Model Predictive Control Scheme for investigating Demand Side Flexibility in Singapore

Sarmad Hanif[1,3*], Dante Fernando Recalde Melo[1†], Mehdi Maasoumy[4‖],
Tobias Massier[1‡], Thomas Hamacher[2§], Thomas Reindl[3¶]
[1]TUM CREATE Limited, Singapore 138602
[2]Technical University of Munich (TUM), Garching 85748, Germany
[3]Solar Energy Research Institute of Singapore (SERIS), National University of Singapore (NUS), Singapore 117574
[4]Department of Electrical Engineering and Computer Science, University of California, Berkeley, CA 94720, USA
[*]sarmad.hanif@tum-create.edu.sg, [†]e120025@e.ntu.edu.sg, [‖]maasoumy@eecs.berkeley.edu,
[‡]tobias.massier@tum-create.edu.sg,
[§]thomas.hamacher@tum.de, [¶]thomas.reindl@nus.edu.sg

***Abstract*—Recently, power systems have experienced various changes, the most important one being the increase in the share of highly variable renewable energy supply (RES). To counteract the variability of RES, provision of flexibility from the demand side seems to be a viable option. In this paper, the heating, ventilation and air conditioning (HVAC) system, mostly installed in medium to large sized office buildings, is selected to provide demand side flexibility. A model predictive control (MPC) scheme in a receding horizon environment is deployed to provide an economic operation of the building, while respecting comfort constraints of dwellers. Furthermore, robustness is introduced in the MPC scheme to participate in both the energy and reserve market. Simulations are performed to demonstrate the performance of the developed controller under various price signals. In doing so, the controller is also evaluated with respect to its sensitivity towards economical and technical constraints. The National Electricity Market of Singapore (NEMS) is used as a case study and the most important parameters governing the challenges for integrating demand side flexibility in the grid are pointed out.**

***Index Terms*—Demand-side Management (DSM), Energy Market, Heating Ventilation Air-Conditioning (HVAC), Model Predictive Control (MPC), Smart Grid.**

I. Introduction

Due to the introduction of large shares of highly variable and uncertain RES, power systems have experienced issues related to stability, reliability, and high cost of operation. As a result, the importance of achieving controllability on both the supply and demand side of the grid is now more than ever. This is mainly because large scale storage technologies are still very expensive. Regarding the demand side, various utilities have already launched demand response (DR) programs, aiming to improve both the operational and economical aspects of the grid [1], [2]. For the case of Singapore, the Energy Market Authority (EMA) is introducing a DR program in 2015 [3]. This program is intended to supplement the already implemented Interruptible Load (IL) program to achieve lower cost of grid operations [4]. Due to Singapore's climate, energy intensive space cooling equipments are used in almost every building. Space cooling, along with the thermal inertia of buildings, provides an inherent flexibility in the consumption of electricity. Hence, exploiting this inherent flexibility of the HVAC system could in principle present us with a great potential to improve the overall power system cost and operation. This paper discusses operation of the HVAC system as a potential flexible demand side resource of the grid under realistic market settings.

In the past, significant amount of work has been done for controlling energy consumption of buildings. Recent contributions regarding price-based and direct load control of buildings is reported in [5]. The applicability of MPC to control building energy consumption is implemented in [6], [7]. A contractual framework is developed for providing supply following demand for the grid in [8]. Particularly for the case of HVACs, the minimization of peak and total energy is demonstrated in [9]. Some applications of controlling thermal electric loads for the provision of ancillary services and reduction of the balancing groups' scheduled deviations are given in [10]–[12]. As a realistic case scenario of DR, the participation in Singaporean DR and IL program, using an electric vehicle car-park is reported in [13].

According to the knowledge of authors, the aforementioned papers either deal with the detailed modeling of HVACs and buildings, or with the application of real market price signals without the consideration of market dependent physical load models. Furthermore, the cost and operational dependency of the developed control scheme under reserve market is not explored in detail.

Hence, the contribution of this paper is threefold. First, it develops an extended model for the HVAC system of a building considering the intended demand side service. An already developed physical based discrete-time linear time invariant (LTI) state space model is extended to include participation in the reserve market. Second, the paper demonstrates the ability of the developed model using an MPC control scheme to participate in NEMS. And third, the evaluation of total cost and demand flexibility is investigated under realistic market settings with both the reserve and energy price signals.

The remainder of the paper is organized as follows. Section II explains the extension of market oriented HVAC and building model, along with the market settings used for developing

MPC scheme. An MPC control scheme is designed in section III. In section IV simulation results are evaluated. Section V concludes this paper with comments on adequacy of MPC scheme for providing flexible demand. And also, comments are made on the need for providing higher incentives to the load operators, for the successful implementation of DR programs in power system.

II. Modeling and Market Environment

A. Modeling Framework

The HVAC system considered in this paper is equipped with variable air volume (VAV) functionality. This provides us the opportunity to modulate the variable frequency drive up or down, to meet the energy demand of a building. The cooling/heating demand is estimated based on a thermal dynamic model given in [14]. The validation of model is presented in [15]. Estimation of the external and internal loads of one room is reported in [9]. The model describes the relationship between the room temperature and the air flow input from HVAC. The thermal dynamic model of a room is considered as a network of $i+j$ nodes. Where i represents a wall and j represents a room. As from [14], [15], differential equations governing the temperature evolution for both walls and rooms are given as:

$$\frac{dT_{wi}}{dt} = \frac{1}{C_{wi}}\left[\sum_{j\in N_{wi}} \frac{T_j - T_{wi}}{R_{ij}} + r_i\alpha_i A_i q''_{radi}\right], \tag{1a}$$

$$\frac{dT_{ri}}{dt} = \frac{1}{C_{ri}}\left[\sum_{j\ni N_{ri}} \frac{T_j - T_{ri}}{R_{ij}} + \dot{m}_{ri}c_p\left(T_{si}-T_{ri}\right) + w_i\tau_{wi}A_{wi}q''_{radi} + \dot{q}_{int}\right], \tag{1b}$$

For each wall i, T_{wi}, C_{wi}, α_i, A_i and c_p represents the temperature, thermal capacitance, absorptivity factor, area, and specific heat capacity, respectively. N_{wi} is the set of all neighboring nodes to w_i. r_i is equal to 0 for internal, and 1 for peripheral walls. Similarly for the i-th room, T_{ri}, C_{ri} and $\dot{m}_{ri}$ represent its temperature, thermal capacitance and air mass flow rate, respectively. The transmittance and area of the i-th window is denoted as τ_{wi} and A_i. q''_{radi} is the radiative heat flux density experienced by room i, and $\dot{q}_{int}$ is the internal heat generated due to equipments, furniture and occupancy. w_i represents windows on the surrounding walls of the room. For further insight into the model, and its parameters, readers are directed to [9], [14], [15]. The resulting nonlinear state space equation for one zone, from equation (1) is:

$$\dot{x}_t = f\left(x_t, u_t, \hat{d}_t\right) \tag{2}$$

Where $x_t \in \mathbb{R}^n$ is a state vector of size $n = i + j$. $u_t \in \mathbb{R}^j$ is the input vector representing the HVAC's mass air flow rate. As evident from equation (1) and (2), the system at hand is non-linear. Linear models are desirable for the purpose of designing a controller. To obtain a linearized model, a method based on Sequential Quadratic Programming (SQP) is used and then Zero-order hold is performed to discretize the resultant linear model (details in [14]). The resultant discrete time LTI state space model of the system is:

$$x_{k+1} = Ax_k + Bu_k + E\hat{d}_k \tag{3}$$

To calculate the power consumed by the HVAC system for all zones at time step k, the power consumption of the HVAC's fan, cooling coil, and heating coil, P_{f,u_k}, P_{c,u_k} and P_{h,u_k}, respectively are considered as:

$$P_{f,u_k} = \sum_{zones} \frac{u_k\Delta P}{\rho\eta_f}, \tag{4a}$$

$$P_{c,u_k} = \sum_{zones} \frac{u_k c_p\left(T_{sp}-T_c\right)}{\eta_c}, \tag{4b}$$

$$P_{h,u_k} = \sum_{zones} \frac{u_k c_p\left(T_h-T_{sp}\right)}{\eta_h}, \tag{4c}$$

Where T_h, T_c and T_{sp} are the temperature of the heating coil, cooling coil, and set point of the zone, respectively. ΔP is the pressure difference across the fan, ρ is air density, and η_f, η_c, and η_h represents the efficiency of the fan, cooling, and heating respectively. The cost of consumption $K(u_k)$ for the electricity price c_k at time step k, and sample time Δt as a function of input u_k is calculated as:

$$K(u_k) = \Delta t\ c_k\left(P_{f,u_k} + P_{c,u_k} + P_{h,u_k}\right) \tag{5}$$

B. Model Extension

To align the model with our objectives, two modifications are performed. First, a building model is created by augmenting single zone thermal network models. To avoid unnecessary complication – and also the focus of this paper is to develop a model for the purpose of designing a control strategy – thermal coupling of adjacent rooms is not considered in this model. The building model from the previous developed zones is given as:

$$x^a_{k+1} = A_d x^a_k + B_d u^a_k + E_d\hat{d}^a_k \tag{6}$$

Where $x^a_{k+1} = \left[x^a_{1,k+1}\ldots x^a_{z,k+1}\right]' \in \mathbb{R}^{z(n)}$ represents temperature of all n states and z zones. Similarly, for zones z, vectors $u^a_k \in \mathbb{R}^{z(j)}$ and $\hat{d}^a_k \in \mathbb{R}^{n_d(n)}$ represent inputs and disturbances for j inputs, and n_d disturbances. The coefficient matrices are subjected to block diagonalizing $A_d = diag\left(A_1\ldots A_z\right)$. Matrices B_d, C_d, E_d are of the appropriate sizes. Since we are considering the whole multi-zone model as a single block – and also to avoid unnecessary increase of variables – from now onwards we use state vectors and coefficient matrices without a and d super and subscript, respectively.

The other extension to the original model is performed based on the idea suggested in [10]. To incorporate the effect of provision of reserves from a building, we have extended the state space model of equation (6), as:

$$x_{k+1} = Ax_k + Bu_k + E\hat{d}_k + B_r r_k \tag{7}$$

Where x_{k+1} represents the temperature of all the states at step $k+1$ with respect to the consideration of availability of reserves $r_k \in \mathbb{R}^{z(j)}$. At each time step k, the matrix $B_r \in \mathbb{R}^{z(n)\times z(j)}$ translates the effect of the extra power in the form of reserves r_k on to the temperature of zones. Matrix B_r can be obtained from operation HB. Where matrix $H \in \mathbb{R}^{z(n)\times z(n)}$ contains diagonal entries of 0 or 1. And it is used to indicate the participation of zones for reserve provision. Significance of including vector r_k at each time step k quantifies the increase in mass air flow of HVAC, necessary to meet the requirement of reserve provision. Note that in equation (7), the extension is only valid for two scenarios i.e. curtailment or not-curtailment of the HVAC's load. Similar to equation (5), the cost $K(r_k)$ of allocating reserve r_k for the reserve price of b_k at time step k is calculated by:

$$K(r_k) = \Delta t\ b_k \left(P_{f,r_k} + P_{c,r_k} + P_{h,r_k}\right) \tag{8}$$

The modeled system of equation (7) is used to predict the future states of the system as:

$$\mathbf{x}_k = \mathbf{A}x_0 + \mathbf{B}\mathbf{u}_k + \mathbf{E}\hat{\mathbf{d}}_k + \mathbf{B}_r\mathbf{r}_k \tag{9}$$

Where $\mathbf{x}_k = \left[x_{k|k}, x_{k|k+1}\dots, x_{k|k+N}\right]' \in \mathbb{R}^{z\times n(N+1)}$ represents the predicted states at time step k along a prediction horizon N. The subscript "$k|k+1$" is used to denote the prediction state at time k for time $k+1$. Similar explanation is valid for other predicted state vectors $\mathbf{u}_k \in \mathbb{R}^{z\times j(N)}$, $\hat{\mathbf{d}}_k \in \mathbb{R}^{z\times n_d(N)}$, and $\mathbf{r}_k \in \mathbb{R}^{z\times n_d(N)}$. The matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{B}_r$, and $\mathbf{E}$ are of appropriate dimensions.

C. Market Environment

In the power system, the term *reserves* is the capacity allocated to deal with the case of generation or load dispatch error. Once the reserves are activated, control procedures in three time activation steps are used to bring the state of the grid to normal. In this paper, as an application of demand flexibility, the market framework of Singapore is considered. In Singapore, the IL program was introduced in 2006 to promote competition in the NEMS. Through this program, consumers can participate in the reserve market by bidding their load and its corresponding capacity as a reserve. If called upon, the load is curtailed, and the consumer is paid based on the reserve price [4]. Hence, the structure of remuneration is based only on availability. A DR program in Singapore is going to be implemented in 2015 [16]. Contestable consumers are able to change their usage in response to real time price signal. To bid into the market, consumer has to bid the total load, the period of participation, and the proposed energy curtailment. The consumer receives an incentive based on the reduction in the overall price of the market [16]. Singapore has a real time competitive market of 30 minutes duration. So, in order to participate in the reserve market, load providers need to ensure the availability of a constant power level for an entire 30 minutes [16]. As a liberalized market, for the participation in the DR program, a load facility can only bid without the possibility of estimating its exact revenue. As it will be shown later, one can only maximize the profit of underlying consumers, which is highly dependent on the price of electricity experienced by users.

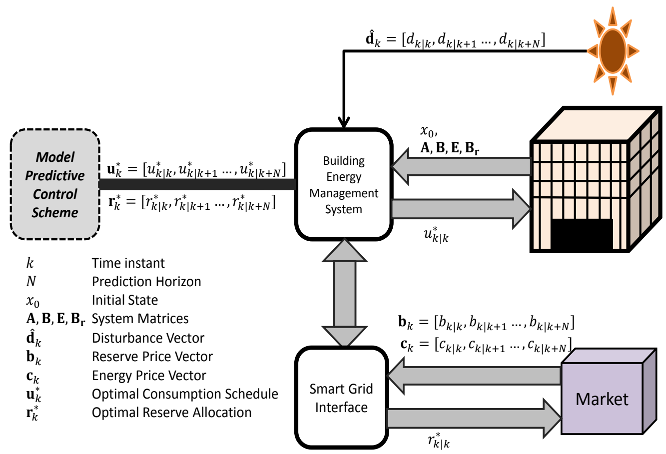

Fig. 1. Experimental set-up of the interaction of MPC control scheme with building and energy market.

III. Controller Design

Figure 1 provides the description of the experimental setup used for this paper. We have assumed a perfect two way communication channel between the smart grid interface (SGI) and the Building Energy Management System (BEMS). At each time step k and prediction horizon N, the SGI communicates forecast of reserves and energy prices to the BEMS. The BEMS, based on the developed models predicts N states, user constraints and disturbances of the building. The prediction along with the current state is provided as an input to the MPC scheme to obtain the consumption and reserve schedule sequence of HVAC for the entire horizon N. From the whole vector, the first value is taken as an optimal consumption and reserve allocation for HVAC. The whole procedure is repeated then for $k+1$ time instant. The MPC scheme shown in figure 1, for each time step k is formulated in equation (10). For the entire prediction horizon N and at each time step k, the objective function is solved for an optimal input $\mathbf{u}^*_k$ and a reserve sequence $\mathbf{r}^*_k$. In this context, optimality is measured in terms of minimization of the total cost of consumption and maximization of total revenue of reserves. The optimization function is subjected to system constraints to make sure of the comfort of users. At each time step, two state trajectories $\mathbf{x}_{NC_{k+1}}$ and $\mathbf{x}_{C_{k+1}}$ are calculated, accounting for both the not curtailed and the curtailed scenario, respectively. The difference between two trajectories is the inclusion of reserve vector $\mathbf{r}_k$ for calculating the worst case scenario of curtailment of power. By adopting this procedure, the MPC scheme is made robust in a sense that the input power necessary to allocate reserves is scheduled, while satisfying comfort constraints. The slack variable $\boldsymbol{\epsilon}_k$ in the objective function is implemented for guaranteeing feasibility of the solution by softening the constraints on upper $\mathbf{x}_k^+$ and lower limits $\mathbf{x}_k^-$ of both scenarios. ρ is used for penalizing the slack variable. $\mathbf{u}_k^+$, $\mathbf{u}_k^-$ imposes the optimal input and reserve vectors to stay within actuator limits of HVAC.

$$\min_{\mathbf{u}_k^*, -\mathbf{r}_k^*} \mathbf{K}\left(\mathbf{u}_k\right) + \mathbf{K}\left(-\mathbf{r}_k\right) + \rho \boldsymbol{\epsilon}_k$$

subject to

$$\begin{aligned}
&\mathbf{x}_{k+1}^{C} = \mathbf{A}\mathbf{x}_k^{C} + \mathbf{B}\mathbf{u}_k + \mathbf{E}\hat{\mathbf{d}}_k \\
&\mathbf{x}_{k+1}^{NC} = \mathbf{A}\mathbf{x}_k^{NC} + \mathbf{B}\mathbf{u}_k + \mathbf{E}\hat{\mathbf{d}}_k + \mathbf{B}_r\mathbf{r}_k \\
&\mathbf{x}_k^- - \boldsymbol{\epsilon}_k \leq \mathbf{x}_k^{C} \leq \mathbf{x}_k^+ + \boldsymbol{\epsilon}_k \\
&\mathbf{x}_k^- - \boldsymbol{\epsilon}_k \leq \mathbf{x}_k^{NC} \leq \mathbf{x}_k^+ + \boldsymbol{\epsilon}_k \\
&\mathbf{u}_k^- - \mathbf{r}_k \leq \mathbf{u}_k \leq \mathbf{u}_k^+ - \mathbf{r}_k \\
&\begin{bmatrix} \mathbf{u}_k \\ \mathbf{r}_k \\ \mathbf{u}_k - \mathbf{r}_k \\ \boldsymbol{\epsilon}_k \end{bmatrix} \geq \mathbf{0}
\end{aligned} \tag{10}$$

The developed MPC scheme is designed to synchronize the time-scale of the intended ancillary service of the grid. Due to the market framework of Singapore, the allocation of reserve as an interruptible load is done in real-time. As a result, the MPC scheme can be considered as one of the best candidates, as it takes the leverage of rolling the prediction horizon with the real time for deciding the optimal consumption schedule. And in doing so, it guarantees feasibility of the system for the whole prediction horizon. Note that, equation (10) is essentially a linear program, and numerous solvers exist which can solve this class of problems very efficiently. For our paper, we have implemented the MPC scheme using YALMIP [17] and CPLEX [18].

IV. Simulation Results

To evaluate the performance of the developed controller, two cases are simulated:

Case 1: Without consideration of participation in the reserve market

Case 2: With consideration of participation in the reserve market

Both cases are simulated with the assumption of perfect knowledge of energy and reserve prices, and disturbances. Time step of 30 minutes is chosen to coincide with the frequency of real time price signal from NEMS. The prediction horizon of 1 day (48 periods) is chosen. In principle, a longer prediction horizon provides more stability to the MPC controller. But for our simulations, a prediction horizon larger than 1 day shows very little improvement in the cost, but increases computational expenses of the MPC scheme tremendously. So, a prediction horizon of 1 day seems a good compromise.

A. Scheduling Evaluation

Minimizing the overall cost of operation is the main task of the developed controller. To compare the effectiveness of the developed controller, same time periods are adopted for simulating both cases. Figure 2 presents results from the simulation of case 1. Figure 2(a) shows the state of the temperature of one of the zones of the building. It can be seen that the temperature is kept within the allowed tolerance, ensuring comfort constraints of dwellers. The MPC controller avoids the high price periods – which occur normally around mid-day – by consuming more energy in low price periods. However, due to high penalty for violating temperature tolerance, the controller can not completely avoid high price periods. As a result, it ends up consuming some energy during those time periods. For case 2, the simulation is repeated for the same time period, but now with consideration of the reserve price. As shown in figure 3, the change in temperature in this case is still kept within the allowed tolerance for both scenarios of scheduling. Both the curtailed and not curtailed scenarios are shown to respect state constraints. As expected, the scheduling of reserves is performed during high reserve price periods.

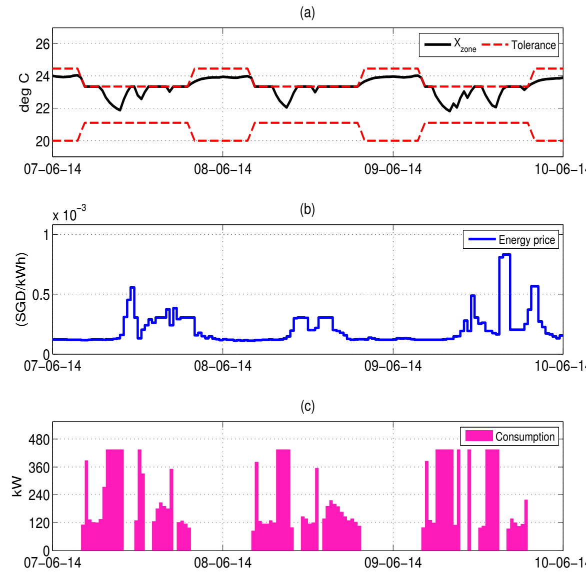

Fig. 2. Results from case 1; (a) Temperature of one zone, (b) Real time energy price in Singapore Dollars (SGD) taken from the NEMS, and (c) Optimal consumption pattern of HVAC.

In Figure 4, results are presented for the simulation of both cases. For comparing both cases, a comparative term *% Normalized Energy Price (NEP)* $= c_k/max(c) \times 100$ is introduced. NEP represents the ratio of energy price at each time step c_k relative to the maximum energy price $max(c)$ experienced by the controller for these 4 months. From figure 4, it can be seen that the developed controller shifts the daily electric load to the low price regions. An observation clearly evident from figure 4 is the sensitivity of the scheduled load for a particular *cut off* value of NEP. Figure 5 explains this sensitivity of scheduled load. At higher prices, scheduling even a small amount of load causes a considerable large increase in the cost. As we have an economical based MPC scheme,

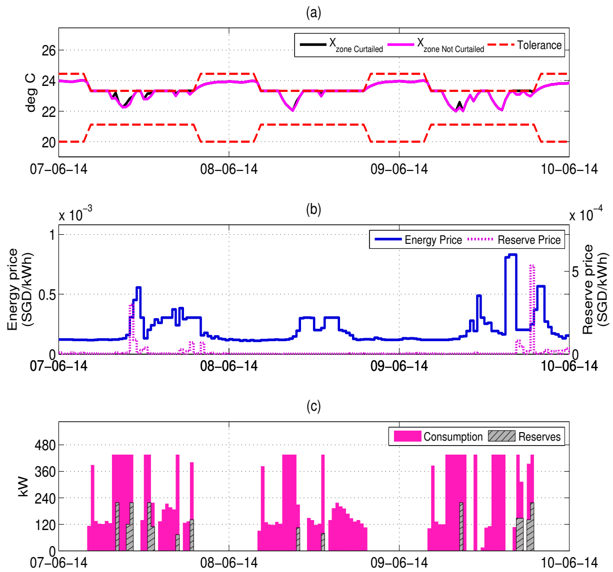

Fig. 3. Results from case 2; (a) Temperature trajectory of one zone for both (Curtailed and Not Curtailed) scenarios, (b) Real time energy and reserve price from NEMS, and (c) Optimal scheduling of consumption due to reserve allocation.

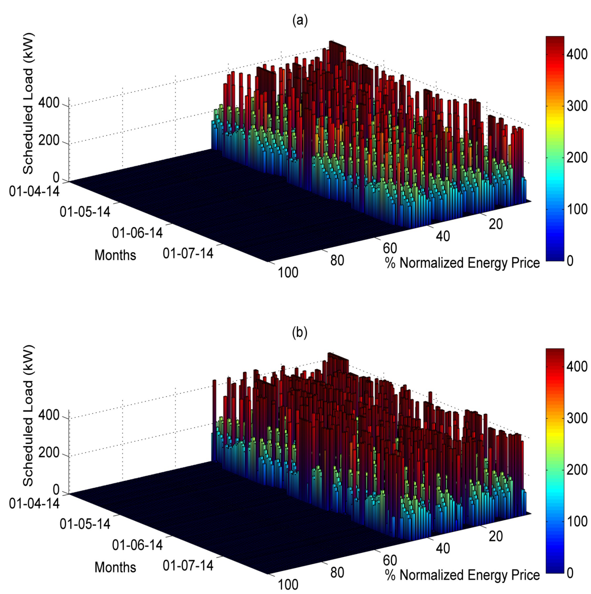

Fig. 4. Scheduled load by the developed MPC scheme for the period of 4 months of the year 2014.

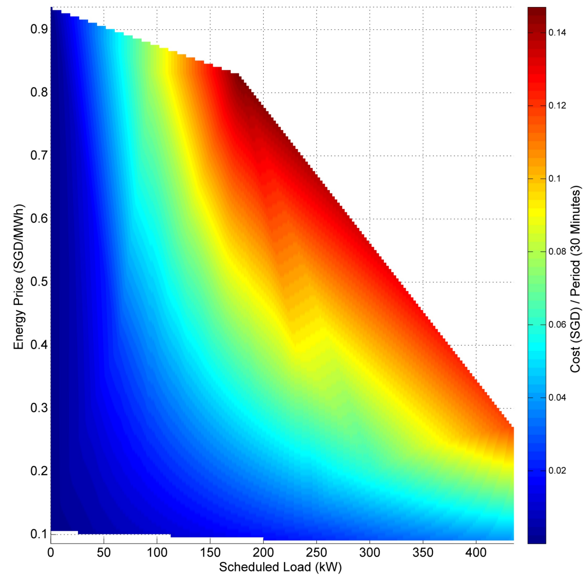

Fig. 5. Behavior of the scheduled load with respect to the cost of the consumption and energy price experienced by the controller - for case 1.

Table I
COST ANALYSIS

Month	Case 1 (SGD)	Case 2 (SGD)	
	Scheduling	Scheduling	Reserves
April	20,515	20,581	-1,039.0
May	21,116	21,244	-1,032.4
June	20,769	20,874	-1,079.3
July	19,855	19,957	-1,190.6

it avoids this high price regions and attempts to schedule the HVAC load before this *cut off* value of NEP. For the case of our simulation setup, it can be seen that this sensitivity of load scheduling starts around at approximately 40% of the maximum energy price.

B. Cost Evaluation

Table I shows the cost analysis of both cases. Total cost of consuming electricity is calculated for 4 months of the year 2014. For case 2, the increase in the cost of consumption is due to the fact that the MPC scheme is solved for not only minimizing the cost of consuming, but also for maximizing the revenue of reserve commitment. An average reduction of 5% in the total cost was observed, which is more than the 1% increase in the consumption of the scheduled load, due to the allocation of reserves. To study the sensitivity of the scheduled reserves, a parameter called *% Relative Price (RP)* $= b_k/c_k \times 100$ is defined. Figure 6 shows the correlation between RP and the scheduling of reserve. RP in figure 6 shows that the competency of the reserve b_k and energy c_k price experienced by the developed MPC scheme is a key

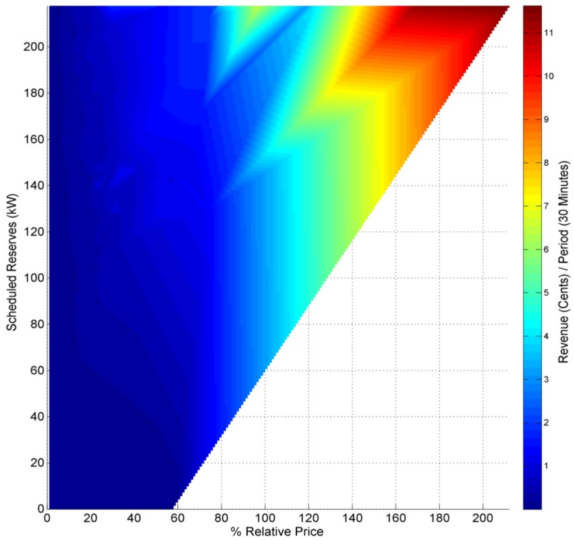

Fig. 6. Scheduling of reserves with respect to the % Relative Price and Revenue.

for scheduling reserves. If the energy price overpowers the reserve price, then the developed MPC scheme does not need to schedule any reserve, as it will only result in increasing the system's cost.

V. Conclusion and Future Work

In this paper, we presented an MPC control framework capable of participating in a real time reserve market, as well as minimizing the total cost of the system. Analyses were performed to evaluate the shifting of consumption patterns in the presence of energy and reserve price signals. Furthermore, economic evaluation of the MPC scheme was done to demonstrate the potential of MPC scheme to actively participate in various ancillary services of the grid. The results show that the MPC scheme is capable of providing demand flexibility under both the energy and reserve market. Furthermore, flexibility in the objective of the developed controller is easily achievable by adopting different cost functions of the system and its constraints. From the simulations presented above, it is evident that to have a meaningful overall lowering of the cost of operation, incentives comparable to energy prices must be introduced. And also, in future there is a strong need for a contractual framework development with the corporation from utility planners, grid operators, and load aggregators. In this way, a co-optimized strategy for all active participants in the grid can be structured, eventually leading towards a cost effective and sustainable power system.

Future work to improve this paper will consist of including model mismatch, uncertainty of price forecast and model dynamics, and more types of ancillary services in the developed MPC scheme.

VI. Acknowledgment

This work was financially supported by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) programme. This work was also sponsored by National Research Foundation, Prime Ministers Office, Singapore under its Competitive Research Programme (CRP grant NRF2011NRF-CRP003-030, Power grid stability with an increasing share of intermittent renewables (such as solar PV) in Singapore).

References

[1] J. Torriti, M.G. Hassan and M. Leach., "Demand response experience in Europe: policies, programmes and implementation." in *Energy*, vol. 35(4):. IEEE, 2014, pp. 1575–1583.
[2] M. H. Albadi and E. F. El-Saadany, "A summary of demand response in electricity markets." in *Electric Power Systems Research*, vol. 78(11):. EPSR, Nov. 2008, pp. 1989–1996.
[3] Energy Market Authority, "Demand Response Programme." [Online]. Available: http://www.ema.gov.sg/dr/
[4] S. Swan, "Interruptible load: new partnerships for better energy management," in *2005 International Power Engineering Conference.*, vol. 2. IEEE, 2005, pp. 888–892.
[5] E. Vrettos et. al., "Predictive control of buildings for demand response with dynamic day ahead and real-time prices." in *European Control Conference*. ECC, June 2013.
[6] F. Oldewurtel et. al., "Energy efficient building and climate control using stochastic model predictive control and weather predictions," in *American Control Conference.* ACC, 2011.
[7] Y. Ma, A. Keman, A. Daly and F. Borrelli, "Predictive control for energy efficient buildings with thermal storage: Modeling, stimulation, and experiments." in *IEEE Control Systems*, vol. 32(1):. IEEE, Feb. 2012, pp. 44–64.
[8] M. Maasoumy et. al., "Model predictive control approach to online computation of demand-side flexibility of commercial buildings HVAC systems for supply following." in *American Control Conference*. IEEE, 2014.
[9] M. Maasoumy and Alberto Sangiovanni-Vincentelli., "Total and peak energy consumption minimization of building HVAC systems using model predictive control." in *Design and Test of Computers.* IEEE, 2012.
[10] E. Vrettos, F. Oldewurtel, F. Zhu and G. Andersson, "Robust Provision of Frequency Reserves by Office Building Aggregations." in *19th IFAC World Congress.*, vol. 19(1):. International Federation of Automatic Control., 2014, pp. 12 068–12 073.
[11] E. Vrettos, F. Oldewurtel, M. Vasiran and G. Andersson, "Centralize and decentralize balance group optimization in electricity markets with demand response." in *IEEE Power Tech Conference.* IEEE, 2013.
[12] S. Koch, F. Barcenas and G. Andersson, "Using controllable household appliances for wind forecast error reduction." in *IFAC Conference on Control Methodologies and Technology for Energy Efficiency.* International Federation of Automatic Control, 2010.
[13] D. F. R. Melo et. al., "Charging of Electic Vehicles and Demand Response Management in a Singaporean Car Park." in *49th University of Power Engineering Conference, UPEC.* IEEE, 2014.
[14] M. Maasoumy, "Modeling and optimal conrol algorithm design for HVAC systems in energy efficient buildings." in *EECS Depart. Univ. California, Berkeley*. Master's thesis, Feb. 2011.
[15] M. Maasoumy et. al., "Model-based hierarchical optimal control design for HVAC systems." in *Dynamic System Control Conference DSCC.* ASME, 2011.
[16] F. Lu and Henry Gan, "National Electricity Market of Singapore," 2005.
[17] J. Loefberg., "YALMIP : A toolbox for modeling and optimization in MATLAB." in *IEEE International Symposium on Computer Aided Control System Design*. IEEE, 2004.
[18] IBM, "IBM ILOG CPLEX Optimization Studio." [Online]. Available: http://www-03.ibm.com/software/products/en/ibmilogcpleoptistud