Effects of Large Scale EV and PV Integration on Power Supply Systems in the Context of Singapore

Matthias Huber, Annette Trippe, Philipp Kuhn, Thomas Hamacher

***Abstract*—Electric vehicles (EVs) are a key technology to reduce dependency on oil imports as well as to diminish environmental effects of individual transportation. Especially in megacities like Singapore where travel distances are moderate, this new mode of transportation is often discussed as a future option. This paper investigates possible effects of large scale EV integration on the power supply system. A unit commitment model combined with an integrated approach for smart charging is used. The mixed-integer linear programming (MILP) formulated unit commitment algorithm cooptimizes energy, regulation, and spinning reserve power. The effects of different charging strategies on the power plant scheduling are analyzed. The power system infrastructure is kept at status quo in a baseline scenario and extended to future scenarios with intermittent photovoltaics (PV) power. Effects on power plants scheduling are evaluated by measuring resulting variable cost of electricity as well as CO_2-emissions. Moreover, effects of EVs providing regulation and spinning reserve by controllable charging are investigated.**

***Index Terms*—Electric Vehicles (EV), Photovoltaic Cells (PV), Singapore, Smart Grid, Unit Commitment.**

I. Nomenclature

Sets

J	Set of indexes for power plants
K	Set of indexes for ancillary services
T_a	Set of time steps of EVs arriving at charging stations
T_m	Set of modeled time steps
T_p	Set of parking durations of EVs

Variables

$as_{k,ev}(t_m)$	Provision of type k ancillary service by EVs
$as_{k,j}(t_m)$	Provision of type k ancillary service by power plant j
$cl(t_m)$	Charging load of all EVs in t_m
$clh(t_m, t_a, t_p)$	Auxiliary variable to calculate charging load
$p_j(t_m)$	Power output of plant j

Parameters

AR_{PV}	Factor for additional regulation requirements as share of CAP_{PV}
$AS_k(tm)$	Requirement for type k ancillary service
CAP_{PV}	PV peak capacity
CL_{max}	Maximal charging load of electric vehicles
$CT(t_a, t_p)$	Charging table of energy requirements
$D(t_m)$	Electricity demand without electric cars
FLH_{PV}	Annual full load hours of PV power
η_j	Efficiency of power plant j
$P_{PV}(t_m)$	Power output from photovoltaics
$R(t_m)$	Solar radiation
$REG_{PV}(t_m)$	Regulation requirement for control of PV power

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II. Introduction

THE electrification of individual transport in the form of EVs has been identified as a key issue to diversify energy demand as well as to reduce CO_2-emissions in the transportation sector. Particularly megacities benefit from the advantages of EVs such as energy efficiency in stop-and-go traffic and zero local emissions. Moreover, EVs are viewed as an important element of future intelligent power systems, often called smart grids. EVs can be charged by smart control strategies or even serve as mobile storage passing power back to the grid as described in [1].

Singapore is an island and has only insignificant grid connections to few of its neighbors. These conditions require high efforts to manage deviation from a predicted load or even power plant blackout. Plans for the integration of highly variable PV power [2] will further challenge the system. In this environment, the integration of EVs offers promising possibilities. The flexibility of EVs regarding their charging strategy can be used for load leveling and EVs could participate in the regulation and reserve markets. The analysis of the interplay between EVs, PVs, and the conventional power system in this environment is main focus of this paper.

Effects of different charging strategies on the charging costs in Singapore have been analyzed in [3] based on statistical market prices. It was found that smart charging strategies could lead to 30 % lower charging costs. In our model however, not only historical prices are used to measure cost reductions, but overall system costs for power generation are calculated in a unit commitment model. This reflects costs in more detail and also allows analyzing effects on fuel mix and emissions. Besides, effects of PV integration or EVs providing ancillary services can be analyzed.

Analysis of effects from EVs on utilities have also been conducted for several other regions, e.g. [4] researched cost effects for Illinois by integrating EV charging into unit commitment. Economic savings of up to 7 % were found for the overall system through smart charging strategies. In [5], an increase of load by 5-10 % at an EV penetration of 50 % was found for several regions in the US, but effects on costs and emissions were not measured in detail. Several other studies did not only consider smart charging but also serving electricity back to the grid in form of Vehicle to Grid (V2G), e.g. [1] or [6]. V2G is not considered in our model, as effects on battery lifetime are not clarified yet. Moreover, unidirectional controlled charging alone allows to shift load and even supply all types of regulation and reserves. If charged below maximum power, the charging load can be increased or decreased at every moment providing up- and down-regulation without any losses of energy through storage.

Singapore not only aims to introduce EVs but also intermittent PV into the power system. In [7], a potential of up to 14 TWh/year PV power, around 30 % of overall production, is reported. This is equivalent to 10.5 GW peak power assuming 1,300 annual full load hours (FLH) [7]. These numbers indicate significant contribution of PV to Singapore's future electricity production. In [8], the influence of PV integration on the energy balance for Singapore is analyzed. The analysis with the unit commitment model as we describe in this paper extends this study. Influences of PV on power plant scheduling, power system stability, as well as the interplay with different EV charging strategies are discussed.

III. Mobility Model

By the end of 2011, 956,704 motor vehicles were registered in Singapore, including cars and station-wagons, taxis, buses, motorcycles and scooters, goods and other vehicles. Thereof 520,614 were private cars [9]. The electrification of private cars is object of this study. The average daily mileage of private cars was estimated at 52 km in 2010 [10]. Assuming all private cars were EVs with an energy consumption in the range of 15 to 20 kWh / 100 km according to project-internal simulations specific to Singapore, the power system would face an additional load of up to 5,414 MWh per day. This accounts for 4.8 % of the daily load in Singapore [11]. The additional load does not occur evenly throughout the day, but during the charging processes of the single cars, which can only take place during parking.

In order to obtain findings on the impact of charging processes on the power system, information on the driving and parking behavior in Singapore is required. Therefore, an agent-based mobility model, which pictures the driving and parking behavior of private cars in Singapore, was implemented. Each agent follows a specific pattern of driving and parking activities, whereas after each trip a parking activity occurs. The model simulates the sequence of destinations, the departure times of the first trip of the day, duration and length of the trips, corresponding energy consumption as well as parking duration. The parking locations were classified into three categories, i.e. residential, work-related, and leisure-related.

The different possible itineraries of an agent throughout a weekday are shown in Fig. 1. This finite automaton indicates the probabilities for a certain itinerary through the different states, which reflect the destination of a trip and at the same time the next parking location. Deriving from data on the employment situation and working hours in Singapore in 2010, 4 % of all employees work part-time with an average of 5 hours per day [12]. This is reflected in the upper half of Fig. 1. Agents depicting full-time employees drive to work and stay there either for a whole workday with an average duration of 9 hours working time [12] plus 1 hour lunch break or for an average 3.5 hours work session followed by a lunch break at a different location and another average 5.5 hours at work. Half of the agents are assumed to drive home directly after work, whereas the other half is going to leisure activities. The 4 % of all agents not going to work include people who are homeworking, which is offered by 2 % of the Singaporean establishments [12], on medical or on other kinds of leave.

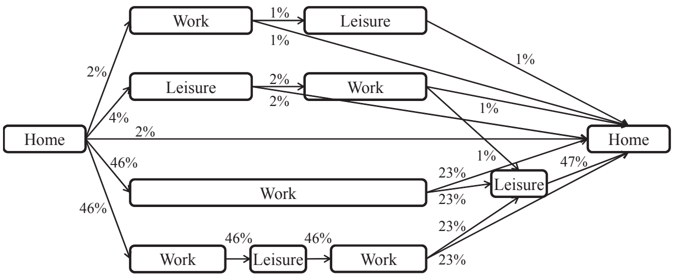

Fig. 1. Finite automaton of mobility model for a weekday.

For weekends, similar finite automatons were developed. On Saturdays, 25 % of the full-time employees excluding shift-workers work half a day and 23 % a full day [12]. Apart from that, the agents follow various sequences of the states 'leisure' and 'home' or stay at home. The behavior on Sundays resembles the behavior of the agents, who are not working on Saturdays, but with a higher proportion staying at home the whole day.

The departure times of the first trip of a weekday are assumed to be normally distributed with a standard deviation of 2 hours and the mean at 8:00, so agents arrive at the workplace in time for regular office hours starting at 9:00. The departure times are limited to a range from 6:00 and 12:00. Departures on Saturdays are divided into three blocks, from 6:00 to 14:00 with the mean at 9:00 and standard deviation of 3 hours mainly for the agents working on Saturdays, from 14:00 to 17:00 and from 17:00 to 21:00 for the people going out after lunch or for dinner with standard deviations of 1 hour and means at 15:30 respectively 19:00. On Sundays, agents depart between 8:00 and 14:00 with the mean at 11:00 and a standard deviation of 3 hours.

The probabilities for the different itineraries result in 3 trips per day on average and thus in a mean trip length of 17.3 km. The mobility model simulates the trip length of each trip with a normal distribution, limited to a minimum of 1 km. 99 % of the trips do not exceed 37.5 km. The trip duration results from trip length and average speed of 21 km / h which was derived from a project-internal fleet-test in Singapore. The energy consumption during each trip is calculated with the trip length and the average consumption of the EVs, which ranges from 15 to 20 kWh / 100 km. A maximum trip length of 37.5 km means that at maximum 75 % of a 10 kWh battery and 38 % of a 20 kWh battery is discharged during a trip. During the parking activities, the batteries are recharged to a favored state of charge (SOC) if possible, otherwise at a maximum power of 5.75 kW. This is the maximum power output of charging stations installed within the scope of the EV test-bedding in Singapore co-leaded by the EMA (Energy Market Authority) and LTA (Land Transport Authority) [13].

The simulation of the parking duration differs between the categories work, leisure and home. The parking durations at work are modeled according to a normal distribution with different means and standard deviations, depending on the kind of working behavior, i.e. full-time or part-time, including lunch break or leaving for lunch. The parking durations reflect the aforementioned average daily working hours from [12]. The parking activities at home overnight are not simulated by means of probability distributions, but arise from the time in between the last trip in the evening and the first in the next morning. Home parking during the day on the weekend is simulated analogously to the parking durations at work, i.e. normally distributed with varying parameters.

In order to simulate the parking behavior at leisure-related car parks, which in Singapore are mainly attached to shopping malls, a probability distribution was determined empirically. Therefore, a field test was conducted at a car park of a shopping mall in downtown Singapore and parking durations, arrival and departure times of the vehicles were recorded. The data was statistically analyzed and the histogram of the parking durations is shown in Fig. 2. It resembles the density function of the Weibull distribution. This hypothesis was statistically tested and accepted at a significance level of 5 %. The data was divided into four time intervals, 7:00-11:00, 11:00-15:00, 15:00-19:00, and 19:00-23:00, as parking behavior varies at different times of the day. The statistical analysis was conducted for each interval resulting in four different Weibull distributions, which are used for the simulation of parking durations at leisure-related parking locations.

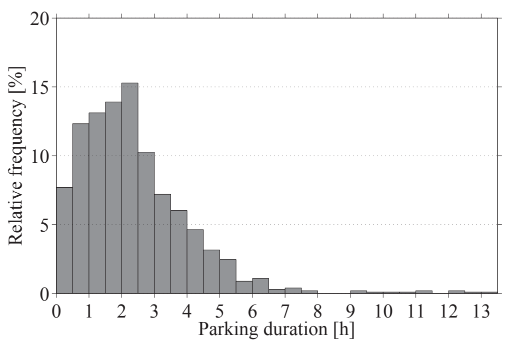

Fig. 2. Histogram of empirical parking durations.

In order to validate the mobility model, the occupancy of leisure-related parking locations derived from simulated data is compared to empirical data, as shown in Fig. 3. Data on the availability of parking lots at 23 car parks downtown in Singapore is publicly available as a live online-service [14] and was logged from December 2011 to April 2012. The availability at these car parks was converted to occupancy and an average week was consolidated. This empirical data on the occupancy of the car parks is displayed in the upper part of Fig. 3. The simulated curve in the lower part is the output of a typical week of the mobility model for 50,000 vehicles. The two curves show a similar developing, especially during the weekdays, and thus the mobility model is capable to simulate realistic mobility behavior. The weekends of the empirical data show lower peaks than the simulated data, as the logged car parks have limits due to their capacity. The simulation model on the other hand includes vehicles driving and parking all over Singapore and not only at a limited number of locations.

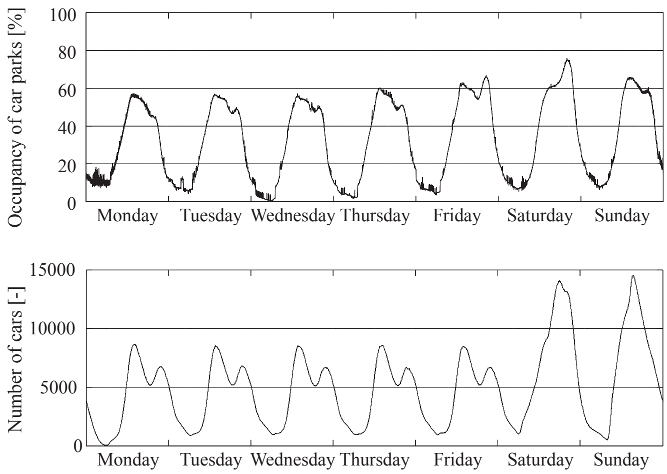

Fig. 3. Occupancy of leisure-related car parks: empirical data of 23 car parks (top) and simulated data with 50,000 vehicles (bottom).

The parking and driving activities of the mobility model are interrelated and influence each other in the generation of the next activity, including start time, duration and location of the activity. The itinerary of each agent is a sequence of driving and parking activities and each activity is based directly on its predecessor.

With the described mobility model, a sample of 50,000 agents was simulated for a duration of 29 days. The resulting parking and driving activities as well as energy consumptions and demands serve as input for the unit commitment model described in the subsequent chapter.

IV. Unit Commitment Model and Smart Charging

Fig. 4 provides an overview of inputs and outputs of the unit commitment model, which is called URBS-Singapore (latin: city). Load is provided in a 30 minute time resolution. Data for power plants include installed capacity and operating parameters. The EV charging table will be described in the following and a time series for PV generation can be included. Outputs are the power plant schedule as well as resulting operating costs and emissions. Moreover, an aggregated charging plan for all EVs is provided. Simulation was conducted for one month as only very small seasonal effects of load and PV power are observed in Singapore. March 2009 was used because solar radiation data for this month is best in terms of availability and quality.

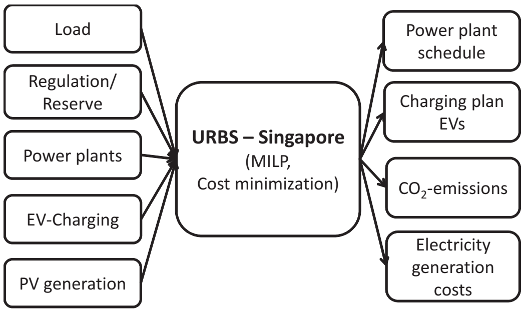

Fig. 4. Inputs and outputs of the MILP formulated program URBS.

A. Power Plant Scheduling

1) Method: The simulation of conventional power plants is based on a MILP-formulated unit commitment problem. A mathematical formulation of the objective function as well as all constraints can be found for instance in [15]. A minimum cost solution for the power plant dispatch is simulated every 30 minutes as it happens in real world [16]. In order to be able to simulate longer time periods with reasonable computational power, a receding horizon is used. Thereby, 72 timesteps of 30 min each are optimized in one step of which the first 48 are used for the solution. The optimization takes the following constraints for power plant operation into account:

- Minimum power
- Minimum up and downtime
- Lower efficiencies in part load
- Maximum power change
- Stochastic power plant outages

In addition to the restrictions in power plant operations, system requirements for regulation and reserves are considered. In each time step, a co-optimization of electricity production and provision of these ancillary system services $AS_k(tm)$ is conducted. According to [16], there are four types of services with different activation times to be included in the process:

- Regulation (Second to second)
- Primary Reserve (8 seconds)
- Secondary Reserve (30 seconds)
- Contingency Reserve (10 minutes)

2) Data: A list of all licensed power plants and their capacity is available from [17]. A study conducted by KEMA [18] provides information about efficiencies for each single plant as well as additional general information for each type of power plant. Data for startup costs of different types was used from [19] and converted with an exchange rate of 1.6 S$/Euro. Table I gives an overview of general parameters used.

Data that was not provided by [18] is the capability of the power plants to provide regulation and reserves. According to [20] all power plants except open cycle gas turbines (OCGTs) are able to provide around 3 %, 6 %, 10 %, 30 % of their net capacity for regulation, primary, secondary and contingency reserve, respectively. OCGTs are only able to provide contingency reserves. Industry power plants are assumed not to take part in these ancillary services. The requirement for

TABLE I
MAJOR POWER PLANTS PARAMETERS [18], [19]. FUEL FOR STARTUP IS EXPRESSED AS SHARE OF 1 HOUR FULL POWER CONSUMPTION.

type	P_{min}	$\frac{\eta_{min}}{\eta_{max}}$	Min. Down	Costs Var	Costs Start	Fuel Startup
CCGT	40 %	85 %	2 h	1 S$/MWh	24 S$/MW	100 %
Steam	40 %	90 %	4 h	1 S$/MWh	24 S$/MW	70 %
OCGT	40 %	40 %	0 h	1 S$/MWh	24 S$/MW	50 %
Industry	100 %	100 %	0 h	1 S$/MWh	24 S$/MW	100 %

these services is around values of 87 MW, 200 MW, 260 MW, 540 MW in each half hour of scheduling [21]. The half hourly system demand for March 2009 is available from [22] and was scaled to an annual consumption of 41.2 TWh in 2010 [11]. Overall losses in transmission and distribution are assumed to 5 % according to [23]. Fuel costs are considered to be at 85 S$/MWh for Oil, 95 S$/MWh for Light fuel oil (used for OCGTs), 42.5 S$/MWh for Orimulsion and 70 S$/MWh for natural gas according to historically determined ratios [18], an oil price of 110 US$/Barrel and an exchange rate of 1.2 S$/US$.

B. EV Charging

1) Method: Optimal charging of EVs is integrated in the unit commitment framework. In addition to the electricity demand $D(t_m)$, the charging load of EVs $cl(t_m)$ has to be considered and provided by power plants in each modeled timestep t_m leading to

$$\sum_{j \in J} p_j(t_m) = D(t_m) + cl(t_m) \tag{1}$$

Four different charging strategies were implemented for analyzing the value of intelligent charging. They can be described as follows:

- 'Dumb': EVs start charging upon arrival and are charged with maximum power of 5.75 kW
- 'Mean': EVs are charged evenly over their parking time
- 'Smart': EVs are charged by minimizing electricity generation costs
- 'SmartPlus': EVs are able to provide regulation and reserve in addition to smart charging

The charging load is an additional parameter for 'Dumb' and 'Mean' charging. For smart strategies however, $cl(t_m)$ can be considered as a variable. EVs are even able to provide one or more of the four ancillary services $as_{k,ev}(t_m)$ with 'SmartPlus'. The optimization decides at which timesteps EVs should be charged and whether they should be scheduled for any ancillary services or not. Together with ancillary services provided by power plants, the system requirements have to be fullfilled:

$$as_{k,ev}(t_m) + \sum_{j \in J} as_{k,j}(t_m) \geq AS_k(t_m) \tag{2}$$

Both, reserve and regulation requires the EVs to be capable of providing additional power to the system within the respective timespan. EVs are able to stop or reduce their load when reserve or regulation is needed:

$$\sum_{k \in K} as_{k,ev}(t_m) \leq cl(t_m) \tag{3}$$

Regulation, $AS_{reg}(t_m)$, not only requires the cars to reduce load, but also to increase load within seconds. For EVs, this leads to another restriction:

$$as_{reg,ev}(t_m) + cl(t_m) \leq CL_{max}(t_m) \tag{4}$$

The charging load has to meet the aggregated energy demand of each single car derived from the results of driving and parking behavior according to chapter III. Therefore, a matrix with information about parking and charging behavior, $CT(t_a, t_p)$, is provided as an additional model input. Table II exemplarily illustrates its structure as an output from the mobility model with 50,000 EVs. It contains the required charging energy for EVs sorted by their arrival time t_a in a parking lot and the duration of their stay, t_p.

TABLE II
ENERGY REQUIREMENTS FOR 50,000 SIMULATED EVS.

	$t_p = 1$	$t_p = 2$	$t_p = 3$	...
...	...	...	...	...
$t_a = 20$	212 kWh	218 kWh	315 kWh	553 kWh
$t_a = 21$	269 kWh	267 kWh	362 kWh	668 kWh
$t_a = 22$	387 kWh	407 kWh	483 kWh	645 kWh
...	...	...	...	...

According to the table $CT(t_a, t_p)$, cars arriving in $t_a = 20$ and staying one period ($t_p = 1$) need to be charged with 212 kWh in $t_m = 20$. Also, cars arriving in $t_a = 21$ must be charged with a fixed amount (269 kWh) in $t_m = 21$ without any flexibility. Cars arriving in $t_a = 20$ and staying $t_p = 2$ periods allow more freedom for smart charging. The 218 kWh can be distributed to $t_m = 20$ and $t_m = 21$. The longer cars are parking, the more freedom for smart charging exists. The resulting restrictions for optimal charging can be formulated with an auxiliary variable $clh(t_m, t_a, t_p)$ as follows:

$$\sum_{t_m = t_a}^{t_a + t_p - 1} clh(t_m, t_a, t_p) = CT(t_a, t_p) \tag{5}$$

$$\sum_{t_a \in T_a} \sum_{t_p \in T_p} clh(t_m, t_a, t_p) = cl(t_m) \tag{6}$$

Since all cars with same (t_a, t_p) are summarized in this table, the number of equations and thus, the computational time of the simulation is independent of number of EVs. At the same time, this simplification does not permit an analytical proof of per-car feasibility of optimization results. However by using a numerical software tool which distributes the cumulated charging loads back to single cars, all solutions obtained were proven feasible within a deviation of less than 1 %.

In the modeling approach it is assumed that drivers want to recharge their batteries after every trip. There are two main reasons for this assumption:

- Battery lifetime: Li-ion batteries loose more lifetime when discharged deeper [24], the state of charge (SOC) should be in the range of 30 to 70 % to maximize lifetime [25], [26]. As energy for 99 % of all trips is lower than 7.5 kWh (see chapter III), an EV with a 20 kWh battery could be operated in this range when recharged after every trip.
- Convenience: In Singapore, traffic jams together with extensive use of air conditioning can significantly reduce range. Charging after every trip minimizes the risk for running out of electricity.

The provider of electricity in a parking lot is assumed to manage charging by minimizing costs. Thus, the assumption of cost-minimal charging within parking periods but not between different parking periods seems reasonable. Nevertheless, the proposed framework also allows to simulate other scenarios, e.g. charging at home only.

2) Data: All data is described in chapter III.

C. Photovoltaics

1) Method: In addition to the analysis of smart charging in the current power system, future integration of photovoltaics (PV) is considered in several scenarios. The PV power output in each timestep is determined from solar radiation data as described in the following. PV power output is assumed to be linear to solar radiation. The power in each step (every 30 min) can thus be calculated by:

$$P_{PV}(t_m) = \frac{R(t_m)}{\sum_{tm \in T_m} R(t_m)} \cdot 2 \cdot FLH_{PV} \cdot CAP_{PV} \tag{7}$$

As PV power is an intermittent source, it will most probably require additional regulation power $REG_{PV}(t_m)$ in the system which is added to $AS_{reg}(t_m)$. This can be considered by:

$$REG_{PV}(t_m) = sign(P_{PV}(t_m)) \cdot CAP_{PV} \cdot AR_{PV} \tag{8}$$

2) Data: Measurement data for solar radiation is available for several stations at schools across Singapore from [27]. Data from six different and geographically spread stations (Henderson Secondary, Hua Yi Secondary, Nanyang, Northbrooks, NTU Intelligent Systems Centre, North Spring) was available for March 2009 in a 5 minute resolution. It was spatially averaged to a Singaporean mean radiation. As power plant scheduling is conducted every 30 minutes only, PV output has to be time averaged as well. Fig. 5 shows the resulting spatial and time averaged data for March 9th 2009, as an example.

The deviation of the real PV power from the 30 min averaged radiation has to be balanced by regulation. The amount of additional regulation and reserve requirements was, according to our best knowledge, not analyzed for Singapore yet. We thus consider two different scenarios. One does not include additional requirements at all. It is assumed, that some new technology will balance the deviations, e.g. local batteries or regulation power provided by air conditioning. In the second scenario, we consider the additional reserve requirements in the power system according to equation 8. Fig. 6 shows the deviation of spatially averaged single measurement points from the 30 min average. The deviation is lower than 15 % peak radiation for almost all data points. In [28], values

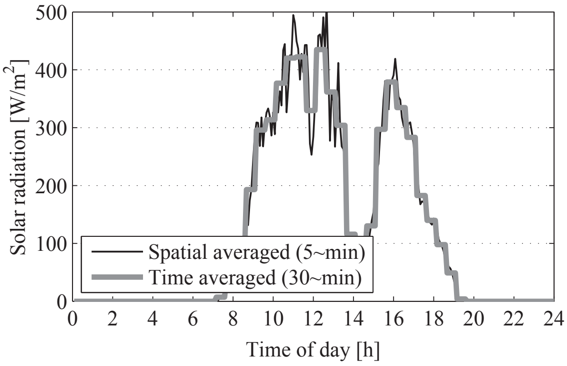

Fig. 5. Average radiation for six measurement stations in Singapore at a typical day. The gray line shows the time averaged values as they are used for the scheduling model.

between 10-20 % of installed PV power were estimated for additional regulation requirement for a geographical spread of 50-170 km in the US. Taking into account these two aspects, the assumption of AR_{PV}=15% seems to be a reasonable approach, but further research has to be done. However, calculating these two scenarios gives an idea about the system effects of PV under different conditions.

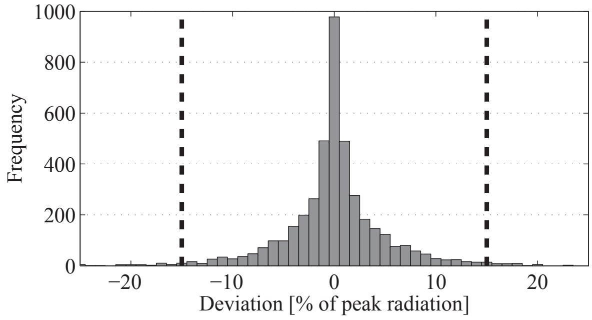

Fig. 6. Deviations of single measurement data from 30 min average as share of peak radiation. Dashed line shows estimated dynamic regulation requirements to balance PV

V. Scenarios and Results

A. Smart Charging and Conventional Power System

Simulations with different levels of EV penetration (0, 200, 400, and 600 thousand EVs) were conducted. The main findings regarding the effects of EVs on the power system are shown in Fig. 7 (a)-(d). Overall additional costs are maximal 6.16 % with 600k EVs and the 'Dumb' charging strategy as shown in (a). This is proportional to the additional electricity demand. With 'Mean' charging, effects on costs are slightly lower with 6.00 %. 'Smart' charging could reduce additional costs to 5.11 % and provision of regulation/reserve with 'SmartPlus' can even reduce costs to only 4.42 %, a 30 % decrease compared to 'Dumb'. Fig. 7 (b) shows effects on CO_2-emissions, which are similar to effects on costs. Lower cost and emissions with smart charging result from load leveling and less startups as shown in (c) and (d). The standard deviation (std) of the load (incl. charging) is 15 % less with smart charging strategies compared to 'Dumb' charging. No additional startups are required even with 600k EVs and smart charging instead of up to 18 % additional startups with 'Mean' charging. The increase in peak load within the simulation period is only 203 MW (3.5 %) with 'Smart' charging instead of 353 MW (6.2 %) with 'Dumb' charging.

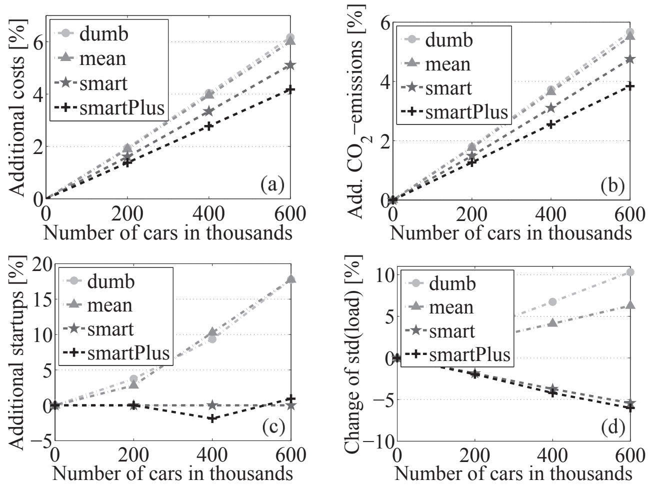

Fig. 7. Effects of charging EVs on conventional power systems. a) Additional costs, b) Additional emissions, c) Additional startups, d) Change in standard deviation of load.

Additional costs and emissions from EVs are relatively low. With the introduction of smart charging, they are even smaller. Moreover, provision of system services from EVs would allow a more efficient power plant operation. Fig. 8 shows the resulting load for the four charging strategies with 600k EVs for a typical weekday. A close resemblance of the load including 'Smart' charging and a typical power plant generation curve can be observed.

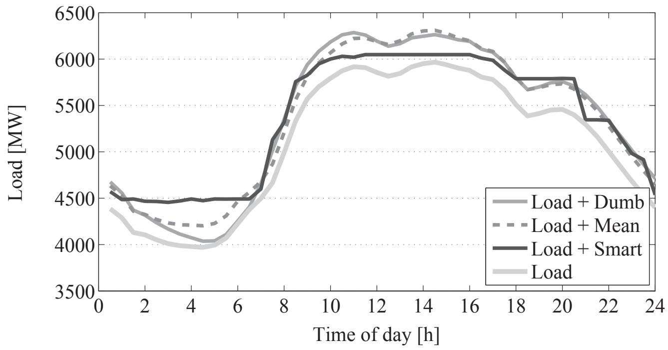

Fig. 8. Comparison of different charging loads for a typical weekday. 600k EVs were simulated in this scenario.

B. Smart Charging and Integration of Intermittent PV Power

Scenarios for different levels of PV power (from 1000 - 11,000 MW) were calculated. In the first block of scenarios, no additional regulation requirements for PV were assumed and EV penetration was set to 600k EVs in the system. Fig. 9 shows emission reductions for different levels of PV and charging strategies. The influence of charging strategies is relatively low. PV can be integrated efficiently up to high levels with all scenarios. Starting with 5000 MW, smart charging allows to integrate PV more efficient.

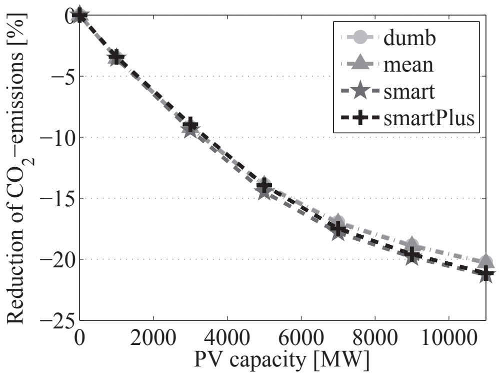

Fig. 9. Emission reduction through PV with different charging strategies (600k EVs) compared to system without PV but same EV penetration and strategy. No additional regulation requirements for PV are imposed.

Assuming additional regulation requirements for PV as discussed in section IV-C, the picture changes dramatically. According to equation 8, additional requirements for regulation will be 15 % of installed PV power. Including power plant maintenance and outages, a maximum of 250 MW regulation power is available from conventional power plants of which 87 MW are required for system operation without any PV. Thus, not more than 1087 MW of PV can be integrated to the system without additional providers of regulation. The black line in Fig. 10 reflects regulation that has to be provided by non-conventional sources. Controllable charging of EVs is one possible option. Data points in Fig. 10 show minimal regulation power provided by EVs in timesteps with higher regulation requirements due to PV. If this data points are below the black line, no feasible solution was obtained for the scenario. 600k EVs could provide 225 MW of regulation power which would allow to integrate maximal 2500 MW PV instead of 1000 MW without EVs.

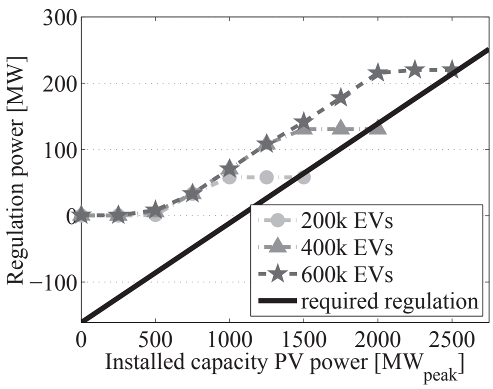

Fig. 10. Minimal regulation power provided by EVs in timesteps with higher regulation requirements due to PV. Black line shows regulation that cannot be provided by the conventional power system.

C. Resulting Emissions and Costs for Charging Mix

One main objective of integrating EVs to future power systems is to reduce emissions and costs of traffic. To measure these reductions, system costs and emissions without EVs were subtracted from those with EVs. These differences were divided by the additional electricity consumption from EVs to get specific costs and emissions for charging. Fig. 11 shows specific emissions at different levels of PV (no additional regulation for PV assumed). Without any PV, emissions are at 477 g/kWh when charging cars with a 'Dumb' strategy, but only 399 g/kWh (16 % less) with 'Smart' charging. Applying 'SmartPlus', emissions are further reduced to 323 g/kWh (33 % less). With high penetrations of PV, advantages from smart strategies get higher as they enable higher PV integration. Specific costs and emissions are independent of the number of EVs.

Reductions of variable costs through PV integration have the same characteristic behavior as emission reductions depicted in Fig. 11. Without PV integration, variable charging costs can be reduced from 0.168 S$/kWh with 'Dumb' to 0.114 S$ (32 % less) with 'SmartPlus'. The numbers for cost savings are in the same region as stated by [3]. This shows, that prices are a good indicator for system cost savings from smart charging if effects on the overall system are relatively small as in our example, Singapore.

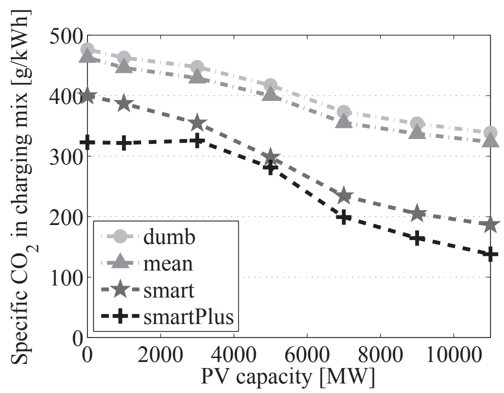

Fig. 11. Specific emissions for charging at different levels of PV in the system. No additional regulation requirements for PV are assumed.

VI. Computational Effectiveness

An advantage of the proposed method is, that calculation time is independent of number of simulated cars. In table III an overview of simulation times for the different scenarios is given. Calculation time is higher with 'SmartPlus' charging. Calculations were performed on a Intel(r) Core(TM) i7 CPU with 3.2 GHz and 24 GB RAM. The FICO XPress Solver [29], called from GAMS [30], was used with a MIP tolerance set to 0.001 in all scenarios.

TABLE III
Average calculation time for one day (72 timesteps are optimized at once).

number of cars	'dumb'	'mean'	'smart'	'smartPlus'
0 EVs	122 s	122 s	122 s	122 s
200k EVs	86 s	95 s	184 s	467 s
400k EVs	76 s	78 s	102 s	484 s
600k EVs	48 s	117 s	60 s	425 s

VII. Conclusion and Outlook

A method to analyze the impact of EVs on the power system was implemented. In several scenarios, the effects of EV integration to the Singapore power system were analyzed. Major findings can be summarized to:

- Overall system effects on costs and emissions are relatively small even with 600,000 EVs.
- Integration of PV is possibly limited by additional regulation requirements.
- Controllable charging of EVs could contribute up to 225 MW regulation power and thus increase maximal level of PV integration.
- Cost and emissions of EVs are up to 30 % less when smart strategies are applied.

Future research will consider the spatial distribution of power generation and consumption. A model of the transmission and distribution grid will be implemented therefore. Results from a detailed traffic model will be used to further analyze the interaction of power and traffic systems. This research will be done within TUM CREATE in the next years.

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IX. Biographies

Matthias Huber received his Dipl.-Ing. (M.Sc.) in Mechanical Engineering from Technische Universität München (TUM) and his B.Sc. in Economics from Ludwig Maximilians University (LMU), both in 2010. He is now pursuing his PhD at the Institute for Energy Economy and Application Technology at TUM and is currently working as a research associate at TUM CREATE Centre for Electromobility in Singapore. His research interests are optimal planning, operation, and economics of power systems.

Annette Trippe graduated in Industrial Engineering and Management from Karlsruhe Institute of Technology (KIT) in 2010. She is currently doing her doctorate at Technische Universität München (TUM) and working as a research associate within TUM CREATE Centre for Electromobility Singapore, which is a an interdisciplinary research project jointly performed by TUM and Nanyang Technological University (NTU), Singapore. It is concerned with the development of innovative technologies and future transportation concepts matching the challenging requirements of fast growing and continuously changing tropical megacities.

Philipp Kuhn graduated from Technische Universität München (TUM) in Electrical Engineering with the focus on energy technologies. Philipp Kuhn is Scientific Associate at the Institute for Energy Economy and Application Technology at TUM. Within his PhD studies, he has been involved in various projects regarding the development of the future power supply and the optimization of power plant operation with unit commitment models. He manages the activities and projects concerning energy storage in power generation at the Institute.

Thomas Hamacher studied Physics in Bonn and Aachen and at Columbia University, New York. After receiving his Ph.D. at DESY (Deutsches Elektronen-Synchrotron) in Hamburg 1993, he worked as a Post-doc at the University of Texas in Austin (HERA-B Experiment). Since 1996 he was employed at Max-Planck-Institut für Plasmaphysik in Garching, where he was appointed as head of the Energy and System Studies Division in 1999. Currently he is Professor and acting director at the Chair of Energy Economy and Application Technology at Technische Universität München (TUM). Prof. Hamacher is member of the Energy Division of the European Physical Society (EPS) and of the Wissenschaftszentrum Umwelt (WZU) of Universität Augsburg.