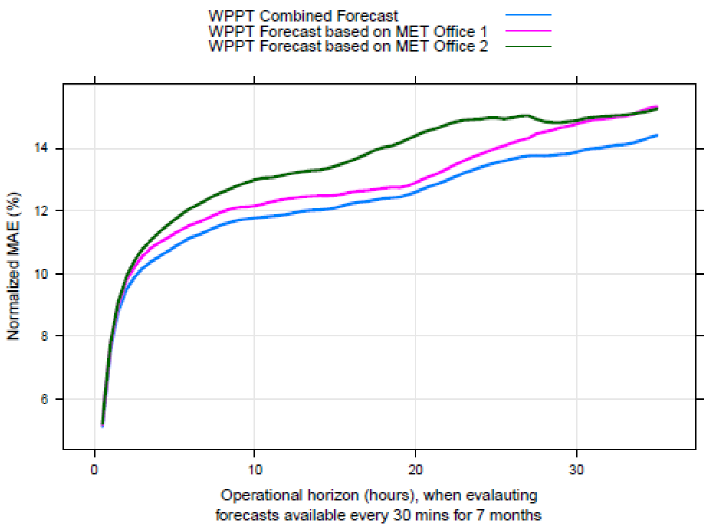

Figure 2.2. Error reduction in the combination module.

Figure 3 represents the normalized mean absolute error (nMAE, %) of the predictions as a function of the time horizon (hours). It is possible to see two different NWP sources represented in green and pink lines that have similar performance for the first 1 to 3 hours and, after that, they start diverging reaching an error of 15% for an operational horizon of 35 hours. It is possible to generate an optimized prediction with a lower error by introducing a combination module for these two NWP models, which is represented by the blue line.

Apart from the improvements in accuracy, the combination module also improves the robustness of the overall system as combined forecasts will always be produced if there is at least one input source.

Finally, the second prediction module is the data-based model. This module is mainly based on the latest recorded measurements and not on the weather predictions. The

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real-time data (PV production) is introduced in a time-series algorithm [4], which generates the short-term predictions (1 to 12 hours ahead).

In order to merge the predictions of the two previous modules (NWP-based and real-time data-based), a substitution module is introduced. This module selects the power production forecast of the real-time data-based model (1-12 hours ahead) and appends the NWP-based predicted values for the rest of the horizon (12 to 48 hours ahead). This generates an optimized time series that covers the 1-48 hours horizon. This can be seen in Figure 2.3. Photovoltaic prediction module.

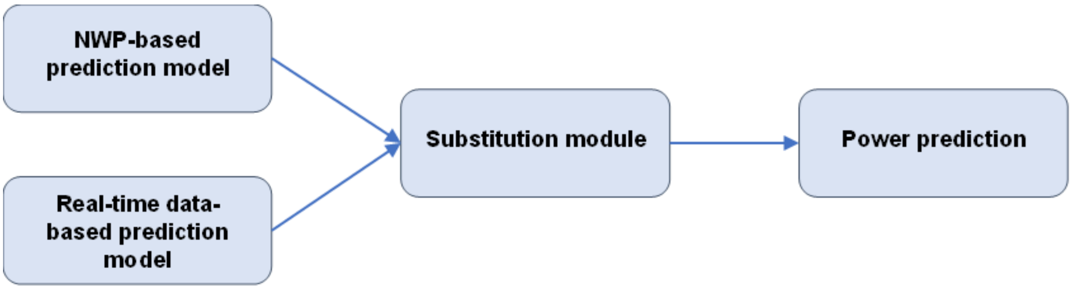

Figure 2.3. Photovoltaic prediction module

3 Electricity Consumption Prediction Module

The electricity consumption prediction module is based on machine learning for automatic calibration of models using historical data and real-time measurements. The load forecast algorithm will be used for “Building Demand Forecasting”, “Vehicle Charging Point Forecasting”, and “Electricity Grid Forecasting” since it can be considered that the three of them follow the same principles.

There are two different sections explaining how the electricity consumption module works. Section 3.1 Inputs and outputs, describes the necessary data required to generate accurate predictions and, also, the expected variables generated by the model. Finally, Section 3.2 Description of the algorithm explains the basis of the model and how it works.

3.1 Inputs and outputs electricity consumption module

The electricity consumption prediction module requires, as the PV algorithm, two different inputs: specific study case data and NWP data.

The study-case data includes, on the one hand, the physical location of the studied building and, also, the expected annual energy consumption (energy/year). The location is necessary to get accurate weather predictions, while the expected annual consumption will provide an estimation of the base consumption of the studied building.

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On the other hand, the demo sites should provide historical and real-time data. In this case, it includes power consumption measurements and, also, the holidays/school calendar for the following years. The former gives insights into the consumption patterns, while the latter helps identify and generate better predictions for non-regular days.

Finally, the NWP data is extracted for the given location providing information about the temperature, solar irradiance, precipitation, and humidity, which help to understand and predict the consumption patterns of the customers.

The inputs are summarized in Table 3.

Table 3. Inputs for the electricity consumption prediction module.

Inputs	Description
Location	Latitude and longitude of the building
Expected annual energy consumption	Expected energy consumption over a common year (energy/year)
Electricity power consumption	Measurements of electricity consumption
Power measurements	Historical and real-time power consumption of the building with a resolution of 15 minutes
Holidays Schedule	National and school holidays of a natural year
NWP models	Numeric Weather Predictions provided by multiple institutions

Regarding the outputs, the prediction model will generate a new power consumption forecast every hour, with a resolution of 15 minutes for the next 1 to 48 hours ahead. This can be summarized in Table 4.

Table 4. Output of the electricity consumption module.

Outputs	Description
Electricity consumption prediction	Forecast of the electricity consumption of the system for the following 1 to 48 hours ahead

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3.2 Description of the consumption prediction module

The electricity consumption module has been designed following the same approach as the PV module.

On the one hand, there is the NWP-based prediction model that combines the historical data with the NWP sources. Based on the input data, the module automatically identifies and takes the systematic behaviour of electricity consumers into account. This means that it continuously adapts to the actual situation by monitoring the consumption and adapts to changes, such as changes in consumer behaviour, number of consumers, meteorological models, or even changes in the physical characteristics of the power grid [5], [6].

On the other hand, the real-time data-based prediction module uses online measurements, creating a time-series model to improve the accuracy for the short horizon (1-12 hours ahead), adapting to sudden changes in the consumers' behaviour and energy flexibility scenarios [7]. Electricity load forecasting is complicated because the dynamics of buildings in some geographic regions affect the cooling or heating demand on an hourly basis. For this reason, a non-linear weather response has been developed to estimate the heating and cooling breaking points as well as the slopes of the heating and cooling demands (highly depending on country and regions). Therefore, the electricity consumption module automatically applies an optimal smoothing effect which solves this issue, such that the physical properties of the underlying energy system are modelled correctly, and the forecast shows the appropriate response to changes in temperature or sun irradiation.

As in the PV forecasting module, the electricity consumption algorithm will generate as many models as NWP sources defined, which are combined to generate the most accurate predictions. Finally, the substitution model will append the predictions of both modules, using the 1 to 12 hours from the real-time data-based model, and the remaining – 12 to 48 hours – from the NWP-based algorithm.

A diagram summarizing the different modules of the electricity consumption prediction model can be seen in Figure 3.4. Electricity consumption prediction module.

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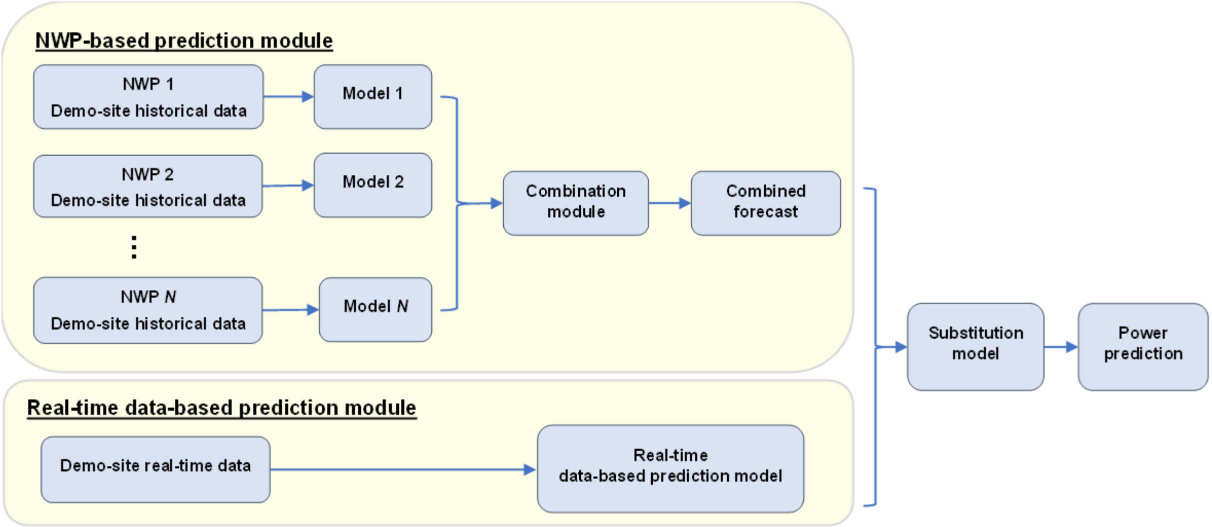

Figure 3.4. Electricity consumption prediction module.

4 Regulation Power Price Prediction Module

Like the previous prediction modules, the regulation power price prediction module is also a self-learning and self-calibrating system. It relies on real-time power system data available through power exchanges. The module predicts a large set of quantiles for each price area, enabling the assessment of worst-case, best-case and anything in between.

The two sections explaining how the Regulating power price prediction module works are the following. Inputs and outputs describe the necessary inputs required to generate accurate predictions and, also, the expected outputs from the model. Description of the regulation power price prediction module explains the basis of the model and how it works.

4.1 Inputs and outputs

The expected output from the prediction module is quantiles of regulating power prices, which defines the distribution of the regulating power prices.

There are five kinds of inputs to the model, two of which are publicly available from power exchanges, and three of which are forecasted produced internally by ENFOR. From power exchanges, the inputs are the spot prices for the price areas, which form the baseline for regulating power price since, on average, spot prices and regulating power prices are equal. Next is the scheduled flow and capacity on interconnectors between the price area in question and surrounding price areas. The difference between these two variables results in the effective capacity, which can be used to cancel out differences between neighbouring price areas, thus reducing overall imbalances. Finally, the three inputs generated by ENFOR are wind and solar

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production and electricity demand. All of these are subject to large uncertainty, which is what causes imbalances.

4.2 Description of the regulation power price prediction module

The prediction module uses operational data from the power grid to assess the probability of up and down-regulation and no regulation. For each of these scenarios, it generates forecasts of the regulation power price (notice that in the case of no regulation, the regulation power price equals the spot price). Fundamentally, what makes the prediction module function is that regulating power prices are, to a large extent, determined by the ability to exchange energy with neighbouring price areas: some areas tend to offer cheap methods for dealing with imbalances through, for example, pumped hydropower. Thus, whether spare capacity is available for exchanging energy with these areas is essential for regulating power prices. The module can decide which of the connections are important automatically.

The module consists of a two-stage random forest. The first stage estimates the probability (weights) of having no regulation, up-regulation, and down-regulation (w_{no}, w_{up}, and w_{down}). Then, the second stage is conditioned upon the kind of regulation. That is, it assumes either no regulation, up-regulation, or down-regulation. Forecasts are produced for each of the three stages, and, ultimately, the weights are assigned according to the occurrence probability of the corresponding scenarios as illustrated in Figure 4.5. Regulation power price module..

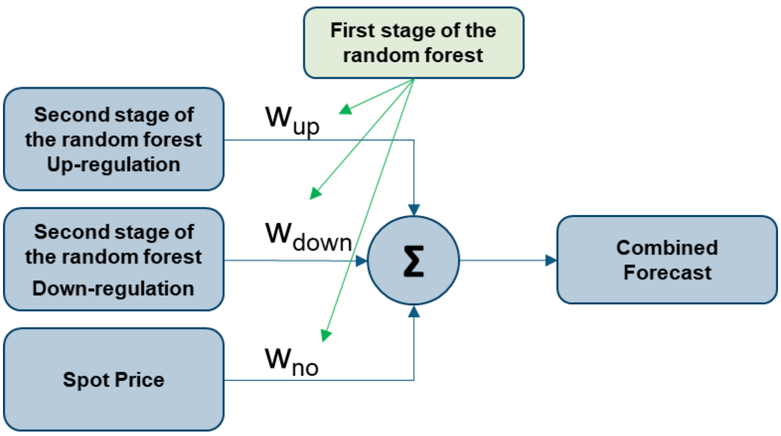

Figure 4.5. Regulation power price module.

5 EV Flexibility Prediction Module

EV flexibility without vehicle-to-grid is a combination of three quantities:

1. Allowed charge rate - higher is better
2. Charging deadline - later is better
3. Energy needed

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A larger charging rate and a later charging deadline (the time when the car must be ready for take-off) is better from the user point of view. However, it is not so clear for the power needs.

In one extreme, if the vehicle does not need energy at all, then it has zero flexibility since it will not accept any charging (this is different when vehicle-to-grid is allowed). The other extreme is that the EV needs so much energy that it must charge at the maximum rate until the charging deadline. In this case, the charging process can never be turned down, and thus, there is also zero flexibility.

Therefore, the optimal amount of needed energy depends on the charging deadline and allowed charging rate. The later the deadline and the higher the charging rate, the more needed energy can be accommodated while still allowing room for flexibility. Assuming that charging rate does not affect efficiency and that up and down-regulation are equally important and likely to happen, the optimal energy amount is exactly such that the car needs to be charged for half of the time at full capacity. In this case, the flexibility of a particular EV is given by the following equation:

$$Flex = E(CrCt - E),$$

where E is the required energy by the EV, C_r is the allowed charging rate, and C_t is the time until the charging deadline. Thus, the unit of $Flex$ is energy squared. This unit makes sense, since the source of energy flexibility originates from two sources; 1) the demanded energy, E, which can potentially be moved around and 2) spare capacity, $C_r C_t - E$, which has the potential to be used to move energy around. Having one without the other leaves **zero room for flexibility**. Conversely, having a lot of either energy demand or spare capacity means that more energy flexibility is gained from increasing the opposite quantity.

For each time step, the EV flexibility index can be computed, yielding a time series. This time series can then be used for training forecasting models that will yield forecasts of future EV flexibility. However, it is not possible to know what models are best suited for this until data is available.

5.1 Flexibility concept for electromobility

Electric vehicle (EV) user are the primary customers of the EV charge management services delivered by the EV charge management company described in this document. The primary goal of the EV charge management service should be to:

A) Lower the costs of charging an EV by reducing electricity costs
B) Provide the EV customer with the feeling that he is contributing to society by charging his car when the electricity system needs it due to "excess" amount of renewables or when the renewable generation rate in the energy mix is higher (greener)

The EV customer will however most likely (also) be a customer at an EV-operator (installer and operator of charging infrastructure) and thereby not be a direct customer at the electric vehicle charging management company. The charging services will

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therefore have to be delivered in cooperation with an EV service operator - which potentially could also be viewed as the customer - depending on the specific business setup.

At the other end of the value chain an electricity trader (consumption balance responsible party) will provide the access to the whole sale electricity markets. The balance responsible party will either be an important partner or could in certain setups/markets also be considered a customer (if they for example sell fix price contract to the EV operator and thereby have a vested interest in reducing actual electricity purchasing costs).

Most likely the value chain will look like something described in Figure 5.6, where customers at EV-operator can have different electricity suppliers (balance responsible parties) and the EV charge management company might end up aggregating load profiles across multiple EV-operators and multiple electricity suppliers. Taking on the role as aggregating load across multiple EV-operators and electricity suppliers should be seen as an advantage. The reason is that the additional value is then added along the value chain as opposed to a linear value chain where both the EV-operator and the electricity supplier can more easily squeeze the EV-charge management company.

Charge points (CP) can be located either a private customer location or at a public accessible locations. The charge management system will link all the players together.

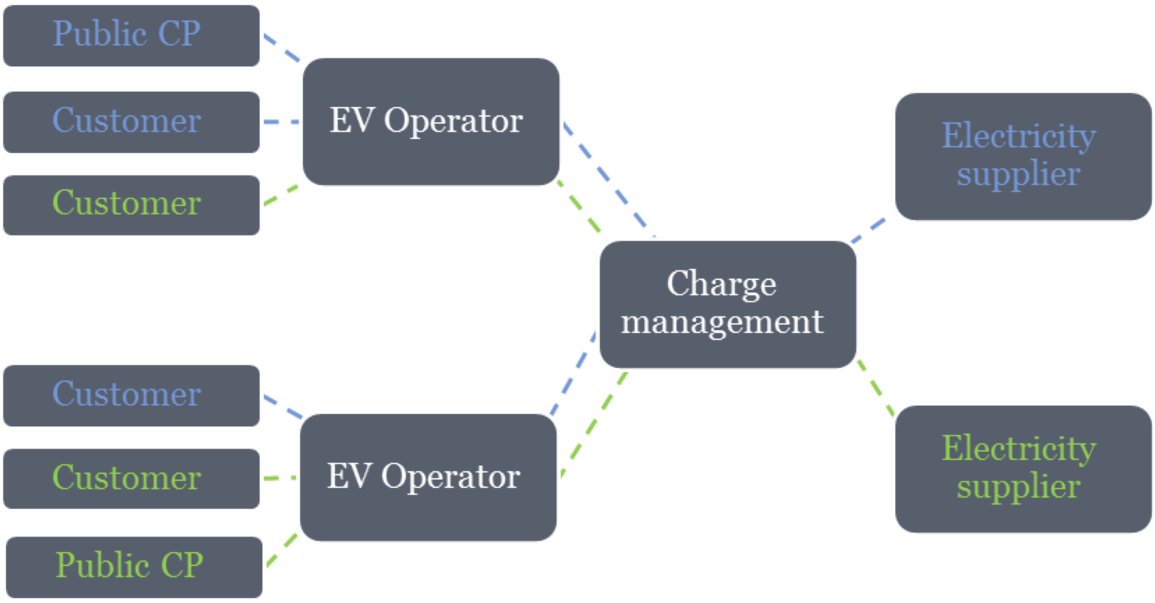

Figure 5.6: The charge management system will connect EV Operators and Electricity suppliers, so private and public charge points can be managed

Flexibility in regard to e-mobility can be considered as an expression of electric vehicles charging speed. When an electric vehicle connects to a charge point it will express both an "option" to charge (as part of the battery will empty) and "obligation" to charge, as the user will need to leave and drive somewhere (requiring a certain amount of energy to be available). In case of vehicle to grid, the connection of a car will also represent an "option" to discharge.

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The charge decision can hence be described by the two extremes: charging as fast as possible vs charging as late as possible. Both of these strategies being defined by how much energy is on the battery when connected, the size of the battery, how much energy has to be on the battery when it leaves, and the maximum charge rate of the car (given the infrastructure it is connected to). Any charge patterns in between those two extremes can also be decided as long as the charge rate is not violated.

Such charge sessions can then be aggregated, and a total flexibility expression can be derived, illustrating how the total flexibility of a charge portfolio can be described.

Collection such a time series of aggregated charge sessions, can then be used for forecasting the flexibility, which again can then be used to plan and schedule the charging of the vehicles, such that the energy is distributed between vehicles.

Value is generated by creating a system which can predict/forecast EV customer behaviour and expose this in a structured way to electricity traders so the electricity can continuously be bought the cheapest possible way and thereby generating savings for the EV customer. The charge management systems could be viewed as a combination of the ability to predict and plan as well as to execute and operate according to the plan.

Conceptually the **charge management system** operates at two different "levels" in order to create value. In one end of the value chain is the electricity markets. Prediction, planning and execution should focus on the aggregated level of the portfolio of customers in order to make it possible to interact with the electricity market. The actual service to the customer is delivered in the other end of the value chain. This has to happen on a customer-by-customer basis. Therefore, the charge management system should provide functionality on both the aggregated level as well as on the individual customer level – and be able to integrate these to levels into one system.

Value can be created in several value pools along the value chain in the utility sector. Some of them are easier accessible than other and some contain more value than others. The description below will outline how value can be created, how it can be accessed and which barriers might exist. Barriers can be technical, regulatory or more structural in terms of who controls the value in the value chain. In the following both potential and barriers will be identified for the different value pools which should prioritize the effort and develop the initial minimum viable product (MVP) and the following road map.

Prediction of customer behaviour should take place in such a way that it:

- Utilize as much information about the customers as possible
- Bothers and interferes with the customers as little as possible
- Follows the logic and processes of the electricity markets
- The results are presented in a structured way which fits the structure of the electricity market and thereby can be optimized by traders.

Fundamentally electricity costs in regard to EVs are made up of CAPEX components and OPEX components at the consumer level. Furthermore, there is a future potential for revenues from delivering system services.

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CAPEX:

- Cost of installation
- Cost of access to the grid at installation time. Often referred to as a "connection fee".

OPEX:

- Cost of metering and access to the grid (re-occurring yearly fee)
- Cost of producing electricity (cost for actually producing one unit of electricity at the power plant)
- Cost of transporting electricity (cost of transporting the electricity from power plant to consumer)
- Taxes (taxes and VAT on electricity)

Revenues:

- Revenues from system services

Additional future revenues could come from battery maintenance service (charging batteries in accordance with the OEM's specification to preserve lifetime) as well as second life battery storage applications.

Charge management should follow the electricity trading process, starting with the rough planning in the day-ahead market, moving into re-iterations of the planning and optimization process, as the intra-day market opens and charge sessions are executed, as seen in Figure 5.7.

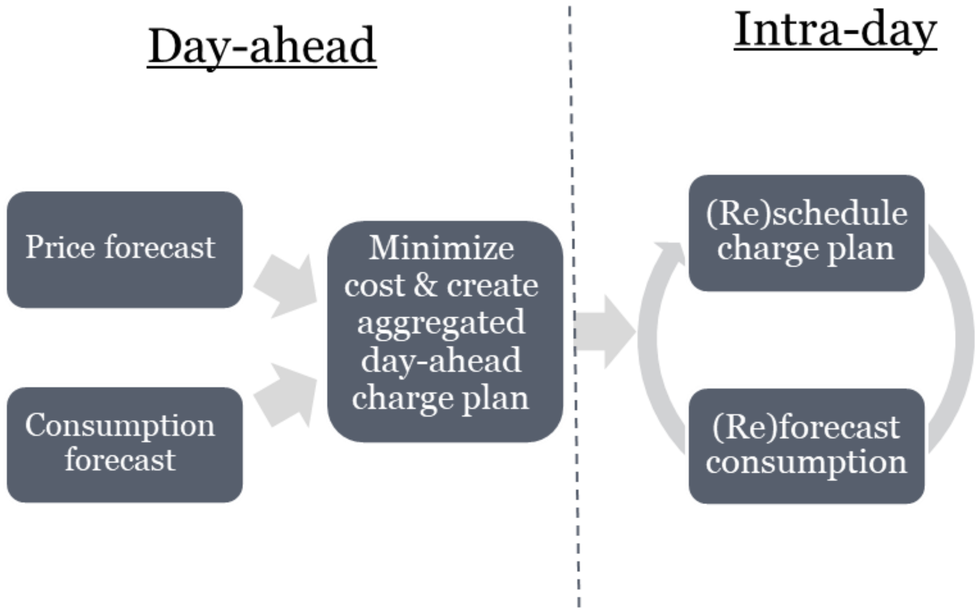

Figure 5.7: Charge management should follow the electricity trading process, starting with the rough planning in the day-ahead market, moving into re-iterations of the planning and optimization process, as the intra-day market opens and charge sessions are executed

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6 Energy exchange Prediction Module

Another approach towards energy flexibility prediction is to involve solutions based on neural network to predict or estimate the exchange of energy at a given node of the energy grid. A module realizing this functionality was initially developed in the e-balance project [8] and will be further evaluated and optimized within the ebalance-plus system. This approach mainly considers the energy system to be a black box, with only a few additional parameters being inputs to the module. In its initial version the module tries to exploit the regularity of the energetic behaviour, but we aim at enhancing the approach with additional information to capture irregular events as well.

6.1 Problem definition

One particular instance of the energy exchange prediction module operates on a given node of the energy grid, modelling the energy exchange at that particular node, referring to a household, neighbourhood or other kind of energy grid branch. In the following description, we refer to that part of the grid as to the neighbourhood.

Let EC > 0 denote the sum of energy consumed by the neighbourhood, let EG > 0 denote the sum of energy generated by the neighbourhood, let EL > 0 denote the sum of energy lost within the neighbourhood, let EW > 0 denote the sum of energy withdrawn from the grid to the neighbourhood, and finally, let EF > 0 denote the sum of energy fed to the grid from the neighbourhood.

A variable EN representing the net energy exchange of the neighbourhood can be defined as follows:

$$EN = EC – EG + EL = EW – EF$$

The energy exchange predictor operates on energy values representing defined time intervals – in the initial implementation this time interval was set to 15 minutes. The historical values define the time-series being fed to the module to train it, and the module is able to generate an array of values representing the predictions for the following 24 hours.

Availability of the predicted EN values can help energy flexibility and resilience algorithms to operate and define their set points in the future.

6.2 The internal structure of the module

The module is implemented as a neural network – multilayer perceptron with a number of inputs and a single output (see Figure 6.8).

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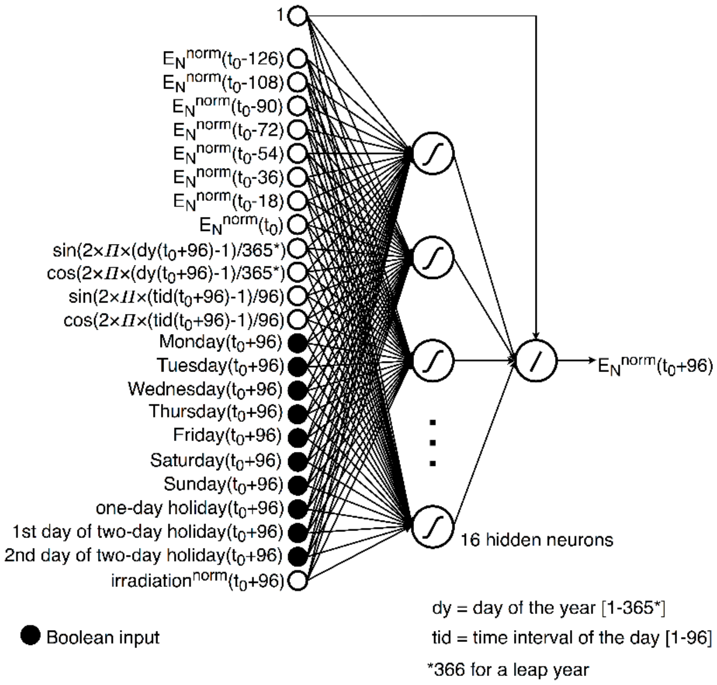

Figure 6.8. The internal structure of the energy exchange prediction module

All the data considered in the module is represented as time-series and the particular values provided to the inputs are a combination of historical values as well as parameters describing the point in the future (24 hours ahead), for which the energy exchange value is to be predicted. The values in the parentheses indicate the temporal relation between these values.

7 Conclusion

Renewable energy and electricity demand forecasting provide valuable information about the expected changes in the energy that must be generated in the near future to meet the population needs. The development of the photovoltaic and electricity consumption prediction modules will help to develop new methods for matching the demand with supply in the most efficient, economic, and sustainable way.

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