SIMULATION PLATFORM FOR COORDINATED CHARGING OF ELECTRIC VEHICLES

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Abstract. *EMERALD is a project funded by the European Commission under the FP7 program focusing on energy use optimization on the integration of the electric vehicles into the transport and energy infrastructure. Between the objectives of EMERALD, enhanced power demand prediction and power flow support management system uses the power flow demand simulation platform considered in this paper. The power flow demand simulation platform is a software tool that defines the estimation of electric vehicles power demand according to different conditions as, arrival and departure curves, the estimation of power production based on renewable energy sources and the electricity cost. The tool coordinates scheduling for charging of electric vehicles in order to minimize the recharging cost, considering the energy balance between the generation and demand power.*

1 INTRODUCTION

The amount of power demand for recharging the electric vehicles energy will be increased in next decade and will have a significant impact in the power grid. On the other hand, the amount of energy produced by Renewable Energy Sources (RES) has rapidly increased in several European countries during the last decade. According to this scenario, increased use of renewable energy technologies and the widespread introduction of electric vehicles can play an important role in reducing carbon dioxide emissions in the power supply and transportation sectors. Unfortunately the massive introduction of RES has having its counterbalance in its partial instability and non-controllability. The uncontrollability and partial unpredictability of RES are so much more significant than their advantages and their disconnection from the grid is more economically convenient than their management. A solution to avoid the building of new infrastructure, it is the use of the excess energy produced by RES for charging electric vehicles.

In order to avoid overloading the grid at peak hours and to take advantage of off-peak charging benefits, it is important to perform intelligent scheduling for recharging the electric vehicles, considering the estimation of energy produced by RES and the energy cost. This solution is in the concept of the smart grid, including activation of demand based on instantaneous interactive information and communication technologies.

The FP7 European co-funded EMERALD project tries to contribute to the solution of these issues proposing the cooperation with the prevision of power demand for electric vehicles according to recharging behaviors, recharging infrastructure available and grid operator as Distributor System Operator (DSO).

2 THE STUDY PROCEDURE

In order to determine the intelligent scheduling for recharging the electric vehicles to avoid overloading the grid and the minimum recharging cost, different boundary conditions have to be considered, as the estimation of power production, the energy cost and the estimation of electric vehicles power demand.

2.1 Estimation of power production for renewable energy sources

The estimation of the total electricity supply includes power supplies from nuclear reactors, coal-fired plants and diversion hydropower systems that could be modelled as constant. In this paper the considered electricity supply is the power production from wind and photovoltaics generators. The fundamental concept of each operation is described in this section.

Weather data are required for the estimation of electricity supply, including clouds, temperature, wind speed and others. Weather data are collecting from OpenWeatherMap web service [1], where the RES localization is defined by a site and a country.

Wind power model

Several wind turbine power curves are shown in next figure, where input is a known wind speed and output is the generated power of the wind turbine. When the wind speed exceeds the cut-out speed, the wind power supply immediately drops to zero.

The wind speeds can vary significantly over short time periods, and the impact of this variation needed to be assessed in greater detail. The wind speed was simulated by a random number based on a Weibull distribution rather than an actual wind speed distribution, as is commonly done [2].

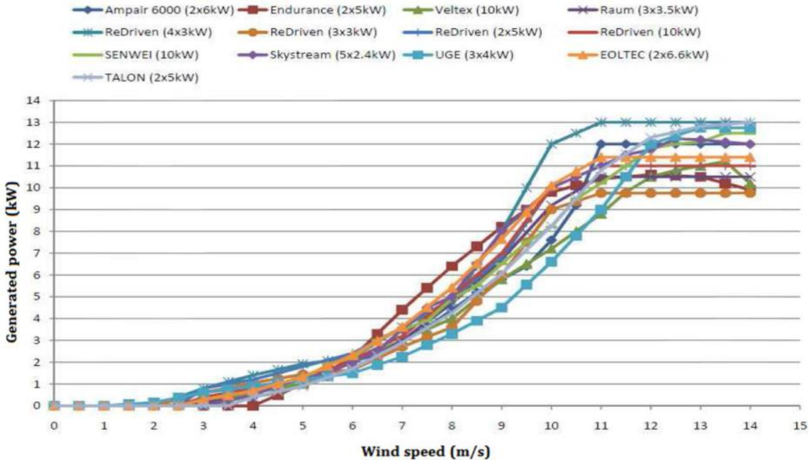

Figure 1. Power curve for wind power model [3]

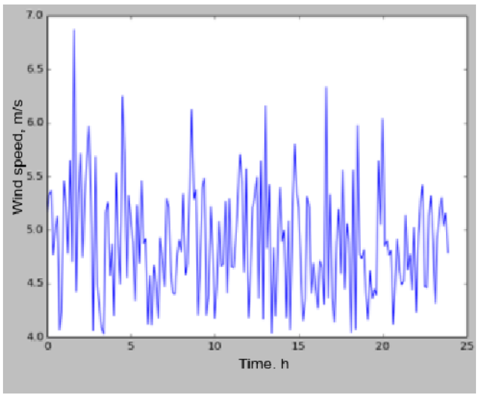

Figure 2. Variable wind speed (average: 5 m/s)

Photovoltaics model

An operational model of photovoltaics power could be a model where the photovoltaics power strongly depends on the time of day and weather conditions [4] & [5].

The power supply from photovoltaics will be given by next equation for the period of time between sun rise and sun set,

$$P_{PV} = C_{PV} \cdot f_{PV} \cdot WF \cdot T^4 \cdot \Delta t\,, \tag{1}$$

$$f_{PV} = -3.24 \cdot 10^{-5} \cdot t^5 + 1.29 \cdot 10^{-3} \cdot t^4 - 0.0134 \cdot t^3 - 0.0777 \cdot t^2 + 2.043 \cdot t - 7.985\,, \tag{2}$$

where "C_{PV}" is a constant set (maximum photovoltaic power), "f_{PV}" is a normalized operation curve panels (an empirical curve), "*WF*" is a factor used to consider the weather condition (sunny weather: WF = 1.0, cloudy weather: WF = 0.65, rainy weather: WF = 0.16),"Δt" is time step, "*T*" is temperature and "*t*" is time.

The photovoltaics normalized operation curve is shown in next figure.

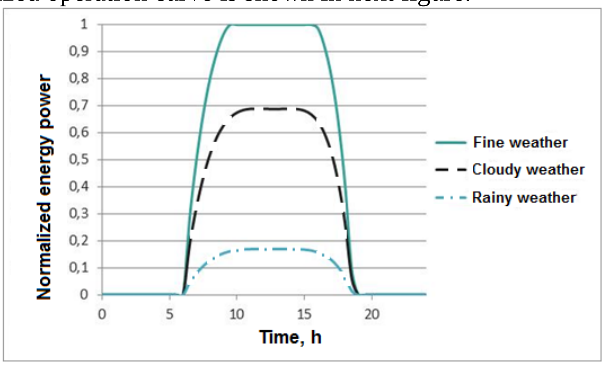

Figure 3: Relative photovoltaics power vs hours according to weather conditions.

2.2 Evaluation of energy cost

The evaluation of the energy cost depends on the agreement of user with electricity retailer. In Spain, the energy cost will be given by a power term and an energy term.

For supplies of small business and communities with less power than10 kW, the power term has a cost of around 3 €/kW per month and the energy term cost will be divided in three periods, as from following table,

Period of time	Tariff	Energy cost (€/kWh)
13:00 h – 23:00 h	Peak hour	0.154049
01:00 h – 07:00 h	Super valley hour	0.051769
Rest	Valley hour	0.069845

Table 1. Energy term cost vs. hour of the day [6]

On the other hand, it is possible to get the energy cost considering the electricity market caters for the trading of electricity between agents (producers, consumers, retailers, etc.) [7].

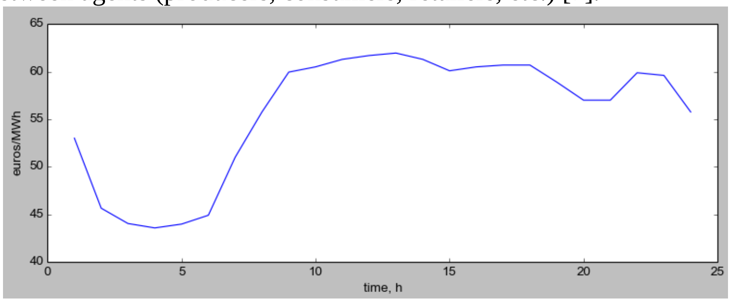

Figure 4: Daily market hourly price -01/06/2015 (Source, Omel)

2.3 Prevision of power demand for electric vehicles

The power demand prevision considers different scheduling strategies for full electric vehicle recharging according to several vehicle arrival and departure models.

The vehicle arrival time refers to time when the electric vehicle arrives at the recharging point and the vehicle departure time refers to time when the electric vehicle departures from the recharging point. The rate parameter can usually be determinated from historical data or estimated from real time traffic data.

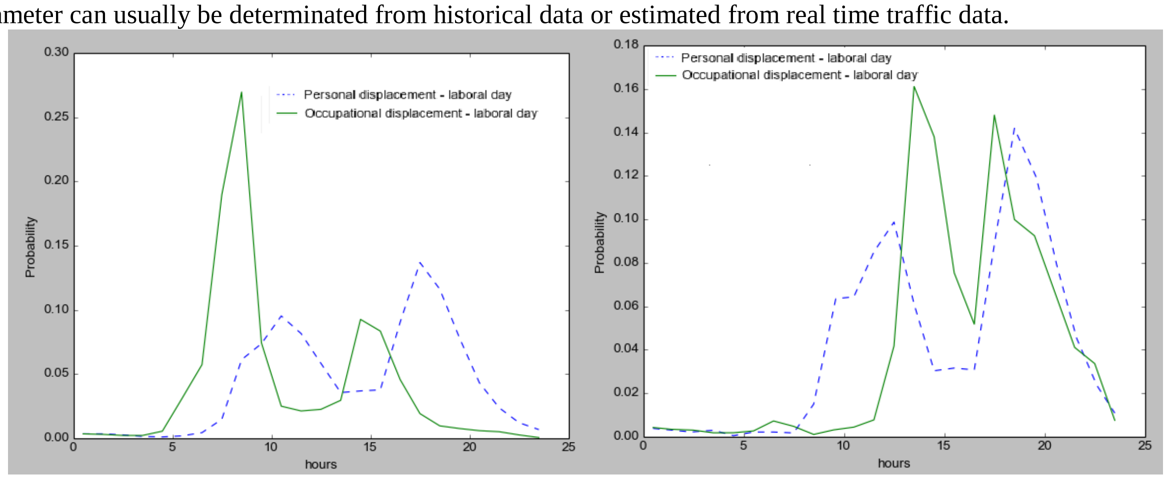

Figure 5: Arrival and departure probability from Barcelona city [8]

The aggregated power demand is the number of vehicles being charged at a particular time multiplied by the recharging mode. This paper assumes that each electric vehicle charges at a constant rate until the level desired by the customer.

Vehicle model	Battery (kWh)	Driving (km)	kWh/km
BMW i3	32	160	0.20
BMW Mini-E	35	240	0.15
Ford Transit	28	105	0.27
Mitsubishi i-Miev	16	160	0.10
Nissan Leaf	24	175	0.14
Peugeot ePartner	27	97	0.28
Pininfarina BlueCar	30	200	0.15
Renault Kangoo ZE	22	185	0.13
Tesla Roadster	53	390	0.13

Table 2: Battery capacity and vehicle range [9]

Population		<10000	10000-50000	50000 -500000	>500000
Number of trips per person per day		2.8	2.9	3.0	2.8
Duration of trip (min)	Public transport	43.5	39.8	36.3	35.8
	Car	20.1	19.3	21.1	26.3
Dedicated time for trips (min/person day)		64	63.9	73.2	81.1
Reason for travel (%)	Jobs and studies	55.1	54.7	52.2	51.1
	Leisure	5.3	5.6	6.5	6.9
	Purchases and others	39.7	39.7	41.3	42.0
Modal split of trips (%)	Public transport	55.1	57.2	45.8	35.7
	Car	5.6	7.1	12.9	26.6

Table 3: Mobility table in Spain according to municipality sizes [10]

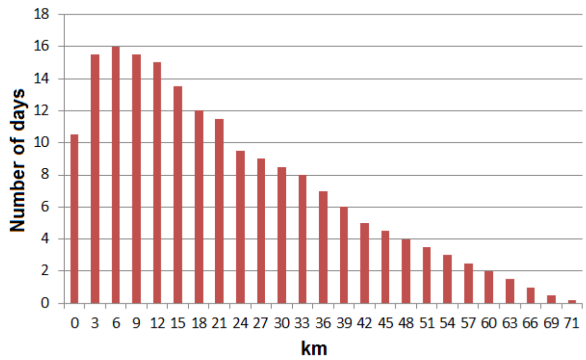

Figure 6: Annual probability of kilometers traveled [11]

It is assumed that the required charging level at arrival of electric vehicles is a constant that will depend on the recharging power, the number of kilometers travelled and the electrical consumption of the electric vehicle by kilometer. The final component is the deadline by which the consumer needs the electric vehicles to be fully charged.

In particular, we consider three scenarios.

A. Industrial scenario

In the industrial scenario, employs arrive at their parking plaza daily in the morning and the departure time for all employees corresponding to the evening. The period of time for the recharging is long.

B. Residential Scenario

In the residential scenario, electric vehicle users arrive at their recharging point daily in the evening and the departure time corresponding to the morning. The period of time for the recharging is long.

C. Commercial scenario

In the commercial scenario, customers arrive at the commercial parking plaza during the commercial hourly. The period of time for the recharging is short.

Each electric vehicle has a range of hours after the arrival until the departure. The arrival and departure curves for each scenario can be defined by statistical, uniform distributions or empirical methods.

2.4 The optimal recharging problem formulation and optimization algorithm

The recharging problem is an optimization problem where the objective function expresses the economic benefit for the recharging of the aggregation electric vehicle power demands. To this purpose, it evaluates the optimization problem for a massive recharge of electric vehicles, taking into account energy production and prices for different time windows, electrical characteristics for different sample vehicles, typical car usage for different population statistics, etc.

As the objective function and the boundary conditions are not linear, heuristic or non-linear programming methods will have to be used for optimization.

Problem formulation

The objective function will minimize the charging cost, according to the following formula,

$$\sum_{t=0}^{P}\left(C_t \cdot NFEV_t \cdot PNFEV_t \cdot t\right), \tag{3}$$

where C_t is the price of electricity in a generic time slot (€/kWh), $NFEV_t$ is the number of electric vehicles that are recharging simultaneously during a time slot, $PNFEV_t$ is the power requested by the each electric vehicle at a generic time slot (kW) and t is a time slot that will be considered constant during the total period of time in hours (P).

The objective function must satisfy the following constraints:

The first constraint is related to the energy cost. The evaluation of the energy cost depends on the agreement of electric vehicle user with electricity retailer. In Spain, the energy cost will be given by a power term and an energy term. The power term has a fixed cost of per month and the energy term cost will be divided in several time slots.

The second constraint concerns the restriction of power supply. In this paper, the power supply is a prediction of power demand production from renewable energy sources, according to the weather conditions, wind power model and photovoltaics model.

The third constraint represents the prevision of power demand for electric vehicles. The constraint depends on how many recharging points and electric vehicles are considered in the different commercial, industrial and residential scenarios. The availability of the electric vehicles will determinate considering the arrival and departures curves, the required level of battery and the maximum charging power level.

Optimization algorithm

The problem is specified by means of an objective function, the equality constraint functions and inequality constraint functions.

The optimization algorithm is a non-linear programming method adopted to solve optimization problems based on a non-linear objective function and restricted by non-linear constrained. This algorithm is based on the discretization of the non-linear problem in a linear one by means of the discretization of total period of time in an amount of time slots, considering constrains in each time slot.

The partial energy cost is sorted by minimum energy cost and time slot. Finally, the minimum energy cost is the integration of partial energy cost by time slot to complete the total recharging of electric vehicles in the total period of time.

The processing time is linear depending on the number of time slots.

3 POWER FLOW SIMULATION PLATFORM

The power flow simulation platform software was developed using Python programing language and several graphical user interaction tools in order to produce a useful and reliable software program, including: software components and agents for the forecasting of energy demand (electric car), forecast of renewables and energy price.

Next figure shows the power production, the energy price, the initial electric vehicle power demand and the optimization of the electric vehicles power demand in order to minimize the energy cost using the power flow simulation platform,

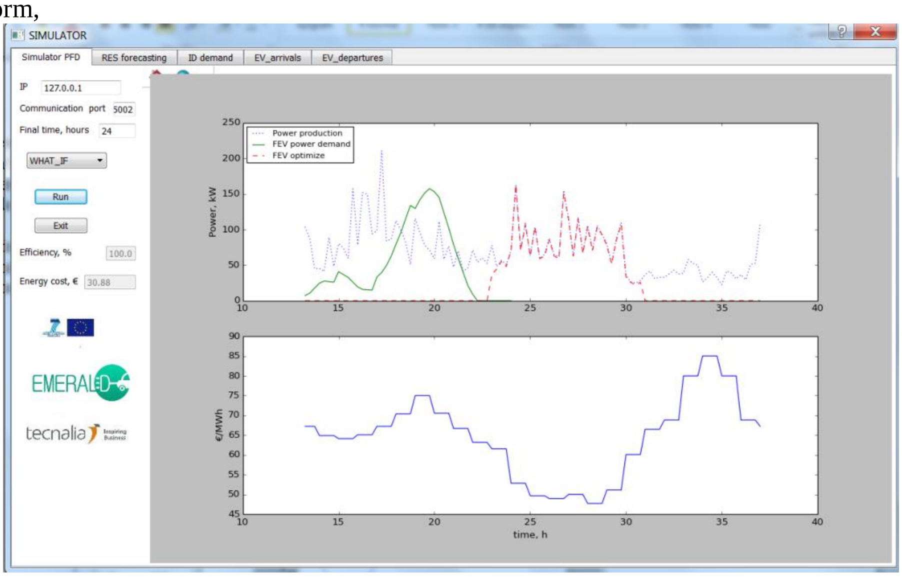

Figure 7: Power flow simulation platform

The results of the simulation were done with 100 electric vehicles for 24 hours, which were divided by industrial, commercial and residential scenarios in percent. The estimation of the power production level was generated by trend of 36 simulated wind generators (Ampair 6000) and 100 simulated solar panels, considering the weather around Vitoria (Spain).

The simulation was running with the following context: the requirements of the electricity were determinated through the kilometers travelled by a user, the average consumption by kilometer and the maximum recharging power, and the electricity price was got by inter-daily Spanish market.

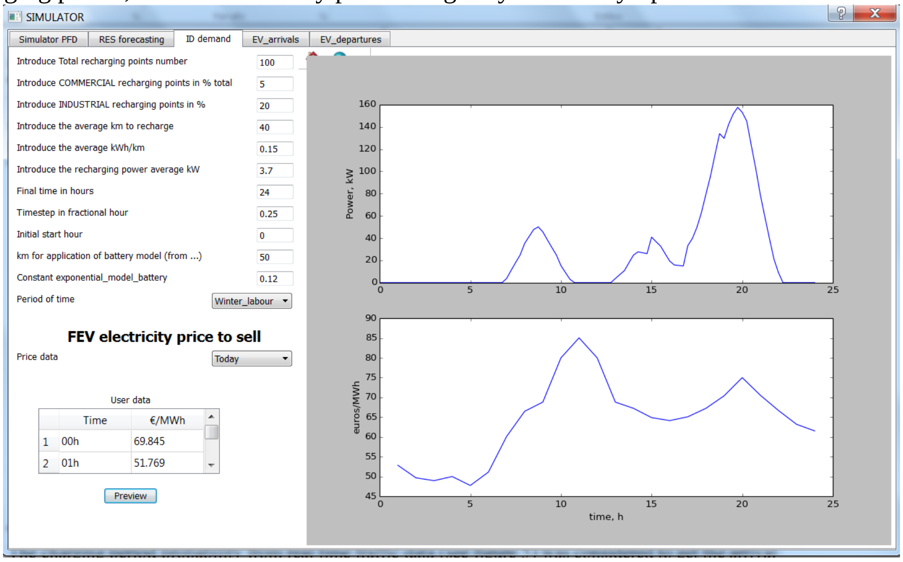

Figure 8: Electric vehicles power demand

The charging period probability from real time traffic data (see figure 5) was considered to get the arrival and departures curves in order to determinate the availability.

Next figure shows the considered arrival and departures curves in the simulation,

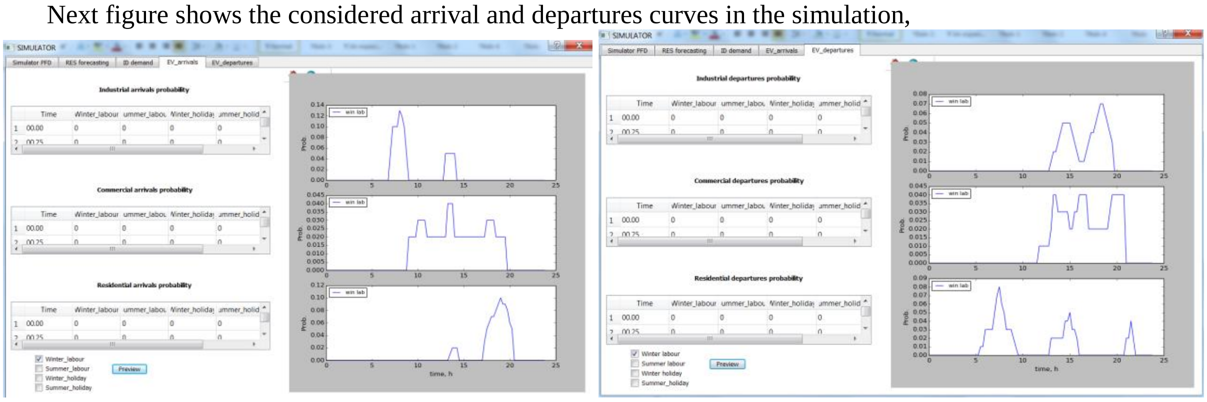

Figure 9: Arrival and departure curves for industrial, commercial and residential scenarios

According to these constrains and where the objective function expresses the economic benefit for the recharging of the aggregation power demand of electric vehicles, the minimum charging cost was 30.88 €/day.

4 CONCLUSIONS

This work describes the power flow demand simulation platform that defines the estimation of full electric vehicles power demand, power production based on renewable energy sources and the electricity cost, and proposes a non-linear programming based algorithm to optimally coordinate scheduling for recharging of full electric vehicle, evaluating the energy cost to get the minimum cost for the recharging according to the energy balance.

The results of the power flow simulation platform will be used in other EMERALD modules, considering the prevision of power demand for electric vehicles, the improvement in the coordination of the scheduling of electric vehicles recharging and the grid requirements to avoid overloads.

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