Integration of Renewables in Singapore: Ramp Rate Support Using Electric Vehicles

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***Abstract*—Renewable energy resources may help reduce system losses and dependency on fossil fuels but introduce a new uncertainty parameter to the already complex problem of power system operation. This paper studies the effect of different solar photovoltaic (PV) penetration levels in Singapore and proposes a flexible charging strategy for private electric vehicles (EVs) to reduce the effect of PV intermittency on ramping and switching of generation units. Intelligently scheduled charging of EVs can help improve overall power system stability, even out energy valleys and also push costs lower by reducing the strain resulting from changes in the generator outputs. Different scenarios with variable PV power and EV penetration and the effect on generation cost are analyzed.**

***Index Terms*—Electric vehicles, Solar PV, Ramping, Power plant operation**

NOMENCLATURE

$P_{max,p}$	Generation capacity of power plant p
P_p	Output power of power plant p
$\eta_{0,p}$	Power plant efficiency at full load
$\phi_{min,p}$	Power plant minimum load factor
$\rho_{max,p}$	Power plant maximum permitted ramp relative to generation capacity
$T_{D,p}$	Power plant minimum down-time
$T_{U,p}$	Power plant minimum up-time
$c_{su,p}$	Power plant start-up cost per MW
C_{su}	Total start-up cost
$R_{lo,p}/R_{hi,p}$	Low / high ramp power value
$c_{lo,p}$ / $c_{hi,p}$	Cost per MW for power plant low / high ramping
C_{ramp}	Total ramping cost
o_p	Power plant on-status
u_p	Power plant start-up status
d_p	Power plant shut-down status
c_{EV}	Charging energy of an electric vehicle
E_{avail}	Available energy electric vehicle charging
$C_{cum,min}$	Cumulative min. required charging energy
$C_{cum,max}$	Cumulative max. available charging energy
t_i	Time step

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I. INTRODUCTION

Increased share of renewable generation in the power generation mix could help countries like Singapore to cut back emission of greenhouse gases into the atmosphere and at the same time reduce the dependency on fossil fuel imports. Solar photovoltaic (PV) systems are viewed as the most promising source of renewable energy in Singapore [1]. The installed capacity at the end of the first quarter of 2017 was about $100\,\mathrm{MWp}$. The Energy Market Authority (EMA) plans to reach $350\,\mathrm{MWp}$ by 2020 and the Solar PV Roadmap for Singapore estimates that the total installed capacity could reach up to $10\,\mathrm{GWp}$ by 2050 [2].

Transportation electrification is viewed as a promising alternative to conventional vehicles. In Singapore, an electric vehicle (EV) test bed was launched in 2010 to test EV prototypes and different charging technologies given the road conditions and local characteristics. Continuing with the push towards transportation electrification, a car sharing program has been commissioned. Under this program, 1000 EVs and the charging infrastructure required to support its use will be deployed in every single Housing & Development Board (HDB) town by 2020. Based on the statistics provided by the land transport authority (LTA) of Singapore, the total private car population was about $540\,000$ vehicles in 2014 [3]. In order to avoid road congestion, registration of private cars is restricted in Singapore. Hence, the number of private cars is not expected to increase a lot in the next years or even decades.

High penetration of EVs could create congestion in both the transmission and distribution network. Smart charging algorithms could be used to reduce the peak demand and ensure that the system limits are not violated [4]. On the other hand, high penetration of renewables poses a new challenge to power system operation. Sudden changes in PV output could compromise the reliable operation of the power system. Shading due to clouds and other atmospheric phenomena could rapidly change the PV output within a very short time span. A phenomenon called the “duck curve” is observed when the share of PV is high in comparison to other generation technologies [5], [6], [7]. This results from the ramp-up of PV generation in the morning and the subsequent ramp-down before sunset. Higher flexibility is required by the conventional generators to prevent "over-generation" and subsequent curtailment of PV generation. Energy storage could be used to provide flexibility but may result in additional cost for the system operator [8]. If successfully implemented, flexible loads such as EVs could help reduce the stress in the generators by providing ramp support throughout the day.

The CO_2 emission reduction potential of PV and EVs in Singapore was analyzed in [9]. Cost minimization of EV battery charging costs in Singapore without installed PV was presented in [10]. In [4], a method to remedy the impact of a high number of EVs in Singapore on the system load was presented. However, ramping costs were not considered, which led to an increase of the ramp rate, particularly in the morning and evening. Integration of PV was addressed, but the benefit of EVs on power plant operation was not discussed in detail.

This paper studies possible future scenarios for Singapore. EVs which are parking and connected to charging stations can provide additional demand when power generation from PV is high. The power system operator decides when to charge the EVs. Increased penetration of PV generation and EVs is considered and the impact on generation cost plus the benefit of combining both PV and EVs is studied. We focus on power system costs and analyze the power supply curve in the presence of PV, incorporating start-up and ramping costs for low and high ramps into the optimization. We do not consider vehicle-to-grid, i.e. discharging of batteries in order to provide power to the grid, as this leads to faster battery aging.

The rest of this paper is organized as follows: Model description and data collection are presented in Section II. The extension of the model is discussed in Section III. The simulation setup and results are shown in Section IV. Section V concludes the paper with a summary of the results and a short discussion about possible areas for further research.

II. Data and model description

a) Model: For our analysis, we require both a power system model and a driving and parking model for EVs in Singapore. For power system modeling, we chose an open source tool called URBS [11]. It was first developed in [12] and has been updated consequently over the years. URBS has been used for a lot of studies, e.g. in [13], [14], [15], [16]. It is a linear model that minimizes power system costs. The user can provide input data in the form of spread sheets with power plant and demand data. The objective function is given in (1) and sums up various cost types.

$$C = C_{inv} + C_{fix} + C_{fuel} + C_{var} + C_{startup} \quad (1)$$

It includes investment costs C_{inv} for construction of new power plants, yearly fixed costs C_{fix} of power plants, variable costs C_{var} of power plants, fuel costs C_{fuel}, and start-up costs $C_{startup}$. Since the model is purely linear, start-up costs are simplified as partial start-up costs. In Section III, we will explain this in more detail. URBS supports extension of the existing power plant park, which is not considered in this study. It also allows consideration of purchase and sale of electricity, which we do not use either. However, URBS does not consider ramping costs, minimum down-time and up-time and it does not include EVs either.

Inputs comprise fuel costs and various power plant parameters such as installed capacity, upper and lower bounds for installed capacity, minimum operating capacity, maximum ramp ratio, efficiency and depreciation. Power plant efficiency is modeled dynamically such that it decreases when the power plant is not operating in full load. Time series for demand and fluctuating renewable energies such as solar photovoltaics are provided by the user.

We extended the model by including ramping costs, constraints for minimum up-time and down-time of power plants, and changed the modeling of the start-up costs such that the full start-up costs occur whenever a power plant is switched on. During start-ups or shut-downs, no ramping costs occur as we consider them to be included in the start-up costs in this case. The modifications are presented in Section III.

For modeling driving and parking of EVs, we used a model presented in [17]. That model includes private electric vehicles traveling around in Singapore and parking in different types of car parks (residential, commercial, industrial) for various periods of time. It is based on surveys and data analysis conducted in Singapore. The modeled cars have different battery capacities from $13\,\mathrm{kWh}$ to $55\,\mathrm{kWh}$ with an average of $24\,\mathrm{kWh}$. The user can specify the desired number of cars, the duration and temporal resolution of the simulation. For each trip between two car parks, the energy demand is output, which yields the minimum and maximum possible charging energy while parking.

b) Data: The parking / driving model includes information on driving patterns in Singapore. The number of EVs to simulate is chosen by the user. We set the maximum to $500\,000$ based on the information provided by LTA.

Power plant data of Singapore are available from the website of the Energy Market Authority of Singapore (EMA) [18]. Data sheets include the generation type and installed capacity. In May 2017, the total installed capacity was $13.3\,\mathrm{GW}$, of which $78\,\%$ were combined cycle gas turbines (CCGT) and $19\,\%$ were steam turbines which could be used with gas or oil. The rest is mainly gas turbines and waste incinerators. The load of combined cycle gas turbines must be at least $55\,\%$, otherwise specific NOx emissions increase vastly [19], [20]. Hourly power demand series for Singapore are published by the Energy Market Company of Singapore [21].

We took further power plant parameters from [22] where a survey on technical parameters of power plants based on various sources was presented. In [7], ramping costs for different power plant types are given. The authors elaborate how the value of the ramping costs changes subject to the current status of a power plant and the steepness of the ramp. In the following section, we model ramping costs as a piecewise linear cost function such that higher costs occur for steep ramps. Table I lists all parameter values used in this paper. We slightly varied the parameters of the current power plants in Singapore based on their age. All costs are given in USD.

TABLE I
POWER PLANT PARAMETERS USED IN THIS PAPER.

Technology	$\eta_{0,p}$ (%)	$\phi_{min,p}$ (%)	$\rho_{max,p}$ (%/min)	$T_{D,p}$ (h)	$T_{U,p}$ (h)	$c_{su,p}$ (USD/MW)	$c_{lo,p}$ (USD/MW)	$c_{hi,p}$ (USD/MW)
CCGT	57–61	55	5	1–2	3–4	35–42	0.5	3.3
Gas turbine	37	30	15	0	0	40	0.5	5
Steam turbine (gas, oil)	38–41	50	6	1–2	3–4	40–45	0.5	6

III. MODEL EXTENSION

In its original form, the URBS model does not support integration of electric vehicles. In addition, it is purely linear such that start-up costs cannot be modeled precisely. Ramping costs are not included either. In this section, we explain how we integrated electric vehicles and how we extended the linear model to a mixed-integer linear model.

a) Integration of electric vehicles: For the integration of electric vehicles, we transformed the output of the EV model from [17] into a useful input for URBS. As described in Section II, for each EV, the mobility model outputs whether the EV is parking or driving for all time steps of the simulation. In addition, when an EV's status changes from driving to parking, the energy demand for the completed trip is output.

We defined three additional parameters E_{avail}, $C_{cum,min}$ and $C_{cum,max}$ for each EV and time step as input for URBS. The available charging energy $E_{avail}(t_i)$ is the maximum possible charging energy when the EV is parking in time step t_i or 0 when it is driving. The cumulative minimum required charging energy $C_{cum,min}(t_i)$ is the minimum accumulated amount of energy required by an EV by time step t_i. The cumulative maximum available charging energy $C_{cum,max}(t_i)$ is the maximum accumulated amount of energy that the EV can have been charged with by time step t_i.

Example: An EV with a battery capacity of $20\,\mathrm{kWh}$ is parked in time step 10 when it has been discharged to $7\,\mathrm{kWh}$. When it leaves the car park in time step 22, it has to be charged to at least $12\,\mathrm{kWh}$. The length of a time step is $15\,\mathrm{min}$ and the maximum charging power is $6\,\mathrm{kW}$. Hence, $1.5\,\mathrm{kWh}$ can be charged per time step. Consequently, the cumulative minimum required charging energy is 0 up to time step 17. In time step 18, at least $0.5\,\mathrm{kWh}$ have to be charged such that in time steps 19 to 21, another $1.5\,\mathrm{kWh}$ can be charged each, which yields $5\,\mathrm{kWh}$ in total. The cumulative maximum available charging energy is $1.5\,\mathrm{kWh}$ in time step 10 and increases to $13\,\mathrm{kWh}$ in time step 18. Later, it remains at $13\,\mathrm{kWh}$ since the battery cannot exceed its maximum charge of $20\,\mathrm{kWh}$.

At the end of each parking period, the difference between $C_{cum,min}$ and $C_{cum,max}$ is equal to the difference between battery capacity and the minimum required energy after the parking period if the EV entered the car park with less than the minimum required energy in its battery.

All EVs are accumulated and a new optimization variable c_{EV} which represents the energy that the EVs can be charged with in each time step is introduced. The higher the number of EVs, the broader the range, c_{EV} can be varied within by the optimizer.

The following constraints have to be fulfilled:

$$0 \leq c_{EV}(t_i) \leq E_{avail}(t_i) \tag{2}$$

$$C_{cum,min}(t_i) \leq \sum_{t=t_0}^{t_i} c_{EV}(t) \tag{3}$$

$$\sum_{t=t_0}^{t_i} c_{EV}(t) \leq C_{cum,max}(t_i) \tag{4}$$

Constraint (2) ensures that the charging energy is lower than the available charging energy in the current time step. Constraints (3) and (4) ensure that the cumulative charging energy in the current time step is between the cumulative minimum required and the cumulative maximum available charging energy in that time step.

b) Model extension: In URBS, start-up costs are modeled by assuming that each power plant consist of an arbitrary number of generators. A variable called online capacity which is the sum of power provided by all generators that are switched on is used. Each time the online capacity increases, partial start-up costs occur. However, due to the linearity of the model, the power output of each generator can be arbitrarily small, which is not realistic. For our analysis, power plant start-ups have to be modeled in a way such that the full start-up costs occur each time a power plant is switched on. Moreover, once a power plant has been shut down, it has to remain idle for some time (minimum down-time). Once it starts up, it has to be running for a certain time as well (minimum up-time). Hence, we extended the linear model to a mixed-integer linear model which includes start-up and ramping costs, and constraints for minimum down-time and up-time.

In order to include start-up costs, we introduced three binary variables $o_p(t_i)$, $d_p(t_i)$ and $u_p(t_i)$. The first one is the on-status. It is true (or 1) when power plant p generates power in time step t_i. The other two are true if a shut-down or start-up, i.e. a change in the on-status, occurs in time step t_i. This yields the following additional constraints:

$$-P_p(t_i) + o_p(t_i)\phi_{min,p}P_{max,p} \leq 0 \tag{5}$$

$$P_p(t_i) - o_p(t_i)P_{max,p} \leq 0 \tag{6}$$

$$d_p(t_i) + u_p(t_i) \leq 1 \tag{7}$$

$$o_p(t_i) - o_p(t_{i-1}) + d_p(t_i) - u_p(t_i) = 0 \tag{8}$$

If the on-status of power plant p is set to 0, the power generated must be 0 as well. Otherwise it must be between the minimum allowed output and the power plant's generation capacity. This is ensured by (5) and (6). Constraint (7) prevents the power plant from being in shut-down and start-up status at the same time. The right assignment of the three binary variables is ensured by (8): When the on-status does not change from time step t_i to t_{i-1}, both shut-down and start-up status are set to 0. If the on-status changes from off to on, the start-up status is set to 1 and the shut-down status to 0. If the on-status changes from on to off, the shut-down status is set to 1 and the start-up status to 0.

Minimum down- and up-time are modeled using the following two additional constraints.

$$o_p(t_i) \leq 1 - \sum_{t=t_i-T_{D,p}+1}^{t_{i-1}} d_p(t) \tag{9}$$

$$1 - o_p(t_i) \leq 1 - \sum_{t=t_i-T_{U,p}+1}^{t_i-1} u_p(t) \tag{10}$$

If a start-up or shut-down occurred later than $T_{D,p}$ or $T_{U,p}$ time steps before t_i, the sum yields 1 such that the power plant has to remain off (9) or on (10) respectively. Note that $u_p(t)$ and $d_p(t)$ are set to 0 for $t < t_0$.

The overall start-up costs are calculated as follows with set $\mathcal{T}$ of time steps and set $\mathcal{P}$ of power plants.

$$C_{su} = \sum_{t\in\mathcal{T}} \sum_{p\in\mathcal{P}} u_p(t) P_{max,p} c_{su,p} \tag{11}$$

Ramping costs are not constant, but depend on the status of the power plant and the ramping speed. Therefore, we define higher costs for higher ramps, i.e. higher difference in power output between two time steps. Lower ramping costs occur for any change in power output. Without consideration of start-ups and shut-downs, the low ramp power value is defined as follows.

$$R_{lo,p}(t_i) = |P_p(t_i) - P_p(t_{i-1})| \tag{12}$$

The ramp value is linearized by substituting (12) with the following two constraints considering start-ups and shut-downs.

$$P_p(t_i) - P_p(t_{i-1}) \leq R_{lo,p}(t_i) + P_{max,p}\big(u_p(t_i) + d_p(t_i)\big) \tag{13}$$

$$-P_p(t_i) + P_p(t_{i-1}) \leq R_{lo,p}(t_i) + P_{max,p}\big(u_p(t_i) + d_p(t_i)\big) \tag{14}$$

The summands with shut-down and start-up status are added such that $R_{lo,p}(t_i)$ and consequently the ramping costs are set to zero when a start-up or shut-down occurs in time step t_i.

We use higher ramping costs when the difference in power is more than half of the maximum permitted ramp of a power plant. The corresponding constraints are given as follows.

$$\begin{aligned} P_p(t_i) - P_p(t_{i-1}) \leq & R_{hi,p}(t_i) + \\ & P_{max,p}\big(\frac{1}{2}\rho_{max,p} + u_p(t_i) + d_p(t_i)\big) \end{aligned} \tag{15}$$

$$\begin{aligned} -P_p(t_i) + P_p(t_{i-1}) \leq & R_{hi,p}(t_i) + \\ & P_{max,p}\big(\frac{1}{2}\rho_{max,p} + u_p(t_i) + d_p(t_i)\big) \end{aligned} \tag{16}$$

The total ramping costs C_{ramp} are calculated accordingly.

$$C_{ramp} = \sum_{t\in\mathcal{T}} \sum_{p\in\mathcal{P}} R_{lo,p}(t) c_{lo,p} + R_{hi,p}(t)(c_{hi,p} - c_{lo,p}) \tag{17}$$

Start-up and ramping costs in (11) and (17) are added to the total cost function of the optimization given in (1).

IV. Results

Since the Solar PV Roadmap of Singapore projects the possible development of PV installation until 2050, we selected the year 2050 for this study. We projected the power demand of 2015 to 2050, assuming a $20\,\%$ increase without EVs. However, we left the power plant park unchanged since the current installed capacity of $13.3\,\mathrm{GW}$ is much higher than the current peak demand of approx. $7.5\,\mathrm{GW}$.

We set the length of the time steps to $15\,\mathrm{min}$ and simulated five days in February and June each. In February, the weather varies a lot with many short cloudy spells, which leads to high fluctuations in the solar irradiance. In June, however, there are fewer weather variations and consequently lower fluctuations. Therefore, we focus on February in this work. In the following, we vary the values of the installed photovoltaic capacity from $0\,\mathrm{GW}$ to $10\,\mathrm{GW}$ and the number of EVs is set to 0, $100\,000$, $300\,000$, or $500\,000$. The maximum charging power is set to $6\,\mathrm{kW}$. In order to reduce battery aging, the state of charge of every EV battery has to be at least $60\,\%$ when the EV leaves a car park. If the parking duration is not sufficient to reach a state of charge of $60\,\%$, the EV has to be charged at maximum power during the parking period. All EVs and consequently E_{avail}, $C_{cum,min}$ and $C_{cum,max}$ are aggregated. An additional constraint ensures that all available PV power is integrated unless it exceeds the demand.

We first analyzed the impact of up to $500\,000$ EVs on the power system with no installed PV. In this case, the EVs are being charged at night in order to reduce ramping and some shut-downs occurring at night due the demand decreasing to its minimum at around 5 a.m. before increasing again. The energy supplied to EVs at night is high enough to make recharging during the day unnecessary. Operating costs per $\mathrm{MW\,h}$ increase when EVs are introduced. For $500\,000$ EVs, however, a slight decrease of $\mathrm{USD}\,0.13/(\mathrm{MW\,h})$ can be observed.

With increasing shares of PV, more and more of the available charging energy is used during the day to avoid high ramping or shut-downs of power plants during the day. Fig. 1 shows the power generation from fossil fuels and $5\,\mathrm{GW}$ of PV and the impact of EV charging for an average day in February. The number of EVs is set to $500\,000$. The pale gray area shows the power generated from fossil fuel power plants. The area with the line pattern shows PV generation. As shown in the top sub-figure, without EVs, the fossil power plants have to ramp up and down often around noon. Additional shut-downs and start-ups are necessary, too. The middle sub-figure shows the optimally generated additional power demand for EV charging. This additional demand yields a smoother power generation curve of fossil fuel power plants and reduction of ramping, shut-downs and start-ups, as shown in the bottom

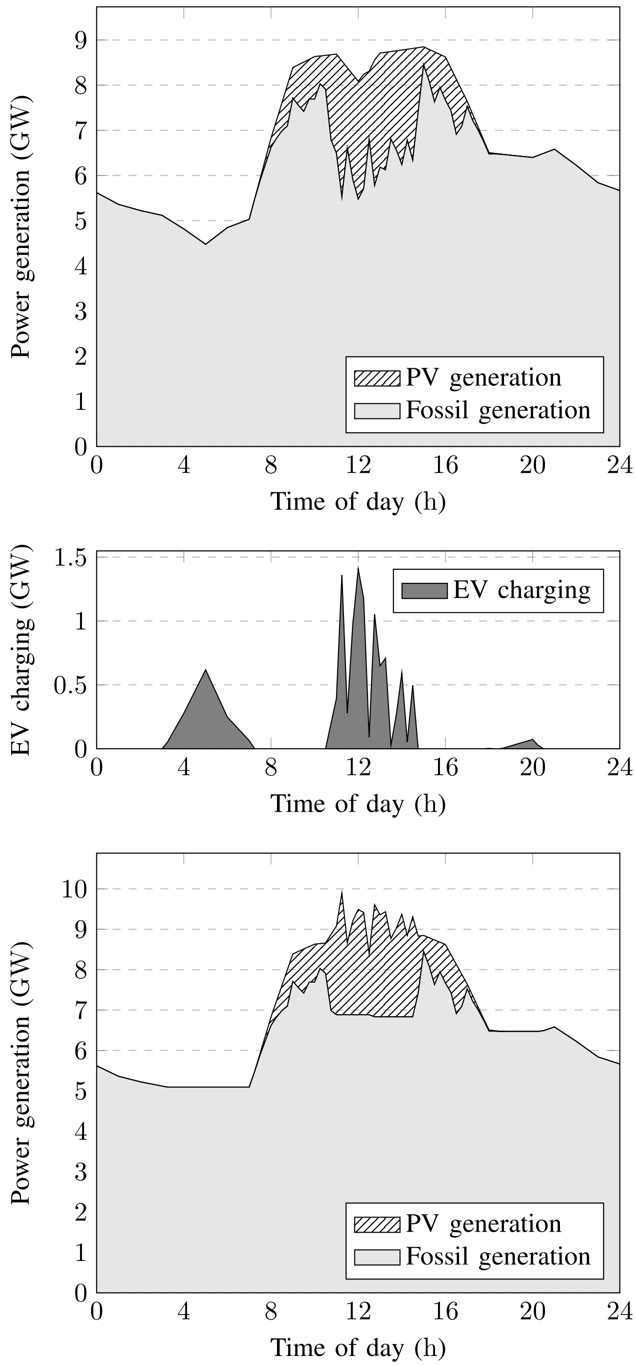

Fig. 1. Power generation on a day in February with 5 GW of PV (top); optimal charging schedule of 500 000 EVs (middle); power generation with additional EV charging load (bottom).

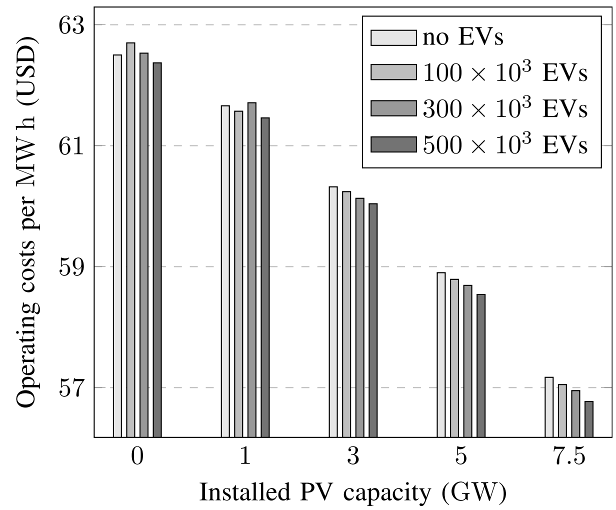

Fig. 2. Operating costs per $\mathrm{MW\,h}$ for different values of installed PV capacity and different numbers of EVs.

TABLE II
COMPARISON OF START-UP AND RAMPING COSTS.

inst. PV (GW)	EVs (10^3)	n_p (–)	n_u (–)	C_u (mill. USD)	C_r (th. USD)
0	0	32	44	9.77	290.26
0	500	36	49	10.93	247.66
1	0	32	43	9.63	366.26
1	500	33	46	10.29	283.41
3	0	30	41	8.86	498.12
3	500	33	49	12.73	346.48
5	0	37	56	10.87	613.29
5	500	33	41	8.81	335.66
7.5	0	36	86	17.57	905.09
7.5	500	36	67	9.03	268.03

sub-figure. Charging of EVs balances the fluctuations pretty well. Fossil generation still has to decrease around noon but remains rather constant for a few hours.

For different scenarios, we calculated the operating costs which include variable costs, start-up and ramping costs, fuel costs, but exclude fixed or investment costs. The resulting specific costs per $\mathrm{MW\,h}$ in February are summarized in Fig. 2. The main cost reduction results from power generation by PV due to fuel savings and lower variable costs. For 0 or 1 GW of installed PV, specific costs can increase a little by introducing EVs, depending on their number, since the benefit from lower ramping does not outweigh the additional fuel costs due to higher power demand. Ramping costs are low compared to fuel costs and with no or little fluctuating supply, sudden forced shut-downs are very unlikely. The additional power demand caused by EVs can also require additional start-ups. However, for 3 GW or more, adding electric vehicles always reduces specific operating costs.

Total operating costs decrease from $\mathrm{USD}\,62.50/(\mathrm{MW\,h})$ to $\mathrm{USD}\,56.80/(\mathrm{MW\,h})$ (or by approx. 9 %) for 7.5 GW of PV and 500 000 EVs.

CO_2 emissions decrease by more than 12 % for 7.5 GW of PV. Using electric vehicles does not lead to lower specific CO_2 emissions from power generation, though.

In Table II, start-up and ramping costs are given for different values of installed PV capacity and 0 or 500 000 EVs. Column n_p represents the number of fossil power plants that were switched on at least once during the optimization period. Column n_u stands for the number of start-ups. This number includes the first start-up of each power plant at the beginning of each optimization run such that $n_u \geq n_p$. The last two columns contain the start-up costs given in million USD and the ramping costs in thousand USD. With EVs, ramping costs decrease. For lower values of PV, the number of start-ups and consequently the start-up costs increase. For $3\,\mathrm{GW}$ of installed PV capacity, start-up costs increase from $\mathrm{USD}\,8.9\,\mathrm{M}$ to $\mathrm{USD}\,12.7\,\mathrm{M}$ when the number of EVs increases from $450\,000$ to $500\,000$, but variable and fuel costs hardly change such that specific operating costs decrease further. For $5\,\mathrm{GW}$ of installed PV capacity and more, the number of start-ups and consequently the start-up costs decrease significantly with $500\,000$ EVs. For $5\,\mathrm{GW}$, the reduction is higher than $\mathrm{USD}\,2\,\mathrm{M}$ ($19\,\%$). For $7.5\,\mathrm{GW}$, it is $\mathrm{USD}\,8.5\,\mathrm{M}$ ($49\,\%$).

For $10\,\mathrm{GW}$ of installed PV capacity, the number of EVs must be at least $300\,000$ such that all of the available PV power can be integrated. Otherwise, the PV power would exceed the demand sometimes and all fossil power plants would have to shut down consequently. Hence, installation of $10\,\mathrm{GW}$ of PV is not advisable without additional measures such as EVs as flexible storage systems. With $300\,000$ EVs, specific operating costs drop to $\mathrm{USD}\,55.30/(\mathrm{MW\,h})$ and start-up costs are $\mathrm{USD}\,19.8\,\mathrm{M}$. For $500\,000$ EVs, specific operating costs are $\mathrm{USD}\,55.15/(\mathrm{MW\,h})$ with start-up costs dropping to $\mathrm{USD}\,8.8\,\mathrm{M}$.

V. Conclusion

In this paper, we presented possible future scenarios for Singapore with high shares of PV power generation and a high number of electric vehicles. Results show that specific operating costs of power plants decrease with increasing share of PV. Though Singapore's power generation system is very flexible with mainly CCGT power plants, EVs can contribute to reducing operating costs, especially for a high amount of installed PV. Ramping and the number of shut-downs and start-ups during times of highly fluctuating solar irradiance are reduced. While introducing EVs with little installed PV power can lead to higher specific operation costs in Singapore's current power generation system, specific operation costs are reduced for any number of EVs with at least 3 GW of installed PV capacity.

Operating costs are reduced by almost $10\,\%$ with $7.5\,\mathrm{GW}$ of installed PV and $500\,000$ EVs. CO_2 emission are reduced by more than $10\,\%$.

In future work, the spatial distribution of supply and demand will be taken into account as well, even though Singapore is a small country. In this context, the impact of PV and EVs on voltage and frequency stability is another topic we will investigate. We also plan to integrate other types of electric vehicles such as buses into the model.

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References

[1] Energy Market Authority, "Solar photovoltaic systems." [Online]. Available: https://www.ema.gov.sg/Solar_Photovoltaic_Systems.aspx

[2] J. Luther and T. Reindl, "Solar photovoltaic (PV) roadmap for Singapore (a summary)," 2013.

[3] Land Transport Authority, "Statistics in brief 2015," 2016. [Online]. Available: https://www.lta.gov.sg/content/ltaweb/en/publications-and-research.html

[4] M. Huber, A. Trippe, P. Kuhn, and T. Hamacher, "Effects of large scale EV and PV integration on power supply systems in the context of Singapore," in *Proc. IEEE PES Innovative Smart Grid Technologies Europe*, 2012.

[5] P. Denholm, M. O'Connell, G. Brinkman, and J. Jorgenson, "Overgeneration from solar energy in California: A field guide to the duck chart," National Renewable Energy Laboratory, Tech. Rep., Nov. 2015. [Online]. Available: http://www.nrel.gov/docs/fy16osti/65453.pdf

[6] K. Van den Bergh and E. Delarue, "Cycling of conventional power plants: Technical limits and actual costs," *Energy Conversion and Management*, vol. 97, pp. 70–77, 2015.

[7] S. Wogrin, D. Galbally, and A. Ramos, "CCGT unit commitment model with first-principle formulation of cycling costs due to fatigue damage," *Energy*, vol. 113, pp. 227–247, 2016.

[8] T. Zhang, S.-X. Chen, H. B. Gooi, and J. Maciejowski, "A hierarchical EMS for aggregated BESSs in energy and performance-based regulation markets," *IEEE Transactions on Power Systems*, vol. 32, no. 3, pp. 1751–1760, May 2017.

[9] M. Wagner, K. Schönsteiner, and T. Hamacher, "Impacts of photovoltaics and electromobility on the Singaporean energy sector," *Energy Procedia*, vol. 25, pp. 126–134, 2011.

[10] G. B. Shrestha and B. C. Chew, "Study on the optimization of charge-discharge cycle of electric vehicle batteries in the context of Singapore," in *Australasian Universities Power Eng. Conf.*, 2007.

[11] Chair of Renewable and Sustainable and Energy Systems, Technical University of Munich, "URBS – A linear optimisation model for distributed energy systems," 2017. [Online]. Available: https://github.com/tum-ens/urbs/,http://urbs.readthedocs.io/

[12] S. Richter, "Entwicklung einer Methode zur integralen Beschreibung und Optimierung urbaner Energiesysteme. Erste Anwendung am Beispiel Augsburg," Ph.D. dissertation, University of Augsburg, 2004.

[13] K. Schaber, F. Steinke, and T. Hamacher, "Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where?" *Energy Policy*, vol. 43, pp. 123–135, 2012.

[14] M. Huber, A. Roger, and T. Hamacher, "Optimizing long-term investments for a sustainable development of the ASEAN power system," *Energy*, no. 88, pp. 180–193, Aug. 2015.

[15] J. Stich and T. Massier, "Enhancing the integration of renewables by trans-border electricity trade in ASEAN," in *Proc. IEEE PES Asia-Pacific Power and Energy Eng. Conf. (APPEEC)*, Nov. 2015.

[16] J. Stich, T. Hamacher, M. Müller, H. Hesse, and A. Jossen, "Sustainable power supply options for large islands – a case study for Belitung Island," in *Proc. IEEE PES Innovative Smart Grid Technologies Asia*. IEEE, Dec. 2016.

[17] A. E. Trippe, P. Hidalgo, M. Lienkamp, and T. Hamacher, "Mobility model for the estimation of the spatiotemporal energy demand of battery electric vehicles in Singapore," in *Proc. IEEE 18th Int. Conf. Intell. Transport. Syst.*, 2015, pp. 578–583.

[18] Energy Market Authority, "Statistics," 2017. [Online]. Available: https://www.ema.gov.sg/Statistics.aspx

[19] KEMA Limited – Energy Market Authority of Singapore, "Review of the LRMC costs of CCGT electricity generation in Singapore to establish the technical parameters for setting the vesting price for the period 1 January 2009 to 31 December 2010," Energy Market Authority, Singapore, Tech. Rep., 2008.

[20] Energy Market Authority, "Review of the vesting contract technical parameters," Energy Market Authority, Singapore, Tech. Rep., 2016.

[21] Energy Market Company, "Market data," 2017. [Online]. Available: https://www.emcsg.com/MarketData/

[22] Deutsches Institut für Wirtschaftsforschung, "Current and prospective costs of electricity generation until 2050," DIW, Berlin, Germany, Tech. Rep., 2013.