Combination of Renewable Generation and Flexible Load Aggregation for Ancillary Services Provision

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***Abstract*—Liberalized markets provide opportunities for load aggregators to reduce their operating cost by participation in the wholesale electricity market. Reduction in operating cost result from shifting flexible loads based on the electricity price and also from incentives paid for ancillary service provision. Increased penetration of distributed renewable generation could help distribution system operators (DSO) reduce energy losses and increase network reliability. On the other hand, variability of renewable sources introduce additional challenges that need to be addressed in order to reduce their adverse effects on the power system. This work proposes an energy management system for aggregation of controllable loads in the distribution system. Local generation uncertainties are considered using model predictive control (MPC). The goal of the controller is to provide a schedule for the controllable loads while considering both local solar photovoltaic (PV) generation and provision of ancillary services. A case study based on the National Electricity Market of Singapore (NEMS) is presented to validate the proposed method.**

***Index Terms*—Energy Management System, Demand Response, Distributed Generation**

I. Introduction

In conventional power systems, demand forecasts are derived based on statistical data and ancillary services are procured to balance any mismatch between the forecasted and the actual value. Greenhouse gas emissions from conventional power generation and the possible effect of these gases on global warming result in government policies promoting the use of renewables. As a result, DSO face new challenges that require an estimation of both demand and generation.

Increased penetration of renewables and the uncertainty inherent to these resources usually result in additional requirements for both reserve and regulation. Conventional generators are unable to follow rapid changes in the demand and more expensive generation is required to restore the system frequency to the nominal value. Utilities and power network operators introduced demand response (DR) initiatives to increase the system flexibility [1], [2]. In these programs, consumers respond to system operator commands and receive incentive payments for changing their electricity usage.

Aggregation of multiple devices is required to participate in the wholesale electricity market and provide ancillary services. In tropical countries, heating, ventilation, and air conditioning (HVAC) represent a high portion of the commercial and residential electricity usage. HVAC systems in commercial buildings present a relatively high inertia and therefore are very suitable for participation in DR programs. Transportation electrification initiatives by many countries result in increased power demand on distribution level. Due to their limited range, electric vehicles (EVs) require multiple charging operations throughout the day. Also, EVs are parked during most of the day, which allows some flexibility to schedule the charging process based on the energy availability and price [3].

Provision of ancillary services using DR has been widely discussed in the literature. DR as spinning reserve for frequency restoration is considered in [4]. Authors in [5] propose performance measures for DR aggregation control service. Both [4] and [5] provide algorithms to control flexible loads but do not consider effects in the total cost for the system. Authors in [6] study price-based control of building HVAC systems for balancing energy costs. A model predictive controller is proposed to control the HVAC systems but other types of controllable consumers are not considered. Possible rewards for direct load control in reserve market is studied in [7]. Centralized and decentralized control methods for aggregation of loads are considered but details of how these individual loads are controlled are not given.

This paper proposes a model to aggregate flexible loads and renewable generation using a MPC based controller. Aggregation of multiple commercial buildings and a carpark is assumed. Local PV generation is considered at these buildings. Demand flexibility is provided by controlling the building HVAC systems and scheduling the chaging of the EVs in the carpark. Uncertainties on both the load and generation side are considered and an optimized schedule is proposed.

Real market data for the NEMS is used to evaluate opportunities of ancillary service provision by the aggregator. Scheduling of both EVs at the carpark and the building HVAC system is considered. A strategy to provide ancillary services is devised. Minimum local reserve provision due to PV generation is ensured and the remaining capacity is bid as interruptible load (IL). The simulation results analize the effect of this strategy in the aggregator operation cost.

Section II describes the models used for the carpark, building HVAC and local PV generation. Section III describe the centralized control strategy and the constraints used by the controller. Simulation results considering the centralized MPC controller are given in Section IV. Conclusions and future research are given in Section V.

II. System Description

A. EV model

The carpark model used in this paper is an extension of the one given in [3]. The carpark is assumed to be located in a non-residential area near the city center. The arrival-departure events are created using probabilistic modeling based on different driver profiles. The model is validated using real occupancy values for a carpark in Singapore [3].

The state space representation for each vehicle in the carpark is given by:

$$x_v^{k+1} = A_v x_v^k + B_v u_v^k + E_v \hat{d}_v^k \tag{1}$$

Where the state x_v^{k+1} represents the EVs battery state of charge (SOC) at the end of period k. Input vector u_v^k and disturbance vector $\hat{d}_v^k$ represent the power consumption and the disturbances during period k respectively.

The coefficients A_v, B_v, and E_v define the relationship between the inputs, state and disturbances and the state of the EV at the beginning of the next market period $k+1$. This paper assumes a charging efficiency η_{EV} of 0.9, no self-discharge and no disturbances. Coefficients are set to $A_v = 1$, $B_v = \eta_c$ and $E_v = 0$ respectively.

Generally, EVs are parked for extended periods during the day. This creates opportunities for carpark operators to schedule the charging process and minimize the charging cost. This work considers participation of the carpark as an ancillary service provider i.e. participation as ILs. EVs are regarded as flexible load if the scheduled charging operation could be curtailed and rescheduled based on the EV availability. Charging operations curtailments that will result in violation of the EV constraints are set as fixed loads.

Equation (1) becomes:

$$x_v^{k+1} = A_v x_v^k + B_v \left[u_v^k + r_v^k\right] + E_v \hat{d}_v^k \tag{2}$$

Where, r_v^k represents the flexible charging power for the EV during period k.

B. HVAC model

The building model is derived from the works in [8]–[10]. The HVAC air flow is controlled by a variable frequency drive. The thermal model of a zone is obtained by considering the heat flux between the walls and rooms [10]. The model is linearized using sequential quadratic programming. Zero-order hold is used to derive the discrete linear time invariant state space representation for each zone.

$$x_z^{k+1} = A_z x_z^k + B_z u_z^k + E_z \hat{d}_z^k \tag{3}$$

The state vector $x_z \in \mathbb{R}^{w+1}$ represent the temperature of each node in the zone i.e. w walls plus the zone temperature. The term u_z^k shows the total power consumption of the zone and $\hat{d}_z^k \in \mathbb{R}^{w+1}$ give the disturbances at each node. A simplified building model is created by aggregation of rooms with similar characteristics into a single zone where thermal coupling between rooms is not considered.

The building model is obtained by aggregating all zones. Each zone is controlled independently based on the state space representation given in (3). Variable frequency drives allow HVAC systems to dynamically control the air flow input into each zone. By introducing an additional term r_z^k, the total power consumption for each zone is then decoupled into fixed and variable load. The fixed load ensures that the temperature remains within the comfort zone of dwellers and the flexible load represent the power consumption that could be curtailed to provide ancillary services. Incentives are paid by the power system operator (PSO) for participation as IL. The payment is received based on the capacity provided for curtailment and the reserve price [11].

Equation (3) is rewritten as:

$$x_z^{k+1} = A_z x_z^k + B_z \left[u_z^k + r_z^k\right] + E_z \hat{d}_z^k \tag{4}$$

C. Local PV generation model

Local renewable generation could help buildings reduce their carbon footprint and may also help reduce the total cost paid for electricity. Uncertainty related to intermittent renewable generation usually results in increased reserve requirements for the PSO. In this work, the solar PV array is modeled as a combination of series and parallel connected PV modules. Individual PV modules are operated in maximum power point tracking (MPPT) mode to maximize the power output.

Irradiance data from a meteorological station in Singapore is used and gaussian noise ε is added to simulate uncertainties in the forecast. For each period k the irradiance forecast is obtained by $I_f^k = I_r^k + \varepsilon$. Where ε is assumed to be normally distributed with parameters $N(0,\alpha\sqrt{I_r^k})$. The term $\alpha \in [0,1]$ models the forecast error for the actual irradiance value I_r^k. Irradiance values are converted to power output assuming MPPT operation of each PV module.

In practice, intermittent generation sources are considered as non-controllable and are not required to submit half-hourly offers in the energy market [12]. The uncertainty is managed by the PSO and is aggregated over the entire system. The non-controllable nature of these resources results in increased regulation and reserve requirements. This paper proposes a method to schedule the PV output and provide reserve locally by means of flexible loads.

III. Centralized MPC controller

This work assumes a centralized control system and perfect two-way communication between the central controller, building management system and the carpark operator. An overview of the aggregator is given in Fig. 1. The centralized controller schedules EVs charging and HVAC operation based

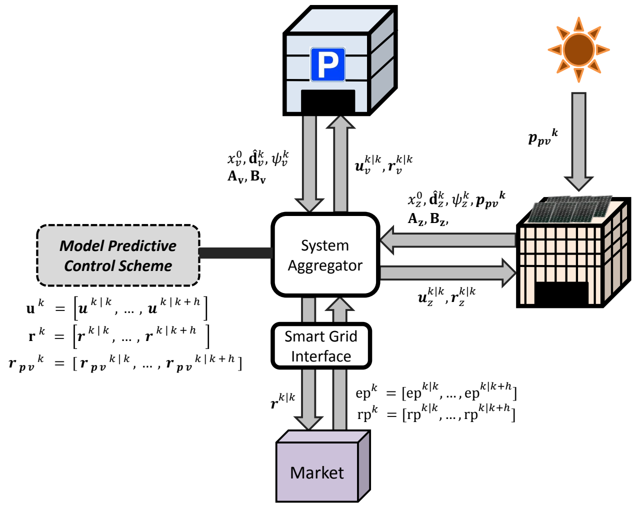


Fig. 1. Carpark and building aggregator considering MPC control scheme

on the energy and reserve prices. This paper considers bids in the reserve market as IL [11]. Flexible loads that could be rescheduled (EVs) or curtailed without compromising the dwellers comfort (HVAC) are bid as interruptible loads. Uncertainty of the local PV generation is considered assuming a PV forecast and a given reserve requirement for each market period k.

The arrival-departure of EVs is modeled assuming 10% penetration of EVs [3]. This results in 200 unique parking events where arrival departures times are known in advance. A total of 450 TS-S425 [13] monocrystalline PV modules are considered for installation at the building rooftops. This comprises a rated capacity of about 190 kWp in total. A total of 375 rooms distributed in 15 different zones are considered.

A. Centralized aggregator model

The state space matrices of the aggregated system model is obtained by diagonal addition of the individual system blocks. For a total of j subsystems ($j = n + m$ with n EVs and m zones). System matrices are given by: $A = diag(A_v^1, .., A_v^n, A_z^1, ..., A_z^m)$, the same procedure is followed to obtain matrices $B = diag(B_v^1, .., B_v^n, B_z^1, ..., B_z^m)$ and $E = diag(E_v^1, .., E_v^n, E_z^1, ..., E_z^m)$.

States for each subsystem are aggregated to obtain the system state $x = [x_v^1, .., x_v^n, x_z^1, ..., x_z^m]'$. Inputs and disturbances are aggregated in the same way. Fixed and flexible loads inputs are aggregated as $u = [u_v^1, .., u_v^n, u_z^1, ..., u_z^m]'$ and $r = [r_v^1, .., r_v^n, r_z^1, ..., r_z^m]'$ respectively. The system disturbance vector is given by $\hat{d} = [\hat{d}_v^1, .., \hat{d}_v^n, \hat{d}_z^1, ..., \hat{d}_z^m]'$.

The state space representation of the aggregated system for a given an initial state x^0 for a time horizon of h periods is given by:

$$\mathbf{x}^k = \mathbf{A}x^0 + \mathbf{B}\left[\mathbf{u}^k + \mathbf{r}^k\right] + \mathbf{E}\hat{\mathbf{d}}^k \tag{5}$$

Where the predicted states for each period k within the prediction horizon H and for a total of h periods is given by $\mathbf{x}^k = \left[x^{k|k}, x^{k|k+1} \dots, x^{k|k+h}\right]'$. Superscript "$k|k+1$" is used to denote the prediction state at time k for time $k+1$. Predicted state vectors $\mathbf{u}_k$, $\mathbf{r}_k$ and $\hat{\mathbf{d}}_k$ are represented in similar way. Matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{E}$ are of appropriate dimensions.

PV output power forecast $\mathbf{p}_{\mathbf{pv}}^k$ for each period k is given as $\mathbf{p_{pv}}^k = [p_{pv}^{k|k}, p_{pv}^{k|k+1}, ..., p_{pv}^{k|k+h}]'$. Local PV reserve requirements $\mathbf{r}_{\mathbf{pv}}^k$ are given based on the maximum forecast error α for each period k .

$$\mathbf{r_{pv}}^k = \alpha[p_{pv}^{k|k}, p_{pv}^{k|k+1}, ..., p_{pv}^{k|k+h}]' \tag{6}$$

Availability of each EV and HVAC zone during period k is given as a binary variable $\psi^{k,i}$. Values for $\psi^{k,i}$ are set to "1" when the subsystem i is available during period k and to "0" otherwise.

Total cost for the aggregator considering local PV generation, carpark and building consumption for each period k is given by:

$$\boldsymbol{J_c^k} = \Delta t \cdot ep^k \cdot \left[\parallel \mathbf{u}^k + \mathbf{r}^k \parallel - \mathbf{p}_{\mathbf{pv}}^k\right] \tag{7}$$

The total system incentive for ancillary service provision in the form of IL during period k is given by:

$$\boldsymbol{J_r^k} = \Delta t \cdot rp^k \cdot \left[\parallel \mathbf{r}^k \parallel - \mathbf{r}_{\mathbf{pv}}^k\right] \tag{8}$$

The aggregator manages the schedule of each EV and building zone based on the following MPC control problem:

$$\min_{\mathbf{u}^k, -\mathbf{r}^k} \sum_{k=1}^{h} \boldsymbol{J_c^k} - \boldsymbol{J_r^k} \tag{9a}$$

subject to:

$$\mathbf{x}_c^{k+1} = \mathbf{A}\,\mathbf{x}_c^k + \mathbf{B}\,\mathbf{u}^k + \mathbf{E}\,\hat{\mathbf{d}}^k \tag{9b}$$

$$x_{min}^k \leq \mathbf{x}_c^k \leq x_{max}^k, \quad \forall\, k \in H \tag{9c}$$

$$\mathbf{x}_{nc}^{k+1} = \mathbf{A}\,\mathbf{x}_{nc}^k + \mathbf{B}\,\left[\mathbf{u}^k + \mathbf{r}^k\right] + \mathbf{E}\,\hat{\mathbf{d}}^k \tag{9d}$$

$$x_{min}^k \leq \mathbf{x}_{nc}^k \leq x_{max}^k, \quad \forall\, k \in H \tag{9e}$$

$$\mathbf{r}^k = \textstyle\sum_{t=k+1}^{h} \mathbf{c}^{k,t} \circ \psi^t \quad \forall\, k \in H \tag{9f}$$

$$u_{min}^k \leq \mathbf{u}^k + \mathbf{r}^k + \mathbf{c}^{t,k} \leq u_{max}^k \circ \psi^k, \quad \forall\, k, t \in H \tag{9g}$$

$$\parallel \mathbf{r}^k \parallel \geq \mathbf{r}_{\mathbf{pv}}^k, \quad \forall\, k \in H \tag{9h}$$

$$\mathbf{u}^k, \mathbf{r}^k, \mathbf{r}_{\mathbf{pv}}^k \geq \mathbf{0} \quad \forall\, k \in H \tag{9i}$$

The objective of the MPC controller is to obtain an optimal fix and flexible loads schedule considering minimization of the total energy cost $\boldsymbol{J_c^k}$ and maximization of the incentives obtained for ancillary service provision $\boldsymbol{J_r^k}$.

Assignment of fixed and flexible loads is considered by calculating two possible trajectories for each period k. First, (9b) calculates the trajectory for a given input power u^k that will result in minimization of the total cost of the system considering the zone temperature constraints and the minimum required charge for EVs given in (9c).

Equation (9d) shows the trajectory considering both fixed and flexible loads, this is done assuming that that r_z^k could be curtailed without compromising dwellers comfort and the final charge requirements of EV owners given in (9e).

Provision of reserve may result in curtailment of loads when the system underfrequency relay is triggered. Due to the

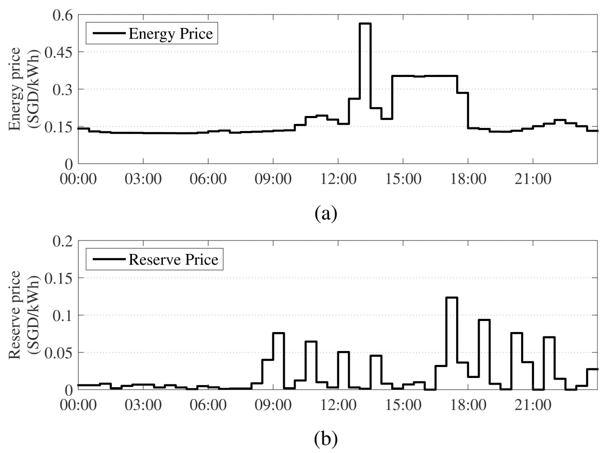


Fig. 2. NEMS energy (a) and reserve (b) price

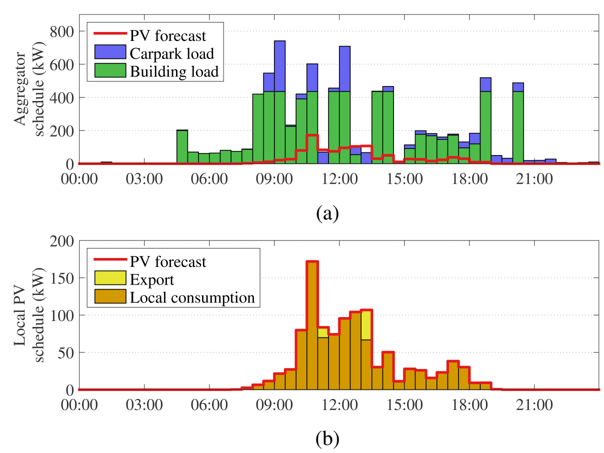


Fig. 3. Aggregator consumption and local PV generation schedule

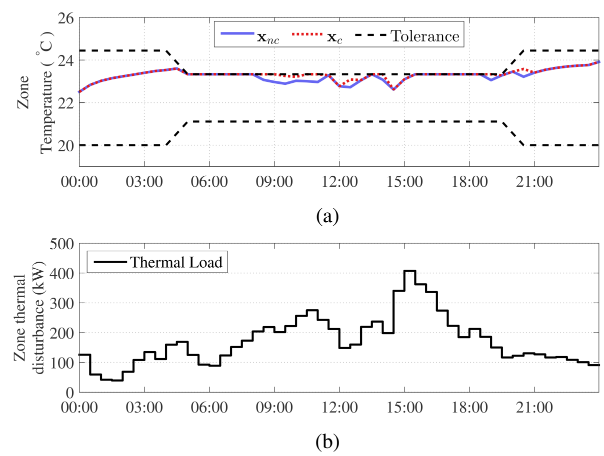


Fig. 4. Zone temperature (a) and thermal disturbances (b)

high thermal inertia and the fact that the comfort of dwellers is already ensured by u^k, curtailment of the flexible HVAC load does not require re-scheduling to future periods. On the other hand, curtailment will result in lower EV SOC before departure. Corrective action need to be implemented and the curtailed flexible load needs to be rescheduled. Equation (9f) shows the auxiliary variable $\mathbf{c}^{k,t}$ that is introduced to ensure that in case of curtailment of flexible loads bid as reserve during period k could be rescheduled to a future period t.

Equation (9g) ensures that the inputs for each period k will be within the maximum and minimum system limits. Rescheduled capacity from period t to current period k is also considered.

Ancillary services are provided in the form of IL. Reserve capacity resulting from the scheduling of flexible loads could be considered both for system and local reserve. Equation (9h) ensures that the increased system reserve requirements resulting from the installation of PV generation is supplied locally.

IV. Simulation Results

The centralized MPC controller introduced in Section III is tested using market data from the NEMS. Simulation results present the effect of local reserve provision on the scheduling of both the EVs and HVAC systems. The optimal schedule for fixed and flexible loads is obtained solving the linear problem in (9a) using YALMIP [14] and CPLEX [15] solver.

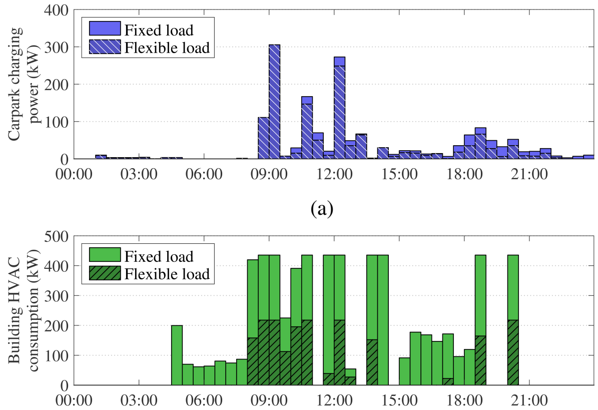
The schedule is obtained by running the optimization problem for a horizon of 48 half-hourly periods. The optimal schedule for current period k is implemented and the optimization parameters are updated. Flexible loads are bid as IL after the local PV reserve requirements are fulfilled. This is repeated before the beginning of each market period. The MPC controller ensures a feasible solution over the entire prediction horizon considering all state, input and local reserve constraints.

A. Aggregator scheduling considering local reserve

The simulation is run considering provision of local reserve to cater for a 60% error of the total PV output i.e. $\alpha = 0.6$. Figure 3(a) shows the total carpark and building load considering the energy and reserve prices for 48 half-hour market periods given in Fig. 2(a) and 2(b). Figure 3(b) shows the proportion of PV generation consumed locally and the export to the grid. It can be seen that consumption is minimized and export of local generation is maximized during high priced periods.

Figure 4(a) shows the zone temperatures for both curtailment and non-curtailment of flexible loads considering the zonal thermal load given in Fig. 4(b). It can be seen that the optimal schedule for both trajectories ensures the zone temperature to be within the upper and lower limits.

Schedule for fixed and flexible loads for the carpark and the building HVAC system are given in Fig. 5(a) and 5(b) respectively. It can be seen that in general EV are more flexible than HVAC systems. EVs are scheduled such that they benefit not only for charging during low priced periods but also during periods with high reserve prices. On the other hand, the main reason for lower flexible load scheduling for HVAC is that the trajectory that minimizes the operating cost is very close to the upper temperature limit. The HVAC system will only consume more energy and deviate from this trajectory when



(a)

(b)

Fig. 5. Total carpark (a) and building (b) fixed and flexible load schedule

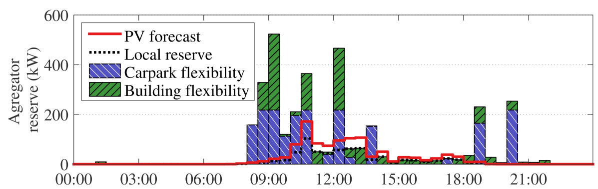


Fig. 6. Local PV forecast and reserve provision by load aggregator

if either the energy price for the subsequent periods is high or revenue for participation as IL is high.

Figure 6 show the flexible load that is schedule to provide ancillary services in the form of IL. The load aggregator gets compensation for providing this flexibility. The capacity bid as reserve is curtailed automatically when the system frequency reaches the minimum threshold. The MPC controller ensures curtailment of these loads will not result in violations of EVs charge requirements and dwellers comfort.

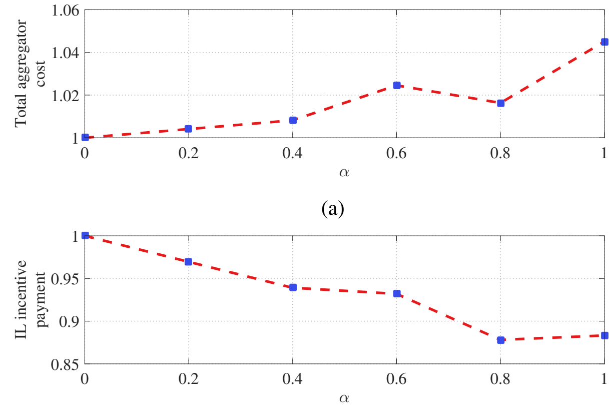
B. Effect of local reserve provision on aggregator operation cost

Figures 7(a) and 7(b) show the effect of different local reserve requirements in the total system cost and the incentives received for participation as IL. The simulation is run considering the same inputs as in Section IV-A. The base case is run considering $\alpha = 0$ i.e. relaxation of constraint (9h). Values of α are then increased to consider local reserves for up to 100% of the total PV forecast and results are normalized with respect to the base case. An increase in the total aggregator cost is observed, this is due to the reduction in the incentives obtained by the aggregator and also to the increase in consumption during high priced periods.

Results for the proposed system show that provision of local reserves to support loss of up to 40% of the total PV generation will result in an increase of about 1% in the total aggregator cost.

V. Conclusion and Outlook

This paper suggests a method to minimize the total operation cost of an aggregator consisting of a combination of



(a)

(b)

Fig. 7. Normalized aggregator cost (a) and incentives (b) considering different local reserve requirements

EVs, building HVAC system and local renewable generation. Participation in the wholesale electricity market is considered and an MPC scheme is devised. A consumption schedule is given to minimize the total cost of the system. Fixed and flexible loads are scheduled based on the energy and reserve price, flexible loads are considered for ancillary service provision.

The aggregator receive incentives for bidding reserve capacity as IL. Possible mismatch between the forecast and the actual renewable generation was considered and the effect of local reserve provision in the total aggregator cost was studied. Simulation results show that provision of local reserves to support loss of up to 40% of the total PV generation will result in an increase of about 1% in the total aggregator cost.

Future work will focus in a robust formulation of the MPC scheme considering load uncertainties and the cost of reserve provision in reference to user preferences.

Acknowledgments

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