Semantically-enriched Electric Car Recharge Optimization Toolkit

Mikhail Simonov[1], Antonio Attanasio[1], and Davide Luzio[2]

[1] ISMB, Via P.C. Boggio 61, 10138 Torino, Italy
[2] Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy

`simonov@ismb.it, attanasio@ismb.it, davide.luzio@hotmail.it`

Abstract. Electric CAr Recharge Optimization Toolkit (e-CARROT) is an integrated system for modelling and optimization of Electric Vehicle recharge processes. It uses semantic technology to conceptualize, model, and optimize battery recharge processes occurring in smart grid. The e-CARROT tool attempts the time shifting postponing the demand exceeding the available energy flows. It is useful for operational planning of saturated electricity grid when the electricity demand exceeds the available resources during some time slots.

1 Introduction

The growing demand of electric energy in EU27 corresponds to annual increments in the energy production. In the last ten years - except 2009 - the volume of produced electricity has continuously increased [1]. Even with such a production trend, the sustainability limits might be exceeded in the next years, when a high number of Electric Vehicles (EVs) will add new electricity requests. Balancing between the available electricity and its demand is possible from within certain stability limits, which depend on the physical characteristics of distribution sub-topologies. The known art AI methods schedule the charging of EVs in a way to respect the local network constraints. Clement et al. [2] use a centralised scheduler accounting declarations about the expected/future EV mobility. Reporting the earlier vehicle withdrawal leads to the preferential charging, but it overloads the grid up to Denial-of-Service (DoS). The work being described presents a modelling and *online optimization* toolkit accompanying the integration of EV in smart grid. Unlike online variants of Vickrey-Clarke-Groves method, the proposed algorithm does not need the knowledge about pending/future mobility. Model-free online settings have been considered by Porter [3] and Hajiaghayi [4]. We extend this work by considering shared knowledge about different types/domains of neighbour's processes. The bid mechanism is used to define at the beginning the recharge priorities and to correct them dynamically while running. Further reading about the related work can be found in [5].

S. Wölfl (Ed.): Poster and Demo Track of the 35th German Conference on
Artificial Intelligence (KI-2012), pp. 88-92, 2012.

2 Recharge process

The authors consider one electricity grid with generation capacity $P_{available}(t) \geq 0$ for any t. EV is considered as an energy consumer with an electricity demand profile $EV_i(t) \leq 0$ for any t. Each EV has a mobility profile depending on its usage by residents and/or tourists. At the end of mobility stage, the EV_i battery has a residual charge $x_i(t_k)$. The aggregated energy demand by *n* EVs is expressed by $P_{demand} = (c_1 - x_1) + (c_2 - x_2) + \ldots + (c_n - x_n)$, where c_i is the full battery capacity for EV_i. The values x_i and t_k are poorly predictable. The EV battery recharge process increases x_i values up to c_i. To supply $(c_i$-$x_i)$ individual energy quantities the grid provides $(c_i$-$x_i)/\Delta t$ elementary flow components along time slots t_k, $t_{k+\Delta t}$ and so on.

Energy domain researchers produced several load shaping models through the adoption of econometric, statistical, engineering and combined approaches. An example comes from [6]. The absolute sustainability limit of the power system, in terms of the overall energy, is expressed by the formula $P_{demand} \leq P_{available}$, while with the time varying expression for a generic instant *t*, is $P_{demand}(t) \leq P_{available}(t)$. To satisfy the above conditions, different EV battery usages are possible. In saturated grid condition with $P_{demand}(t) > P_{available}(t)$ for some t, electric cars have to wait in the queue until some energy become available. The immediate recharge originates DoS for newcomers when $P_{demand}(t) > 0.99 * P_{available}(t)$. Compared with immediate recharge option, the delayed recharge scheme optimizes the available energy use by postponing the service for certain EVs for a while. It reduces the number of DoS occurrences when EV availability for operations is longer compared with the recharge time.

3 Semantically-enriched toolkit

The e-CARROT contains several modules being integrated in one toolkit. The *Dataset Generation module* implements the EV behavioral model and functions supplying events and their distribution in time-space. It is a simulation tool producing a dataset containing the daily population of EVs demanding battery recharge services. The *Model Application Utility* runs the simulation of the growing demand until the sustainability limits of the system will be reached. It is a batch tool varying input parameters and calling the dataset generator to obtain the collection of datasets simulating the evolutionary trends on an island, those populating a data warehouse. The *Semantic Framework* is the “core” of the system. The recharge service requests formulated by EVs are input data going to populate the knowledge repository. The system applies the rules and takes decisions about the optimization, if any.

The framework operates *time shifting* by moving the immediate energy demand exceeding the grid capacity $P_{demand}(t_k) > P_{available}(t_k)$ to the future time slots t_l with $P_{demand}(t_l) < P_{available}(t_l)$. It triggers four main events belonging to the battery recharge process: *EV_plugging_in* (coming from outside the grid, detected by sensor), *relè_on_outgoing* (the effective start of EV recharge), *relè_off_outgoing* (the effective end of EV recharge), and *EV_unplug* (from outside the grid). Two additional events (*relè_on_incoming*, *relè_off_incoming*) come from the inverted flow usage known as

EV discharge. Until EVs remain plugged into the electricity grid, the intended use of their batteries - from the user viewpoint - is the recharge mode steadily increasing the energy resource up to 100% and then detaching the EVs. From the grid operator viewpoint more modalities are desirable to better manage the demand. Thus, the *Optimization module* operates time shifting of EV recharge requests. During the peak time slots it delays the electricity demand by postponing the recharge time slots. Thanks to the presence of the idle time, i.e. the time exceeding that necessary to reach full charge, the process contains alternation of recharge and idle components. The intelligent sequence of optimized recharge-discharge cycles leverages load peaks.

The method is designed for an island-like topology. It assumes that an average time spent in a vehicle is less than 2 hours. During the remaining time, EVs are attached to the electricity grid. The island is populated by a number of residents owning an EV and a number of tourists getting EVs from local car rentals. The model incorporates external events impacting on the EV usage by tourists such as arrivals/departures of the ships and airplanes. Those come from publicly available timetables. The usage of EVs on the island determines the time slots in which recharge operations occur. The estimation of possible travel plans by tourists is grounded on the assumption that tourists rent cars upon their arrivals and release them before the definitive departures. The working hours of residents determine their house-workplace mobility and the consequential statistical distribution of the respective recharge periods.

The authors encoded an ontological model of recharge system. It includes a semantic model of electro-mobility, the e-CARROT ontology encoded in OWL using Protégé to keep interoperability with external OWL-compliant modules, a set of rules based on the knowledge of the local island-like topology, the main entities, and the relationships of EV use, EV recharge, and electricity supply. The control module and the rules have been developed using the Apache Jena API and Java. It schedules EVs recharge processes and constantly monitors the sustainability condition. The ontology describes main entities and relations: EVs and their usage, Power Plants, Power Flows that participate to the energy distribution processes through the electricity grid. An *Electric Vehicle* connects to a *Power Plug,* which is located inside a specific *Parking*. While charging, it executes a *Charge Process,* which describes, on a time dimension, the evolution of the *Power Flow* used by the EV. The structure of the *Electric Grid* is deducible from the *connectedOf* properties owned by *Power Plug, Parking* and *Power Plant* entities. *Power Series Array Element* and its sub-classes are used to model the trend of energy consumption, production and availability over time. A discrete time domain is considered, divided in constant intervals called time slots. The *powerValue* property is used to express the power intensities for the corresponding time slot.

The basic inference mechanism is executed according to the following assumptions. While an *Electric Vehicle* is *connectedTo* a *Power Plug,* a *Virtual Charge Process* (sub-class of *Charge Process*) is executed and its power flow is derived from the estimation of the departure time of the EV. Virtual processes are not considered for power balancing, but they are used to forecast the aggregate energy request (*Estimated Aggregate Power Consumption*) arriving from all EVs. A *Real Charge Process* implies the presence of a *Power Flow* from the electricity grid. The aggregated energy request by these processes at every instant (*Effective Aggregate Power Consumption*) is the main grid sustainability issue. Assigning negative values to consumed power and positive values to supplied ones (*Aggregate Power Production*), their sum gives the *Effective Total Available Power*, which should always remain greater than zero. The *Estimated Total Available Power* is a sum of *Aggregate Power Production* and (the negative value of) *Estimated Aggregate Power Consumption*. All these instantaneous aggregated power flows are sub-classes of *Power Series Array Element*. A *Control Agent* processes system *Events*. Two major sensor-generated external events are considered: *EV_plugging_in* and *EV_unplug*. In practice, the method calls semantic reasoner each time an EV is plugged into (or unplugged from) the electricity grid. At each event, the *Control Agent* activates a sequence of rules (recognized *Situations* and executed *Actions*). It takes appropriate control decisions about EVs charge processes then. No other event is considered until the inference cycle ends.

At the end of each time slot, an additional inference cycle is called to update the properties of plugged EVs and to check the electrical energy balance (Cyclic Update). For example, when an EV is plugged into the grid, the reasoner *fires* the appropriate rules in order to decide whether or not to allow the charging. Moreover, a priority ranking is assigned and periodically updated to the EV, based on its residual charge. Since a minimum charge level for every EV should be guaranteed, EVs which have already overcome this threshold receive the lowest priority becoming *detachable*. If an EV has a residual charge lower than the threshold, but, according to its estimated departure time, it is still possible to introduce some idle time before charging, it receives a medium priority (e.g. deferrable EV). When an EV has to be immediately put in recharge in order to reach the minimum charge level (set up accordingly the Service Level Agreement), it receives the highest priority. When available power runs out, the Control Agent stops detachable EVs, delays the deferrable processes operating time-shift, but keeps online the highest priority processes. In the example shown on Fig. 1 the optimization threshold is set to 0.95.

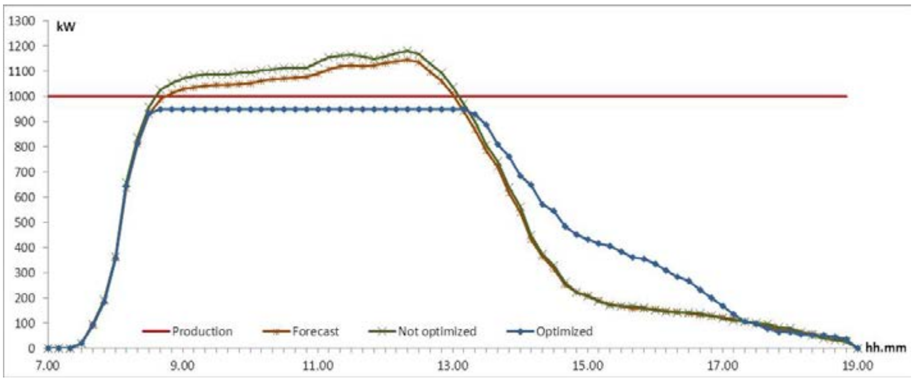

Figure 1. Optimization results: aggregated electricity consumption is leveraged to remain below the threshold.

4 Conclusions

The authors described new modeling and optimization tool used to simulate the recharge of Electric Vehicles on local topology served by a number of energy plants supplying one electricity flow. Authors modeled different categories of users including residents traveling between the houses and work places and tourists renting EVs. Combining a variable number of individuals belonging to above clusters/classes and varying the said ratio along the time, the method gives an improved scheme of the available electricity use. The real-life events occurring in time dimension accordingly the model have contributed to determine the EV battery's recharge schemes. The e-CARROT attempts the time shift optimization of the available energy flows at daily basis. Compared with earlier models assuming the same charging speed for all EVs, new algorithm accepts a wide range of maximum charging speeds.

The method makes possible a greedy allocation of EV units to the remotely controllable charging slots, while the clock-driven optimization algorithm – supported by semantic model at each step - controls their intermittent (on/off) actuation. The authors gave priority to the timely control of EVs being integrated into saturated grid. For this reason the explicit semantic rules were adopted. The new time shifting optimization method is useful when the sustainability limits are reached and the known FIFO disciplined recharge processes results in DoS because exceeding the energy limits. Invoking the Model Application Utility in back office to run a day-ahead simulation, it could reveal the sustainability limits of the current configuration. It might be useful for operational planning of grid operations going beyond the known art [7].

In the current implementation, the time-shifting algorithm uses the recharge/energy purchase and idle modes. The future work will add the discharge/energy selling mode.

References

1. Report "Electricity production and supply statistics", Eurostat 2012/5/3, available online at http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Electricity_production_and_supply_statistics, seen on 29/5/2012.
2. K. Clement, E. Haesen, and J. Driesen. Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids. In Proc. of the IEEE/PES Power Systems Conference and Exposition, pp. 1-7, 2009.
3. R. Porter. Mechanism design for online real-time scheduling. In Proc. 5th ACM Conference on Electronic Commerce (EC'04), pp. 61-70, 2004.
4. M. Hajiaghayi, R. Kleinberg, M. Mahdian, and D. C. Parkes. Online auctions with re-usable goods. In 6th ACM Conference on Electronic Commerce (EC'05), pages 165-174, 2005.
5. Y. He, B. Venkatesh, L. Guan, Optimal Scheduling for Charging and Discharging of Electric Vehicles, IEEE Transactions on Smart Grid , vol.3, no.3, pp.1095-1105, Sept. 2012.
6. C. Gellings, R.W. Taylor, Electric load curve synthesis – A computer simulation of an electric utility load shape, IEEE Transactions on Power Apparatus and Systems, 1 (PAS-100), pp.60-65, IEEE Press, New York, 1981.
7. P. Evans, S. Kuloor, B. Kroposki, Impacts of plug-in vehicles and distributed storage on electric power delivery networks, In Vehicle Power and Propulsion Conference, VPPC '09. IEEE, pp. 838, IEEE, NJ (USA), 2009.