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Robust Electric Vehicle Aggregation for Ancillary Service Provision considering Battery Aging

Dante F. Recalde Melo, *Student Member, IEEE,* Annette Trippe, Gooi Hoay Beng, *Senior Member, IEEE*, and Tobias Massier

***Abstract*—Introduction of demand response (DR) programs could help improve the overall power system stability, even out energy valleys and also push the prices lower due to the increased competitiveness. Liberalization of electricity markets provides possibilities for load aggregators to schedule consumption and obtain revenue by direct participation in demand response programs. This paper proposes a robust algorithm for aggregation of flexible loads within the same distribution network. Participation in DR programs is investigated considering electric vehicle (EVs) located at the same carpark. Battery aging is considered and a utilization compensation scheme is proposed for EV drivers. A robust algorithm based on a receding horizon linear problem is designed for the load aggregator considering EV constraints, price uncertainties and battery aging.**

***Index Terms*—Demand Response, Electric Vehicles, Battery Aging**

NOMENCLATURE

A. Sets and Indices

c, C	Index for EV and set of all EVs
j, J	Index and set of all battery aging tangent hyperplanes
k, K	Current time period and set of all time periods
t	Future market period index
U^e, U^r	Energy and reserve uncertainty sets

B. Parameters

τ_c^a, τ_c^d	EV arrival and departure time
$\psi_{c,k}$	Availability for EV c during period k
γ^{min}	Lower limit for charging rate $[kW]$
γ^{max}	Upper limit for charging rate $[kW]$
λ_k^d	Deterministic energy price $[\$/kWh]$
λ_k^f	Energy price forecast $[\$/kWh]$
λ_k^z	Scaled energy price error
$\widehat{\lambda}_k$	Maximum expected error for energy price $[\$/kWh]$
φ_k^d	Deterministic reserve price $[\$/kWh]$
φ_k^f	Reserve price forecast $[\$/kWh]$
$\widehat{\varphi}_k$	Maximum expected error for reserve price $[\$/kWh]$
Γ^e	Energy risk aversion value
Γ^r	Reserve risk aversion value
σ	Probability of load interruption
ν_c^{bat}	Total EV battery cost
ν_c^{eol}	Battery end of life capacity
c^{rate}	Battery charging rate
E^{max}	Upper limit for battery energy content $[kWh]$
E^{min}	Lower limit for battery energy content $[kWh]$
E^{req}	Required battery energy before departure $[kWh]$
x^f	Final battery SOC
x^i	Initial battery SOC
y_j^a	Aging parameter related to inital SOC $[\$/kWh]$
y_j^b	Aging parameter related to final SOC $[\$/kWh]$
y_j^c	Aging parameter related to charging rate $[\$/kW]$
y_j^d	Constant aging factor [\$]

C. Variables

$\delta_{c,k}^{fix}$	Fixed battery utilization index
$\delta_{c,k}^{flex}$	Flexible battery utilization index
$\delta_{c,k}^{tot}$	Total battery utilization index
μ	Energy procurement cost \$
ν	Battery aging cost [\$]
π	Reserve provision cost [\$]
ρ	Energy cost in case of load curtailment [\$]
ξ_k^e, β^e	Dual variables for robust energy procurement
ξ_k^r, β^r	Dual variables for robust reserve provision
$r_{c,k}$	Flexible charging schedule $[kW]$
$s_{c,k,t}$	Re-scheduled capacity from period k to t
$u_{c,k}$	Fixed charging schedule $[kW]$
$x_{c,k}$	Battery energy content $[kWh]$

D. Constants

η	Charging efficiency
$\triangle t$	Time duration of each market period
H	Time horizon for robust optimization problem
V	Number of EVs
z_{1-13}	Constants for the battery aging model

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D.F. Recalde Melo and H.B. Gooi are with School of Electrical and Electronic Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798 (e-mail: e120025@e.ntu.edu.sg; ehbgooi@ntu.edu.sg).

A. Trippe is with the Institute for Renewable and Sustainable Energy Systems, Technische Universitat Munchen (TUM), 80333 Munich, Germany and TUM CREATE, Singapore 138602 (e-mail: annette.trippe@tum.de).

T. Massier is with TUM CREATE, Singapore 138602 (e-mail: tobias.massier@tum-create.edu.sg).

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I. Introduction

Electric vehicles are viewed as a promising technology that can help reduce greenhouse gas emissions in the transportation sector and contribute to lower drivers' carbon footprint. However, a high penetration of electric vehicles may affect the power system operation and stability [1]–[4]. Uncontrolled charging may result in increased reserve requirements, higher electricity prices and may require network reinforcement. Introduction of smart charging strategies could help improve the overall power system stability, even out energy valleys and also lower electricity prices due to the increased competitiveness [5]–[7].

Liberalization of electricity markets provides possibilities for electric loads to bid their capacities in the energy and ancillary markets as a virtual power plant (VPP). By participating as market players, aggregators buy electricity directly in the wholesale market and receive incentives for provision of reserve and regulation [8]–[10]. Demand response programs are being implemented around the globe [8]. Due to their limited size and relative low impact on the system, participation of small consumers in DR programs is generally achieved through aggregators [11]–[13].

Extensive literature is available regarding load scheduling for participation in the wholesale electricity market and provision of ancillary services. Issues related to incentive payment on different market time frames are considered in [14]–[16]. In [14], the authors design a DR payment system considering load and system uncertainties. Imbalance settlement between the day-ahead and real-time market is studied in [15]. It introduces mechanism design and public good theory to derive an optimal settlement mechanism for incentives. Reference [16] proposes a fairness index to settle the incentives paid to aggregators. All these methods calculate incentive payments assuming known cost functions for loads. Although aggregation of the energy requirements for EVs can be derived using standard driving profiles, i.e. Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Test (HWFET). Randomness resulting from different driving behaviors will have an effect on the temporal distribution of these EV charging requests. Variations in the energy price together with the temporal sparsity of the charging requests will make obtaining accurate load-price curves for individual EVs very difficult. This work derives an optimized charging schedule based on the battery state, energy requirements, arrival time and proposed departure time provided by the EV owners.

Batteries installed in EVs degrade over time. Aging is characterized by loss of capacity and increased impedance [17], [18]. Aging is dependent on different factors namely charging power, initial state of charge (SOC), final SOC, and temperature. Battery costs comprise a high proportion of the total cost of EVs and aging costs should be considered in order to promote participation of EV drivers in DR programs. Some authors have developed very complex models to measure battery degradation [19], [20]. Although there are some publications combining battery aging and EV scheduling [21], [22], in these works the authors use simplified battery aging models. This work derives a battery aging model using a piecewise linear approximation of a four-dimensional function. Battery aging is considered while deriving an optimized charging schedule. A battery utilization index is proposed to compensate EV drivers for use of the batteries to provide reserve capacity.

Charging of electric vehicles under uncertainties is studied extensively in the literature. In [23], the effect of uncertain departure times in the charging schedule of EV is analyzed. In [24], the authors propose scheduling of EVs charging operations in the day-ahead market as flexible and inflexible loads. Day-ahead and hour-ahead operations are carried out to mitigate forecast errors.

Stochastic programming has been applied to EV scheduling in a smart grid environment [25]–[28]. The authors in [25], [26] consider uncertainties while scheduling EV charging for participation in the day-ahead market. In [27], the authors maximize the aggregator's profit considering the least profitable scenarios and different risk aversion attitudes. Risk averse scheduling of EVs for participation in the day-ahead and balancing markets considering conditional values at risk is studied in [28]. In Stochastic programming, it is assumed that the uncertain parameter can be defined or at least approximated using a probability distribution. Optimal scheduling is obtained by considering multiple scenarios. Although scenario reduction techniques can be implemented, stochastic programming may result in higher computational requirements than those of deterministic problems.

Non-probabilistic methods are used as an alternative to stochastic programming in order to reduce the computational burden and to provide a robust formulation under uncertainties [7], [29], [30]. A robust optimization tool for scheduling of virtual power plants under uncertain electricity price is proposed in [29]. An optimal bidding strategy under uncertain energy price is proposed by [30]. The authors in [7] propose a robust algorithm to adjust the load level in response to prices. This work proposes a robust optimization framework to reduce the computational requirements seen in stochastic programming while still considering price uncertainties for energy and reserve.

Although the authors in [31]–[36] consider uncertainties for some parameters, a perfect forecast is assumed for both energy and reserve prices. Some works in the literature also consider uncertainties in the electricity price [7], [29], [30] but works that considering both energy and reserve price uncertainties simultaneously are rare.

Aggregators make decisions based on market prices. An accurate forecast for these market prices is necessary to reduce the risks resulting from price volatilities that may increase operation costs for load aggregators. Different techniques have been proposed to forecast electricity prices. The authors in [37] propose forecast models to predict next-day electricity market prices based on the autoregresive integrated moving average (ARIMA) methodology. The authors in [38] propose a hybrid approach combining artificial neural networks (ANNs) and fuzzy logic to improve the forecasting accuracy and at the same time reduce the computational time. Stationarity is assumed over days, weeks, months, etc. For intra-hour forecast,

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different bidding strategies may be implemented by generation company (generation companies). This will change depending on the hour of the day, i.e. off-peak, mid-peak, peak periods, the offer lead time and variance of the demand. This may result in a lower accuracy for models which assume stationarity of the data over all daily market periods. This work proposes two ARIMA models to forecast the energy and reserve prices in the National Electricity Market of Singapore (NEMS). These forecast models reduce the uncertainties in prices resulting from changes in bidding strategies by generation companies over different times of the day.

The main focus of this publication is to propose a robust scheduling algorithm for load aggregators considering both battery aging and uncertainties in energy and reserve market prices.

The main contributions are:

- Propose a robust formulation for scheduling EV charging operations. Charging operation for each EV is scheduled as fixed or flexible based on the availability of EVs. The aggregator co-optimizes procurement of energy while providing flexibility as ancillary services in the form of interruptible load. An analysis of how different risk aversion values affect the scheduling of energy and reserve is designed.
- Develop an aging model to estimate battery degradation during the charging cycle based on different battery parameters , i.e. initial SOC, final SOC and charging rate.
- Introduce a compensation scheme for EV owners based on the battery utilization index. This index is introduced to provide compensations in case the battery is aged faster due to the provision of ancillary services.

The remaining sections are organized as follows. In Section II the forecast models used for both energy and reserve price predictions are presented and a robust formulation for load scheduling and ancillary service provision by the load aggregator is designed. In Section III, the battery aging model is explained together with the battery utilization compensation formulation. The simulation framework is presented in Section IV and the results are shown in Section V. Conclusions and an outlook of future works is given in Section VI.

II. Charge Scheduling for Ancillary Service Provision

This section formulates the optimization problem from the load aggregator point of view. A centralized load aggregator control mechanism for participation in the wholesale energy and reserve markets is proposed. This work considers aggregation of EVs within the same carpark. This ensures that aggregators are able to control the charging process in a near real-time manner for provision of ancillary services. The aggregator gets status updates and sends control signals to each EV through the electric vehicle supply equipment (EVSE). A two-way communication link is used to obtain the NEMS price updates and submit the reserve capacity bids.

This paper considers only uni-directional power flow from the grid into the vehicle. Although it has been proved [19], [39]–[41] that vehicle-to-grid (V2G) may be a viable and even profitable way for EV drivers to obtain incentives. Some shortcomings that may discourage EV users to participate in V2G programs are: reduced battery lifetime due to increased cycling, range anxiety in case of emergencies due to early departure and high battery replacement costs.

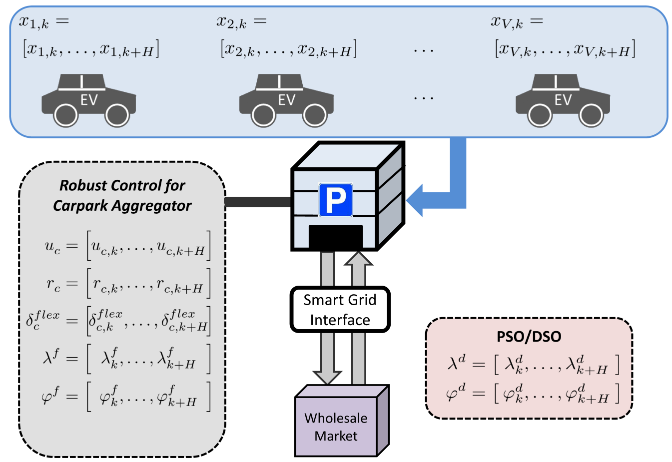

Fig. 1. Aggregator diagram considering ancillary service provision and battery aging

An overview of the proposed system is shown in Fig. 1. The objective of the carpark aggregator is to minimize the total charging cost of all EVs $c \in C = \{1, 2, ..., V\}$ over the optimization horizon $k \in K = \{1, 2, ..., H\}$ while maximizing the revenue obtained for provision of ancillary services. The smart grid interface allows the carpark aggregator to derive both the energy "λ^f" and reserve "φ^f" price forecasts. Forecasts are derived using the ARIMA model introduced in Section II-A and the day ahead energy "λ^d" and reserve "φ^d" price forecasts provided by the system operator. An optimized fixed "u_c" and flexible "r_c" charging schedule is obtained considering both the price uncertainties and the compensation to EV owners "δ_c^{flex}" for battery utilization.

A. Multiplicative ARIMA Model

Liberalization of the electricity market results in the introduction of different market structures. Some consider day-ahead and balancing markets [28]. Others, like the NEMS, clear all energy and ancillary prices in a real-time manner. All market participants are required to maintain standing bids and are allowed to change the bids up to 65 minutes before the actual trading period begins. The market clearing engine (MCE) is run for every half-hourly period and a forecast for the following 24 hours is provided based on these standing bids.

The day-ahead price forecasts are provided by the market operator based on the standing bids from all the participants.

$$\boldsymbol{\lambda}^d \triangleq \left[\lambda_k^d, \lambda_{k+1}^d, \dots, \lambda_{k+H}^d\right] \tag{1}$$

$$\boldsymbol{\varphi}^d \triangleq \left[\varphi_k^d, \varphi_{k+1}^d, \dots, \varphi_{k+H}^d\right] \tag{2}$$

where $\boldsymbol{\lambda}^d$ and $\boldsymbol{\varphi}^d$ are the energy and reserve price forecasts provided by the power system operator (PSO) for the following

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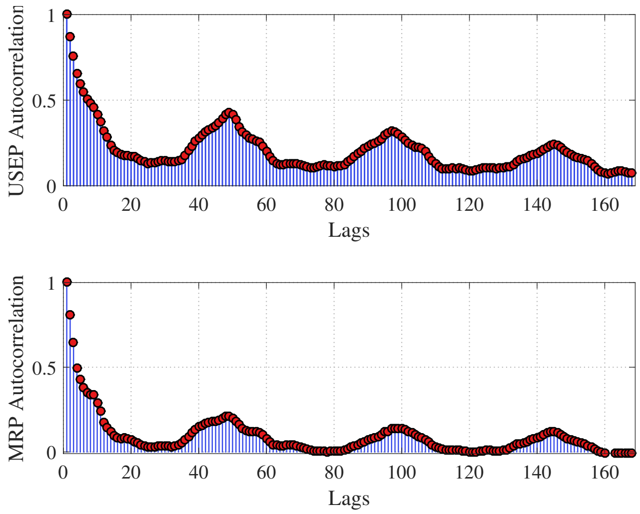

Fig. 2. Autocorrelation for (a) USEP and (b) MRP prices in the NEMS during 2014

$H \geq 1$ market periods. This forecast is updated every period based on the standing bids from the market participants.

Time-series are considered stationary if the frequency distribution for the observations at time $\{t_1, t_2, ...t_h\}$ are the same as the ones for $\{t_1 + t, t_2 + t, ...t_h + t\}$ [42]. Fig. 2 shows the autocorrelation for the energy and reserve prices during the year 2014. Jumps in the autocorrelation indicate a non-stationary process but show high seasonal correlation. Seasonal integration could be used to filter the seasonal component.

A multiplicative ARIMA model is created based on past price data for the NEMS. A seasonal and a non-seasonal model is created based on the general multiplicative ARIMA formulation [37].

Data from the year 2014 was used to train the ARIMA predictor for both the energy (USEP) and reserve (MRP) prices. The model orders were obtained using a combination of Akaike information criteria (AIC) and Bayesial information criteria (BIC). Parameters for the ARIMAs model were estimated using the maximum likelihood method proposed by Box-Jenkins [43].

Two independent models were created, one for the energy and another for the reserve prices. Predicted energy λ^f and reserve φ^f prices during period k and for $H \geq 1$ future periods are defined as:

$$\lambda^f \triangleq \left[\lambda^f_k, \lambda^f_{k+1}, \ldots, \lambda^f_{k+H}\right] \quad (3)$$

$$\varphi^f \triangleq \left[\varphi^f_k, \varphi^f_{k+1}, \ldots, \varphi^f_{k+H}\right] \quad (4)$$

B. Carpark aggregator model

A limited battery size and high uncertainties about future trips will require EVs to charge up during peak hours. Vehicles in general are parked for extended periods. Commercial carparks will accommodate a high portion of EVs parked during the day. This will create opportunities for carpark operators to procure energy in the wholesale electricity market. The carpark model presented in [8] is used to obtain the arrival-departure times for the EVs in a carpark. Charging operation is assumed to be possible within the interval $[\tau^a_c, \tau^d_c]$. The parameter $\psi_{c,k} \in \{0, 1\}$ is updated based on the availability of EV.

The battery SOC for each EV is defined as:

$$x_c \triangleq \left[x_{c,k}, x_{c,k+1}, ..., x_{c,k+H}\right] \ \forall \, c \in C \quad (5)$$

The load aggregator schedules EVs as fixed or flexible loads based on their availability and the system constraints. Fixed and flexible scheduling vectors for all EVs are defined as:

$$u_c \triangleq \left[u_{c,k}, u_{c,k+1}, \ldots, u_{c,k+H}\right] \ \forall \, c \in C \quad (6)$$

$$r_c \triangleq \left[r_{c,k}, r_{c,k+1}, \ldots, r_{c,k+H}\right] \ \forall \, c \in C \quad (7)$$

The total fixed and flexible charging power for each EV $c \in C$ is limited between $[\gamma^{min}, \gamma^{max}]$ to avoid excessive aging in the batteries.

$$\gamma^{min} \leq u_c + r_c \leq \gamma^{max} \quad (8)$$

The updated SOC for each EV is calculated using:

$$x_{c,k+1} = x_{c,k} + \triangle t \cdot \eta \left[u_{c,k} + r_{c,k}\right] \quad (9)$$

The energy for each EV at departure should be greater or equal to the minimum charging requirements. This is accomplished introducing the following constraint:

$$x_{c,\tau^d_c+1} \geq E^{req} \quad (10)$$

The battery state for each EV $c \in C$ at each period $k \in K$ should comply with the following constraint.

$$E^{min} \leq x_{c,k} \leq E^{max} \quad (11)$$

The cost of energy procurement for the aggregator is defined as:

$$\mu \triangleq \sum_{k=1}^{H} \sum_{c=1}^{V} \left[u_{c,k} + r_{c,k}\right] \cdot \triangle t \cdot \lambda^f_k \quad (12)$$

Flexibility resulting from the long waiting times could be exploited by providing this flexibility in the charging process as an ancillary service to the grid. Incentives obtained for reserve provision are defined as:

$$\pi \triangleq \sum_{k=1}^{H} \sum_{c=1}^{V} r_{c,k} \cdot \triangle t \cdot \varphi^f_k \quad (13)$$

The charging process should be re-scheduled to future periods if EVs are required to curtail their loads during system contingencies. The cost of shifting the charging operation $s_{c,k,t}$ from period k to a future period t is given by:

$$\rho \triangleq \sum_{t=1}^{H} \sum_{k=1}^{H} \sum_{c=1}^{V} s_{c,k,t} \cdot \triangle t \cdot \lambda^f_t \quad (14)$$

The aggregator schedules the charging operations based on the following problem:

$$\min_{u,-r} \ \mu - \pi + \sigma \cdot \rho \tag{15}$$

subject to:

Equations (9) to (11)

$$\textstyle\sum_{t=k+1}^{H} s_{c,k,t} \cdot \psi_{c,t} \geq r_{c,k} \ \ \forall \, k \in K \tag{16}$$

$$\gamma^{min} \leq u_{c,k} + r_{c,k} + s_{c,k,t} \leq \gamma^{max} \ \ \forall \, k,t \in H \tag{17}$$

$$u_{c,k}, r_{c,k}, s_{c,k,t} \geq 0 \ \ \forall \, c \in C \text{ and } k,t \in K \tag{18}$$

Equation (16) ensures that the flexible loads which are curtailed during period k could be re-scheduled to future periods $\{k+1, ...k+H\}$. Equation (17) ensures that the re-scheduled power does not violate the charging constraints in (8) and that (10) is still feasible. Parameter σ is introduced to penalize the re-scheduling cost based on the probability of load curtailment.

Flexible loads are considered to be interruptible, i.e. the charging process can be re-scheduled for future periods. Curtailments of the charging operation that will violate the EV constraints are scheduled as fixed loads. The optimal decision for the current period is implemented and the time is stepped forward in one period. Receding horizon control is used to ensure the optimal control sequence is updated based on the latest information available.

C. Robust formulation

Imperfect information on prices could result in increased operational costs for aggregators. This work proposes a robust formulation against increase in costs resulting from higher energy prices and loss of incentives due to lower reserve prices. A robust optimization model similar to the one presented in [7] is implemented for the carpark aggregator. This work is extended to include both uncertainties in the energy and reserve prices. Price uncertainties are defined by the polyhedral sets:

$$U^e \triangleq \left\{ \lambda_k^f \in \mathbb{R} \, \forall \, k, \lambda_k^f \in [\lambda_k^f + \widehat{\lambda}_k] \right\} \tag{19}$$

$$U^r \triangleq \left\{ \varphi_k^f \in \mathbb{R} \, \forall \, k, \varphi_k^f \in [\varphi_k^f - \widehat{\varphi}_k] \right\} \tag{20}$$

where $\widehat{\lambda}_k$ is defined as the expected deviation between the ARIMA energy forecast λ_k^f and the deterministic λ_k^d energy price that will result in increased energy procurement cost.

$$\widehat{\lambda}_k = \lambda_k^d - \lambda_k^f \quad \forall \, k \in K \tag{21}$$

Similarly, $\widehat{\varphi}_k$ is defined as the expected deviation between the ARIMA reserve forecast φ_k^f and the deterministic reserve φ_k^d prices that will result in reduced incentive payments for participation as interruptible loads.

$$\widehat{\varphi}_k = \varphi_k^f - \varphi_k^d \quad \forall \, k \in K \tag{22}$$

The scaled deviation of the energy price from its nominal value λ_k^z is defined as:

$$\lambda_k^z = \frac{\lambda_k - \lambda_k^d}{\widehat{\lambda}_k} \quad \forall \, k \in K \tag{23}$$

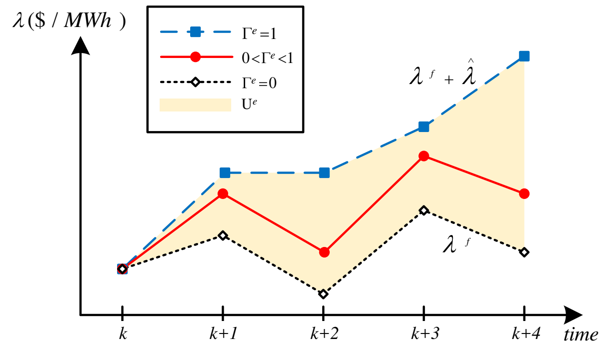

Fig. 3. Robust formulation for uncertain energy price

where parameter λ_k^z belongs to $[0,1]$. The risk aversion value for the aggregator towards errors in the energy price is set to:

$$\frac{\sum_{k=1}^{H} \lambda_k^z}{|H|} \leq \Gamma^e \tag{24}$$

Parameters Γ^e and Γ^r represent the risk aversion attitude of the aggregator with respect to the energy and reserve prices respectively. The deviations are bounded within $\Gamma^e = [0,1]$ and $\Gamma^r = [0,1]$. A value of "1" represents a very conservative risk averse attitude. The load aggregator assumes the worst value for both $\widehat{\lambda}_k$ and $\widehat{\varphi}_k$ during all optimization periods [44]. A value of "0" represents a risk seeking attitude The aggregator assumes a perfect forecast with no protection against uncertainties. A value between $(0,1)$ will represent a trade-off between a risk averse and a risk seeking attitude. Figure 3 shows an example of how the expected energy price λ_k^f changes for different values of Γ^e.

The robust counterparts of (12) and (13) are given by:

$$\mu \triangleq \sum_{k=1}^{H} \sum_{c=1}^{V} [u_{c,k} + r_{c,k}] \cdot \triangle t \cdot \lambda_k^f + \xi_k^e + \Gamma^e \cdot \beta^e \tag{25}$$

$$\pi \triangleq \sum_{k=1}^{H} \sum_{c=1}^{V} r_{c,k} \cdot \triangle t \cdot \varphi_k^f + \xi_k^r + \Gamma^r \cdot \beta^r \tag{26}$$

and the following constraints are added:

$$\xi_k^e + \beta^e \geq \textstyle\sum_{c=1}^{V} [u_{c,k} + r_{c,k}] \cdot \triangle t \cdot \widehat{\lambda}_k \quad \forall \, k \in K \tag{27}$$

$$\xi_k^r + \beta^r \geq \textstyle\sum_{c=1}^{V} r_{c,k} \cdot \triangle t \cdot \widehat{\varphi}_k \quad \forall \, k \in K \tag{28}$$

$$\beta^e, \beta^r \ \geq 0 \qquad \xi_k^e, \xi_k^r \geq 0 \quad \forall \, k \in K \tag{29}$$

The first term in (25) and (26) represent the expected cost considering the price forecasts. The last two terms define the robust formulation derived using duality theory [7], [45]. Equations (27) and (28) are the auxiliary constraints used to limit the energy and reserve price error within their expected uncertainty range defined by (19) and (20). A detailed explanation on the robust formulation is given in [7], [44], [45]

III. Battery Aging

The battery aging model is an improved version of the model presented in [17]. In order to evaluate the battery aging behavior of battery electric vehicles, aging tests were conducted where cells were cycled through different SOCs

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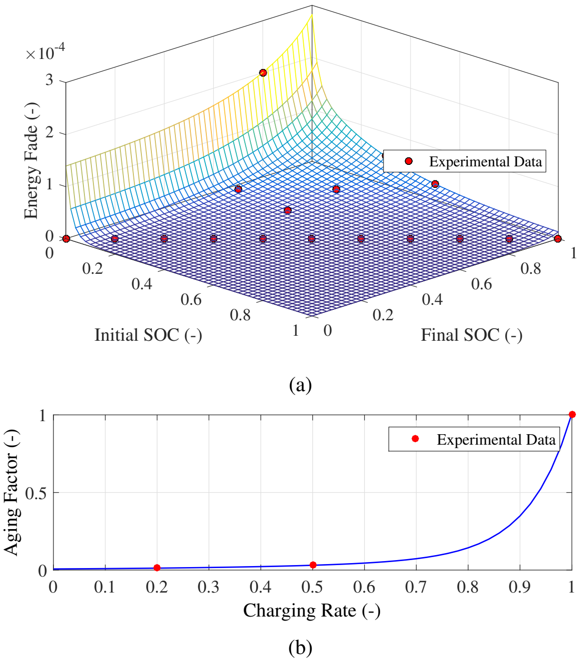

Fig. 4. Battery aging parameters: (a) energy fade and (b) aging factor

and with different battery charging rates (C-rates), since the variation of these parameters has an effect on the aging behavior. After periodical time intervals, characterization tests were conducted for the determination of the remaining energy content of the test cells. ICR18650-22FM batteries from manufacturer *Samsung SDI* were used for the tests. It is assumed that aging within the battery pack of electric vehicles occurs in the same way as in the test cells.

The decrease of the energy content of the cells over the course of the aging tests was evaluated for each test condition and values for the normalized energy fade during the charging process were derived. The energy fade values of the test cells which were charged between different combinations of initial and final SOC at the standard charging rate are plotted in Fig. 4(a) and described in the following equation:

$$f(x^i, x^f) = z_1 \cdot e^{z_2\left(x^i - x^f - z_3\right)} + z_4 \cdot e^{z_5\left(1 - x^i\right)} + z_6 \cdot e^{z_7\left(x^f - 1\right)} \quad (30)$$

where $z_1, z_2, z_3, z_4, z_5, z_6$ and z_7 are constants, and x^i,x^f depict the initial and final battery SOC respectively.

The energy fade values for the aging tests at different charge rates between a fixed SOC combination were compared and an aging factor for different charge rates was derived.

$$g(c^{rate}) = z_8 \cdot e^{z_9(c^{rate} - z10)} + z_{11} \cdot e^{z_{12}\left(c^{rate} - z_{13}\right)} \quad (31)$$

where $z_8, z_9, z_{10}, z_{11}, z_{12}$ and z_{13} are constants and c^{rate} represents the battery charging rate. An example of the aging factor values for the test cells and the fitted function is given in Fig. 4(b)

The energy fade of a specific charge process with values for initial SOC, final SOC, and battery charging rate (C-rate) can be calculated by multiplying the normalized energy fade with the aging factor corresponding to the specific C-rate. This results in a four-dimensional function with input parameters which include initial SOC, final SOC, and C-rate and the energy fade as function values.

$$h(x^i, x^f, c^{rate}) = f(x^i, x^f) \cdot g(c^{rate}) \quad (32)$$

A battery aging function is proposed using a piecewise linear approximation of the four-dimensional function with tangent hyperplanes in several points of the energy fade function. A compromise is required in order to model the battery aging accurately without increasing the complexity of the optimization problem. In this work, the equations of the hyperplanes are calculated for 142 different combinations of initial SOC, final SOC, and C-rates. The piecewise linear approximation is given by:

$$h(x^i, x^f, c^{rate}) = y_j^a \cdot x^i + y_j^b \cdot x^f + y_j^c \cdot c^{rate} + y_j^d \qquad \forall j \in J \quad (33)$$

The total energy fade for EV c during period k is approximated using:

$$\delta_{c,k}^{tot} \geq y_j^a \cdot x_{c,k} + y_j^b \cdot x_{c,k+1} + y_j^c \cdot [u_{c,k} + r_{c,k}] + y_j^d \quad (34)$$

$$\delta_{c,k}^{tot} \geq 0 \quad \forall\, k \in K,\ c \in C \quad (35)$$

Parameters y_j^a, y_j^b, y_j^c, and y_j^d are defined for each tangent hyperplanes $j \in J$ and are calculated from the experimental data using regression.

The total costs of the aggregator comprises both the payment for energy consumption and the incentives for provision of reserves. EV drivers may not be willing to shoulder higher battery aging costs for provision of reserves unless they receive a compensation for the increased battery utilization. This work proposes a payment mechanism for EV drivers to offset the higher battery aging costs. The total energy fade in (34) is then split into two components, the capacity fade due to fixed charging scheduling and the capacity fade due to the flexible charging schedule.

$$\delta_{c,k}^{fix} \geq y_j^a \cdot x_{c,k} + y_j^b \cdot x_{c,k+1} + y_j^c \cdot u_{c,k} + y_j^d \quad (36)$$

$$\delta_{c,k}^{fix} \geq 0 \quad \forall\, k \in K,\ c \in C \quad (37)$$

The total battery aging cost for the EV drivers is calculated using:

$$\nu = \sum_{k=1}^{H} \sum_{c=1}^{V} \frac{\delta_{c,k}^{tot}}{(1 - \nu_c^{eol})} \cdot \nu_c^{bat} \quad (38)$$

where ν_c^{bat} represents the total battery costs for EV c and ν_c^{eol} depicts the lower limit for the battery capacity before replacement is needed due to the end of useful life. Equation (15) is updated to include the battery aging costs:

$$\min_{u,-r} \ \mu - \pi + \sigma \cdot \rho + \nu \quad (39)$$

subject to:

Equations (8) to (11)

Equations (16) to (18)

Equations (27) to (29) and (34) to (38)

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It should be noted that including (38) in the objective function will result in minimization of the total battery aging cost. Flexible charging will only be considered when the incentives received as reserve providers are greater than the battery aging costs. The compensation for battery utilization is then calculated by the difference between the aging cost resulting from the fixed and flexible charging operations;

$$\delta_{c,k}^{flex} = \delta_{c,k}^{tot} - \delta_{c,k}^{fix} \quad \forall\, k \in K,\ c \in C \tag{40}$$

$$\nu_{c,k}^{flex} = \frac{\delta_{c,k}^{flex}}{(1-\nu_c^{eol})} \cdot \nu_c^{bat} \quad \forall\, k \in K,\ c \in C \tag{41}$$

IV. Simulation Framework

The effect of different risk aversion values in the energy procurement cost and ancillary service provision incentives for load aggregators is studied. Data analysis and model estimation is achieved using the econometrics toolbox in MATLAB©. The optimization problem is implemented using YALMIP [46] and is solved using Gurobi 6.5.0 [47]. The linear problem is solved using the interior point method and Gurobi default parameters. The average computational time required to solve one iteration of the optimization problem is 14 s on a machine with an Intel Xeon E5-2630 v3 @ 2.4 GHz processor and 128 GB of RAM.

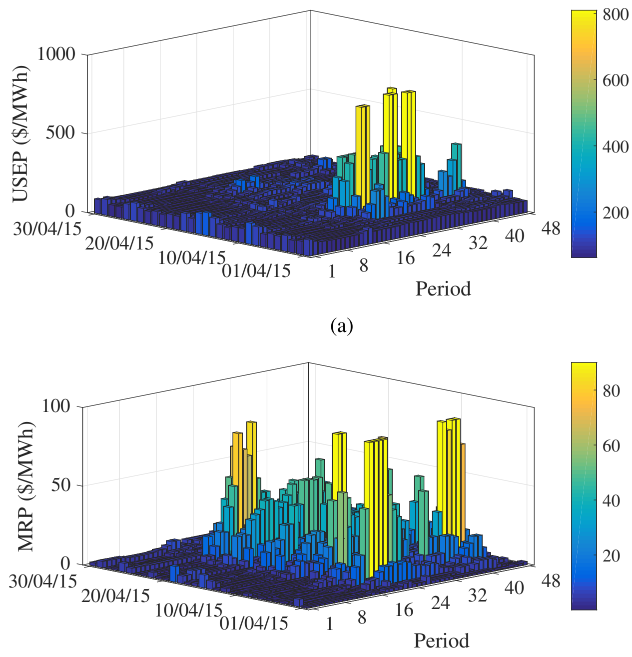
Parameters like arrival time, parking time and energy consumption for each EV are derived using the model presented in [8]. A list of the EV parameters used in the simulation is given in Table I. This work assumes that all EVs in the carpark have the same parameters. This assumption could be relaxed and different parameters could be used for each EV without any increase in the problem complexity.

The NEMS framework is used in the paper. A detailed explanation of how the prices are cleared is given in Section II-A. Under this framework, the interruptible load (IL) program allows load providers to submit a set of price-quantity bids before each market period and receive incentives for providing system reserves. The MCE considers reserves from both generators and load providers equal and provides an optimal schedule based on the system constraints and the price bids. Load providers are required to react when the under-frequency relay is triggered according to the market operation rules detailed in [48].

The following assumptions are made while scheduling reserves provided by the EVs:

– The load aggregator bids in the contingency reserve market and is paid based on the contingency reserve price for the NEMS.
– Bids by the load aggregator are low enough such that they are always scheduled by the MCE.
– The under-frequency relay is not activated during the optimization horizon.

Data from the NEMS for the entire year 2014 was used to train the energy and reserve price forecast model presented in Section II-A. Forecast for each market period k was created using energy and reserve prices for the past $\{k-48, k-47, ..., k-1\}$ and the current k half-hourly market periods. Fig. 5(a) and 5(b) show the energy and reserve prices for April 2015.



(a)

(b)

Fig. 5. NEMS (a) energy and (b) reserve prices for April 2015

Table I
Simulation Parameters

Optimization parameters		
V	400	number of EVs
H	48	optimization horizon
$\lvert J\rvert$	142	number of hyperplanes
Δt	0.5 h	period duration
EV parameters		
γ^{min}	0	min charging rate
γ^{max}	24 kW	max charging rate
E^{min}	4.8 kWh	min battery capacity
E^{max}	24 kWh	battery capacity
η	0.9	charging efficiency
ν^{bat}	7200 $	battery cost
ν^{eol}	0.8	battery end of life capacity

The optimization problem defined in (39) was solved using the market data for April 2015 and the parameters shown in Table I, a rolling window with an horizon of $H = 48$ periods was used.

A. Base Case

The base case is solved using the energy and reserve price forecast data provided by the NEMS. These prices are obtained based on the standing offers for market participants. The problem in (15) is solved considering (12) to (14) as the energy procurement cost, incentive payments and the reschedule costs respectively. This is considered as a baseline and its solution is compared with that of the proposed method.

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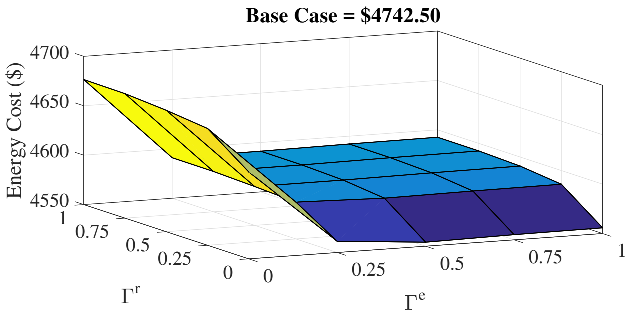


Fig. 6. Energy procurement cost for different risk aversion values

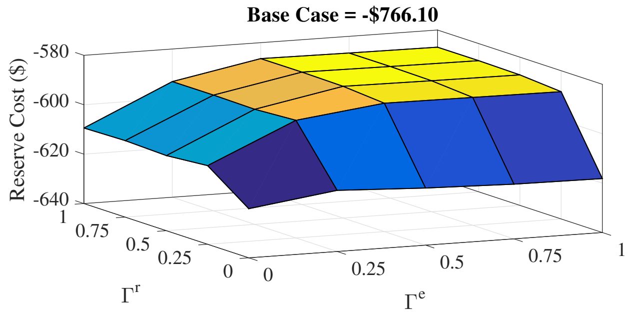


Fig. 7. Reserve cost for different risk aversion values

B. Robust model considering battery aging

This scenario considers the robust formulation and the battery aging incentives presented in Sections II-C and III respectively. The effect of different risk aversion values in the total cost for the load aggregator is studied. The results for the problem stated in (39) are analyzed and then are compared with those of the baseline.

The values for Γ^e and Γ^r represent the risk aversion for the load aggregator towards future energy and reserve prices respectively. Γ^e and Γ^r can take values in the range of $[0, 1]$. A value of 1 for both Γ^e and Γ^r describes a conservative scenario that expects the worst case value for each future market period in the horizon. On the other hand, a value of 0 for both Γ^e and Γ^r will describe an optimistic attitude assuming a perfect forecast.

V. Simulation Results

The proposed method is analyzed using real market prices for an entire month of April 2015. This allows a more representative view of the effect of different risk aversion values on the cost incurred by the load aggregator over an entire month.

The total energy procurement cost for the entire month is given in Fig. 6. It can be seen that the results obtained with the proposed method leads to savings of 4.0% in the best case, and 1.4% in the worst case. Energy procurement costs were better than those of the base case for all Γ^e and Γ^r values. Increasing the value of Γ^e, i.e. assuming higher energy price than the forecast, results in a steep reduction of the energy cost. On the other hand, increasing Γ^r results in higher energy costs. This is due to the increase in flexible load scheduled by the load aggregator.

Reserve costs for the load aggregator are given in Fig. 7. A negative value means that the load aggregator receives payments from the PSO for the provision of reserves. It

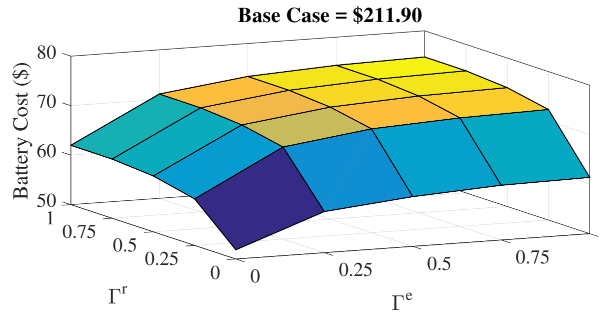
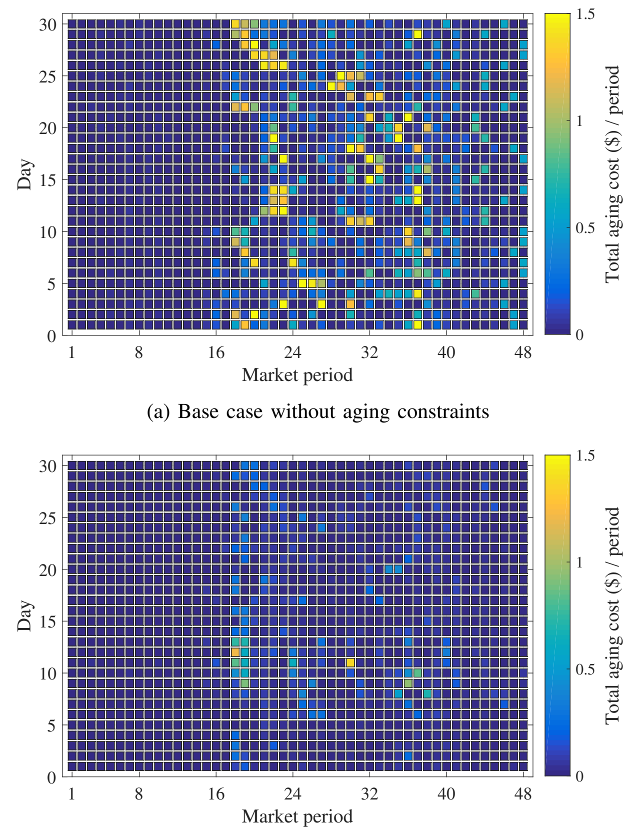


Fig. 8. Battery cost for different energy and reserve risk aversion values



(a) Base case without aging constraints

(b) $\Gamma^e = 0, \Gamma^r = 0$ with aging constraints

Fig. 9. Total aging cost per period comparison

can be seen that contrary to what happens with the energy cost, a reduction of incentives is observed using the robust formulation. These reductions represent a drop of 23.5% and 19.1% for the worst and best case respectively. It can be seen that the reserve incentives are generally lower (less negative) than those in the deterministic case. The main reason for this is due to a higher volatility observed in the reserve market. During these periods of higher volatility, the ARIMA model is unable to accurately forecast the jumps in the reserve price resulting in less incentive payments to the load aggregator.

Risk hedging by increasing Γ^e and Γ^r protects the aggregator from jumps in the energy and reserve prices. But at the same time, it makes less attractive for the load aggregator to schedule flexible loads for provision of reserve capacity.

The total battery cost is given in Fig. 8. Battery costs increase with higher values of Γ^e and Γ^r. This is due to

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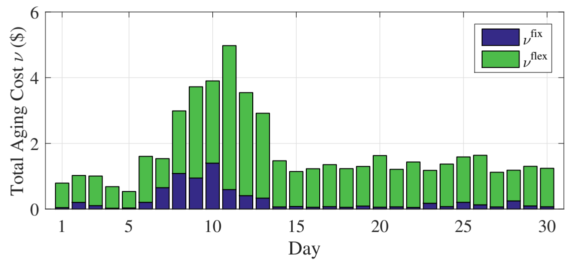

Fig. 10. Battery aging costs due to fixed and flexible charging schedules for $\Gamma^e = 0$ and $\Gamma^r = 0$

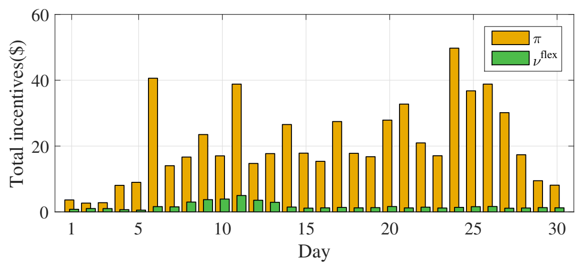

Fig. 11. Battery utilization and reserve incentive payments for $\Gamma^e = 0$ and $\Gamma^r = 0$

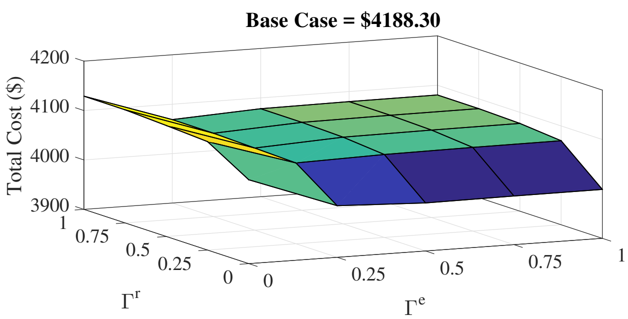

Fig. 12. Total cost for different energy and reserve risk aversion values

the higher battery aging resulting from an increase in the flexible loads scheduled. Aging costs are directly proportional to the capacity lost in the battery. Reduction in the battery aging cost represents not only savings for the EV drivers, at the same time extends the battery lifetime. Figure 9 shows a comparison of the aggregated aging costs for the carpark during each market period. Savings in the batery aging cost are achieved by reducing the C-rate of the EV and shifting the increased consumption which will result in increased battery degradation to other periods where the EV is also available.

A comparison between aging costs resulting from fixed and flexible charging operation is given in Fig. 10. The battery compensation payment and the total incentives for reserve provision are shown in Fig. 11. Part of the incentives obtained for provision of reserves is used to compensate EV drivers for the reduction in the battery lifetime due to provision of ancillary services.

Figure 12 shows the total cost for the load aggregator considering the combination of the energy procurement cost, reserve provision incentive and the battery utilization costs. A summary of the best and worst case for the proposed method is given in Table II. The proposed method performs better than

Table II
TOTAL SYSTEM COSTS

Scenario		Energy Cost $	Reserve Cost $	Battery Cost $	Total Cost $
Base Case		4742.5	-766.1	211.9	4188.3
Γ^e=0	Γ^r=0	4638.0	-620.1	51.9	4069.7
Γ^e=0	Γ^r=0.5	4672.9	-609.6	61.3	4124.6
Γ^e=0	Γ^r=1	4676.5	-609.4	62.0	4129.1
Γ^e=0.5	Γ^r=0	4554.0	-616.9	60.0	3997.2
Γ^e=0.5	Γ^r=0.5	4589.5	-586.7	72.6	4075.4
Γ^e=0.5	Γ^r=1	4591.2	-586.5	73.3	4078.1
Γ^e=1	Γ^r=0	4555.8	-618.2	61.4	3999.0
Γ^e=1	Γ^r=0.5	4590.8	-587.2	74.0	4077.6
Γ^e=1	Γ^r=1	4592.5	-586.9	74.7	4080.3

the deterministic case and can lead to savings of up to 4.6% when the risk aversion values are set to $\Gamma^e = 0.5$ and $\Gamma^r = 0$ respectively.

VI. CONCLUSIONS

This paper proposes a scheduling mechanism for an load aggregator for participation in the wholesale market under uncertain energy and reserve prices. Scheduling of flexible loads allows provision of ancillary services in the form of interruptible loads. In case of curtailment, the aggregator ensures that the curtailed capacity is re-scheduled in the future market periods while ensuring that EV constraints are not violated.

Uncertainties are modeled using a robust optimization framework. This allows the load aggregator to hedge against changes in prices that will result in increased cost without a big increase in computational complexity. It also allows EV drivers to hedge the risk due to increased battery aging under uncertain reserve prices. Different risk aversion attitudes by the load aggregator are investigated and their impact in the total cost is analyzed. The results show that load aggregators could benefit from a less risk averse attitude in the energy market but further improvements are required in the reserve price forecast model in order to increase the incentives obtained for the provision of ancillary services.

Payments to EV owners in the form of a battery utilization compensation scheme is devised. This compensation ensures EV drivers are paid for the battery aging resulting from participation as ancillary service providers. Simulations show that a 50% reduction in the total battery degradation costs is possible without increasing the total cost.

The proposed method has the advantage of being solved independently by each load aggregator. This setup ensures that local EV information is not broadcast to any higher level controller while reducing the problem complexity. A multi-carpark setup can be enabled by solving the problem for each load aggregator independently and providing a hierarchical market structure where aggregators exchange partial information and solve the higher level problem iteratively to prevent possible congestion in the distribution system.

Research areas to be considered in the future work include: (i) Study the effect of congestion in the total cost for multiple load aggregators; (ii) Improve the energy and reserve price forecast by modeling price jumps; and (iii) design a distributed algorithm for controlling multiple load aggregators managed by a single distribution grid operator.

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Dante F. Recalde Melo (S'12) received the B.S. and M.S. degrees in electrical engineering from the National Cheng-Kung University, Taiwan, in 2010 and 2012, respectively. Since 2012 he is working towards the Ph.D. degree at Nanyang Technological University, Singapore.

His research interest includes renewable energy sources integration, electric vehicles, and distribution system optimization.

Annette Trippe received her Dipl.-Wi.-Ing. (M.Sc.) in Industrial Engineering and Management from Karlsruhe Institute of Technology (KIT) in 2010. She is currently pursuing her PhD at Technische Universität München (TUM) at the Institute for Renewable and Sustainable Energy Systems.

Her research interest is intelligent charging of electric vehicles including power system and battery aging constraints.

Hoay Beng Gooi H. B. Gooi (SM95) received the B.S. degree in EE from National Taiwan University in 1978; the M.S. degree in EE from the University of New Brunswick in 1980; and the Ph.D. degree in EE from Ohio State University in 1983. From 1983 to 1985, he was an Assistant Professor with Lafayette College, Easton. From 1985 to 1991, he was a Senior Engineer with Empros (now Siemens), Minneapolis, where he was responsible for the design and testing coordination of domestic and international energy management system projects. In 1991, he joined the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, as a Senior Lecturer, where he has been an Associate Professor since 1999. He was the Deputy Head of Power Engineering Division during 2008-2014. He has been an Editor of IEEE Transactions on Power Systems since 2016. His current research interests include microgrid energy management systems, electricity markets, spinning reserve, energy efficiency, and renewable energy sources.

Tobias Massier received his diploma (M.Sc.) and his doctoral degree from Technische Universität München (TUM) in 2002 and 2010 respectively. He worked on the structural analysis of analog integrated circuits.

In 2013, he joined TUM CREATE, a joint project between Technische Universität München, Germany, and Nanyang Technological University, Singapore, as Principal Investigator. He is leading the research group "Electrification Suite and Test Lab which is working on integration of electric mobility into the power system and sustainable energy supply. His work includes defining new research areas and establishing collaborations with research institutes and industry.