An approach for Plug-In Hybrid Electric Vehicle (PHEV) integration into Power Systems

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1 Introduction

The PHEV initiative, recently accelerated for political, environmental and security reasons, offers a possibility to substantially shift energy demand for transportation from crude oil to electricity. PHEV are meant to recharge their batteries through the grid. Their internal combustion engine (ICE) is only used as an ancillary power source. They are easily understood to introduce a new load as well as a distributed, mobile storage to be used for the power system once connected [1].

Inevitably, both utilization schemes lead to an integration of power and transportation systems. Therefore an integrated model for analysis has to be developed. Agent based modelling (ABM) is intuitive as it is widely used in transportation theory [2] and suitability becomes blatant when considering that PHEV are independent entities with different objectives.

Therefore, the power system model should incorporate agents and be as general as possible to integrate the yet non existent PHEV fleet. Possible repercussions may not ultimately be confined to the electricity network. For this issue the Energy Hub approach [3] is chosen.

2 Agent Based Modelling Approach

In [4] agents are defined to have certain properties like: *Reactivity, Autonomy, Pro-activeness, Intelligence*. The agent based approach refers to the fact that two entities need to communicate in order to act intelligently. PHEVs, inherently *autonomic*, are presumed to arrive in a certain area at a certain time and need to communicate with their supervising entity for recharging. They reveal their demand, departure time, etc. The supervisor, referred to as PHEV Manager, receives the information, stores and uses it, while distributing available power and imposing load/storage management schemes, incorporating *autonomy*, *reactivity* and *pro-activeness* dependent on the actions and information of the PHEV Hubs.

2.1 The PHEV Energy Hub Model

In [3] the Energy Hub was accentuated to represent an abstract unit of a multi energy carrier system featuring *input* and *output*, *conversion* and *storage*, being obviously true for PHEV. Now, the Energy Hub equation needs to be adjusted to the demands of typical PHEV utilization schemes, which besides driving are charging, frequency regulation and refuelling. They can be incorporated through a set of situations

$$\Xi = \{\mathtt{D}, \mathtt{RF}, \mathtt{R}\} \tag{1}$$

where D represents driving, RF represents refuelling and R represents charging and discharging (frequency regulation).The output is only kinetic as the demanded electric out- or input in situation R can easily be incorporated through the input vector of the model. An expression including the situations into the model of the PHEV Energy Hub is formulated through a situation decision function. Equation (2) shows the complete model. For simplicity only a series PHEV Hub is modelled.

$$\mathbf{L} = \mathcal{E}(\Xi)\left(\mathbf{C} - \mathbf{S}\right)\begin{pmatrix}\mathbf{P}\\ \dot{\mathbf{E}}\end{pmatrix} \tag{2}$$

with

$$\mathcal{E}(\Xi) = \frac{\partial}{\partial \Xi}\left(\mathtt{D}\ \mathtt{RF}\ \mathtt{R}\right)$$

and

$$\mathbf{C} = \begin{pmatrix} c_{e\,\mathtt{D}}(\mathbf{L}) & c_{gas\,\mathtt{D}} & 1 \\ c_{e\,\mathtt{R}} & c_{gas\,\mathtt{R}} & 0 \\ c_{e\,\mathtt{RF}} & c_{gas\,\mathtt{RF}} & 0 \end{pmatrix} \mathbf{S} = \begin{pmatrix} \frac{c_{e\,\mathtt{D}}}{\eta_e}(\mathbf{L}) & \frac{c_{gas\,\mathtt{D}}}{\eta_{gas}} \\ \frac{c_{e\,\mathtt{R}}}{\eta_e} & \frac{c_{gas\,\mathtt{R}}}{\eta_{gas}} \\ \frac{c_{e\,\mathtt{RF}}}{\eta_e} & \frac{c_{gas\,\mathtt{RF}}}{\eta_{gas}} \end{pmatrix} \mathbf{P} = \begin{pmatrix} P_{e\,\Xi} \\ P_{gas\,\Xi} \\ P_{dis} \end{pmatrix} \dot{\mathbf{E}} = \begin{pmatrix} \dot{E}_e \\ \dot{E}_{gas} \end{pmatrix}$$

Here, **C** denotes the coupling and **S** the storage coupling matrix, respectively, containing the coupling factors for the different situations which are composed of the converter and storage efficiencies of the power paths. The kinetic load **L** can be calculated according to Newton's second law. $P_{e\,\Xi}$ and $P_{gas\,\Xi}$ denote the power inputs in the particular situation. P_{dis} denotes the dissipated energy. $\dot{E}_e$ and $\dot{E}_{gas}$ denote the power drawn from the battery and the gasoline tank. Regenerative breaking is incorporated through a load dependency of the coupling factors. A more detailed derivation can be found in [5].

Each PHEV Energy Hub Agent simulates driving behavior and chooses departure, track and parking time independently. As soon as connecting, the agent transmits information to the PHEV Manager Agent including *Identity NR, State of Charge (SOC), Arrival Time, Departure Time.*

2.2 The PHEV Manager

The PHEV Manager Agent is an abstract entity relying on intelligent interfaces. He supervises a defined area, registers when PHEV are connecting to the network and receives the information mentioned before. The PHEV Manager updates the connectivity list of PHEV in 15 minute time intervals and adjusts it. Smaller intervals result in more accurate simulation but in longer computation times. Further, cars which are parking shorter than 15 minutes are not considered for recharging and load/storage management. The PHEV Manager Agent aggregates the PHEVs arriving in the supervised area enabling management schemes as well as possible ancillary services as proposed in [6]. In this paper the PHEV Manager will be utilized to study the load shape imposed by the PHEVs connecting in one area and to shed light on possible ancillary potential of the fleet.

3 PHEV Energy Hub Optimization Results

For energy demand estimation stemming from PHEV cycles like UDDS, HWFET [7] etc. a control scheme needs to be implemented. It was proposed to use PHEV mainly in electric mode and switch to a blended mode when the battery cannot supply the demand or to charge sustaining mode once a certain SOC is reached [8].

Keeping the simulations fast, preferring grid charged electricity and using pessimistic assumptions of efficiencies, linear programming was chosen as a control scheme for a worst case scenario. The optimization scheme is denoted in (3). The objective function dependents on the storage outputs multiplied by energy carrier market prices. The focus is laid on grid charged electricity. Deeply depleting battery results in shorter lifetime which is accounted for by $\frac{\kappa}{SOC}$ assuring that the battery is more expensive than gasoline once 20 % of SOC are reached. The constraints are resulting from the Hub equation and converter specifications [5]. The first and second inequality constraint refer to the total load drawn from the ICE and battery, respectively. The SOC is constrained to lie between

20 % and 100 %. The output power derivatives for battery and ICE are considered as well. The last two constraints refer to the fact that once the ICE is switched on, it runs with the demanded power for at least 300 seconds, coping with the load or recharging the battery. Figure 1a shows the PHEV Hub cycling through different drive cycles starting with NYCC, UDDS and HWFET. The plot shows the speed profile, the power demand, the power drawn from the battery, the resulting SOC, the power drawn from the ICE and the depletion of the gasoline tank. Obviously, most of the power is drawn from the battery. However, when the battery cannot supply the load due to power or power derivative constraints the ICE starts and keeps its demanded output power for 300s. As the ICE is completely disconnected from the torque constraints of the wheels it is assumed to be operated at constant efficiency for each power output. Once 20 % SOC is reached the ICE supplies more of the load while recharging the battery. This control scheme implies a typical utilization scheme for PHEV minimizing consumer costs presuming discharging the battery down to 20 % does not affect lifetime. The total driven distance is found to be ca. 130km.

$$
\begin{array}{ll}
min & \mathscr{F}(\dot{E}_e, \dot{E}_{gas}) \\
with & \frac{d\mathscr{F}(\dot{E}_e,\dot{E}_{gas})}{d\dot{E}_e} = Price_e \frac{\kappa}{SOC} \\
 & \frac{d\mathscr{F}(\dot{E}_e,\dot{E}_{gas})}{d\dot{E}_{gas}} = Price_{gas} \\
s.t. & \mathbf{L} = \mathcal{E}(\Xi) \left(\mathbf{C} - \mathbf{S} \right) \begin{pmatrix} \mathbf{P} \\ \dot{\mathbf{E}} \end{pmatrix} \\
 & \delta_{gaso} \underline{\dot{E}}_{gas\,\mathtt{D}} \leq \dot{E}_{gas\,\mathtt{D}} \leq \overline{\dot{E}}_{gas\,\mathtt{D}} \\
 & \underline{\dot{E}}_{e\,\mathtt{D}} \leq \dot{E}_{e\,\mathtt{D}} \leq \overline{\dot{E}}_{e\,\mathtt{D}} \\
 & \underline{SOC} \leq SOC \leq \overline{SOC} \\
 & \underline{\dot{P}}_{e\,\mathtt{D}} \leq \frac{d\dot{E}_{e\,\mathtt{D}}}{dt} \leq \overline{\dot{P}}_{e\,\mathtt{D}} \\
 & \underline{\dot{P}}_{gas\,\mathtt{D}} \leq \frac{d\dot{E}_{gas\,\mathtt{D}}}{dt} \leq \overline{\dot{P}}_{gas\,\mathtt{D}} \\
 & \delta_{gas} = 1 \; if \dot{E}_{gas\,\mathtt{D}} \geq 0 \wedge t_{gas} \leq 300 \\
 & \underline{\dot{E}}_{gas\,\mathtt{D}} = \dot{E}_{gas\,\mathtt{D}} \\
 & P_{dis} \leq 0
\end{array}
\tag{3}
$$

Each PHEV Hub Agent is assumed to leave its home location between 5 a.m. and 9 a.m. The probability for departure from its home location is given in figure 1b and drawn from [9]. The agents choose the number and shape of their drive cycles individually. The probabilities for both are uniformly distributed. One to five cycles can be chosen out of: 1. UDDS, NYCC, 2. HWFET,NYCC, 3. FTP 4. NYCC. It is assumed that all PHEV Hub Agents arrive at the same location (work location with connection points). Choosing the drive cycles differently implicates different driving behavior (e. g. aggressive, non-aggressive) and different distance for each Agent.

4 PHEV Manager Simulation at one Network Hub

The PHEV Manager is modelled for only one node in a possible network. Establishing such entities at each node of a Hub network presumes a decentralized control of the PHEV fleet. Especially for large agglomerations it seems realistic considering computation power and time. The PHEV Manager updates his connectivity list while imposing a new load on the Hub. Presuming a known base load pattern (e.g. household or industrial) the overall load pattern changes dependent on the distribution of PHEV Hub arrival and SOC at this Hub node. The manager offers a tool to study the mutation of known load patterns. Obviously, total PHEV load in one time interval is partly dependent on the preceding one, since additionally to the arriving cars in the current period, PHEV already connected can by then be either fully charged or still be charging. No network congestions are assumed. Figure 2a shows the pattern of the adequately aggregated load imposed by 500, 1000

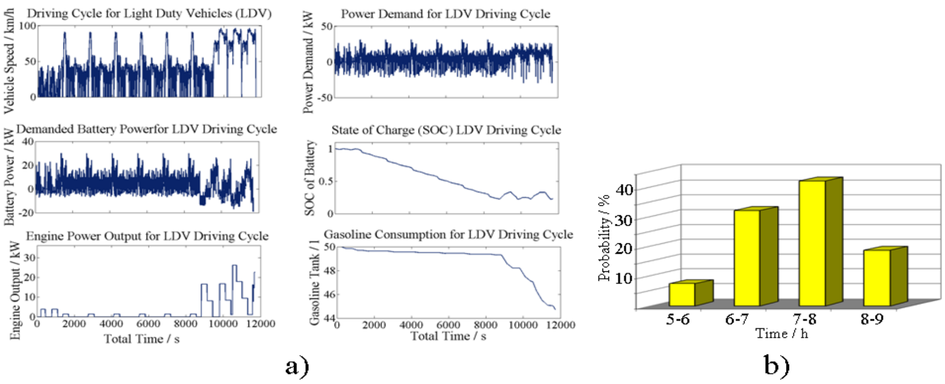

Fig. 1: a: PHEV simulation for specific cycle
b: Departure probabilities for PHEV

and 3000 PHEV Hubs whose energy demand was simulated with the approach described in section III. The PHEV Manager recharges the PHEV Hubs as he communicates and allocates energy in every time interval to each PHEV Hub. The Manager considers the maximum plug capacity- and the SOC constraint, as well as the charging efficiency and departure time of all PHEV Hubs.

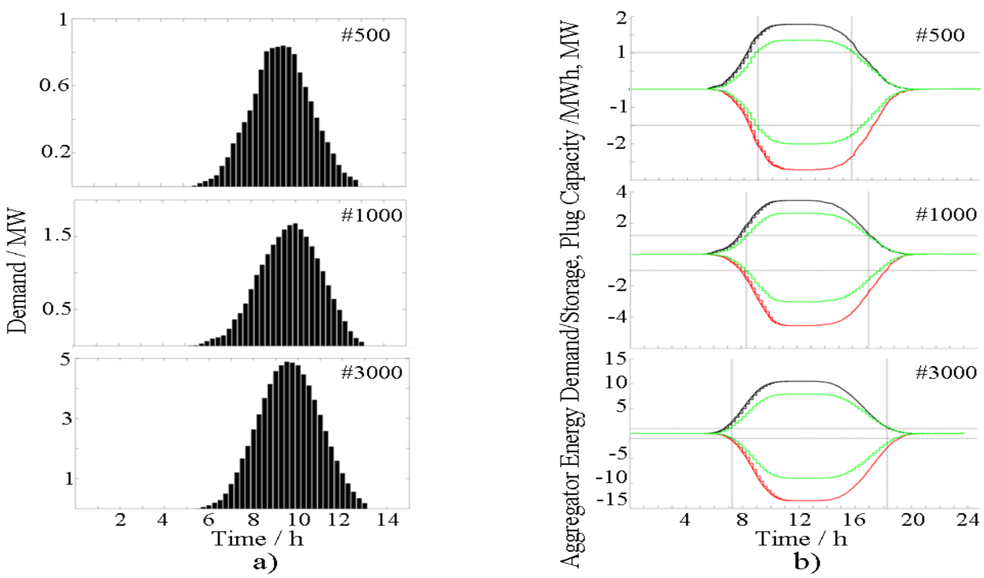

Fig. 2: a: Load demand for 500, 1000 and 3000 PHEV
b: Ancillary services resources for 500, 1000 and 3000 PHEV

Clearly, the peak load is proportional to the amount of PHEVs. The time of peak demand slightly shifts to later times as PHEV amount grows. One main finding is that peak load can be expected two hours after the highest probability of departure. Strikingly, this is independent of the drive cycles as heterogeneous cycles are chosen. The expected value for driving time can be calculated to be 1.2 hours. The value results from an average of 24.2 minutes of driving and three drive cycles, respectively. The shape of the load pattern becomes much more smooth and similar to a gaussian distribution. Cars parking less than 15 minutes are not considered as the minimum parking time is considered to be 7, maximum loading time to be 3 hours, respectively.

Figure 2b shows another aspect of PHEV grid integration mentioned already in [1]. The graphs show the storage and the total load aggregate (no recharging) over time being useful for an analysis of ancillary services potential. The black lines show the total storage at the Hub node, the red lines show the total energy demand, respectively. The stairs depict updating of the manager's connectivity list. The green lines denote the total capacity in MW for regulation down (negative) and regulation up (positive). The Manager is presumed to supply secondary control, so the contracted regulation amount has to be available 100 % of the time. The PHEV Manager calculates the regulation capacity in dependence of the individual SOC assuring demanded secondary regulation (up or down) for an hour. A PHEV Hub with 2.5 kWh total storage (SOC = 25%) cannot be evaluated to add regulation up capacity of 3.5 kW, as only 0.5 kW are available for the duration of an hour until the battery is depleted. On the other hand, the PHEV is able to supply 3.5 kW of negative reserve. Evidently, the regulation capacity is smaller than the total demand/storage over a wide window, enabling these services. In figure 2b the contracted capacity is presumed to be 1 MW and minimum time frame 1h, though many TSO have other regularities. Clearly, the contract time frame increases with PHEV amount. The Manager faces an optimization problem, maximizing total profit from ancillary services, either contracting longer but with less power or the other way around.

5 Conclusion

This paper introduces a flexible modelling method for PHEV, able to integrate battery, ICE and even more energy storages and converters. Through its simplicity the Energy Hub approach is able to deliver a worst case electric energy demand scenario for the network minimizing driving costs. Further, the paper introduces a smart grid entity, the PHEV Manager. It is able to aggregate large amounts of PHEV through intelligent communication and is an extension to the known Energy Hub network approach, integrating PHEV into the multi energy carrier network. New load patterns and ancillary service potential can be studied through the entity. Extension to demand management schemes and utilization during black outs are topics for future work.

References

1. J. Tomic and W. Kempton. Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources*, 168(2):459–469, 2007.
2. B. Raney, N. Cetin, A. Voellmy, M. Vritic, and K. W. Axhausen. An agent based microsimulation of swiss travel: First results. *Networks and Spatial Economics*, 3(1):23–42, 2003.
3. M. Geidl and G. Andersson. Optimal power flow of multiple energy carriers. *IEEE Transactions on Power Systems*, 22(1):145–155, 2007. 0885-8950.
4. M. Wooldridge. Intelligent agents. In G. Weiss, editor, *Multi Agent Systems: A Modern Approach to Distributed Artificial Intelligence*, volume 1, pages 27–77. The MIT Press, Cambridge, MA, USA, London, UK, 1999.
5. M. D. Galus. Overview of plug-in electric vehicles (phev), their impacts on utilities and their modelling as situation dependent energy hubs. Technical report, Power Systems Laboratory, ETH Zurich, 2008.
6. J. Gordijn and H. Akkermans. Business models for distributed generation in a liberalized market environment. *Electric Power Systems Research*, 77(9):1178–1188, 2007.
7. US EPA. Dynamometer driver's aid, testing and measurement. Available on: `http://www.epa.gov/otaq/emisslab/testing/dynamometer.htm#vehcycles`, accessed 17th August 2007.
8. J. Gonder and T. Markel. Energy management strategies for plug-in hybrid electric vehicles. In *SAE World Congress, 2007*, pages 1–5, Detroit MI, 2007.
9. Bundesamt fuer Statistik. Bundesamt fuer statistik und bundesamt fuer raumentwicklung mikrozensus verkehrsverhalten 2005. Technical report, 2006.