Demonstration of Peak-Load Shifting with Optimal Residential Thermal Energy Management

Ali Baniasadi, Daryoush Habibi, Waleed Al-Saedi and Mohammad S. Masoum

May 2, 2019

Demonstration of Peak-Load Shifting with Optimal Residential Thermal Energy Management

Ali Baniasadi, Daryoush Habibi, Waleed Al-Saedi
School of Engineering
Edith Cowan University
Perth, Australia
abaniasa@our.ecu.edu.au, d.habibi@ecu.edu.au, w.al-saedi@ecu.edu.au

Mohammad A.S. Masoum
Department of Engineering
Utah Valley University
UT, USA
m.masoum@ieee.org

***Abstract*—The high penetration of renewable energy resources (RES), in particular the rooftop photovoltaic (PV) systems in power systems, causes rapid ramps in power generation to supply load during peak-load periods. In smart residential buildings, variations in rooftop PV power causes a mismatch between generation and load demand. This paper deals with shifting heat pumps loads to either the lower electricity price period or whenever PV generation is available. A strategy is proposed for managing heat pump operation based on real-time pricing tariff to minimize the operation cost of a smart building by controlling the room temperature. Simulation results demonstrate the cost benefits and effectiveness of the proposed thermal energy management strategy.**

***Index Terms*—Smart building, demand response, energy efficiency, heat pump, thermal storage system, thermal energy management.**

I. Introduction

The massive deployment of rooftop photovoltaic (PV) systems in the residential networks and commercial buildings has led to the rapid growth of PV power penetration in power systems. The integration of PV generation offers environmental and economic benefits, in addition to introduce significant challenges for grid operations. On the other hand, buildings consume about 40% of the total generated electricity [1]. Heating, ventilating and air-conditioning (HVAC) systems are one of the major energy consumers in buildings. HVAC systems exacerbate the demand in peak-load periods [2]. Therefore, thermal energy management in residential buildings can be utilized to increase the use of PV generation and thus decrease the peak demand by exporting PV generation to the utility. HVAC systems also have a substantial potential to facilitate demand response (DR) program.

An optimal energy management strategy is largely required to enhance the utilization of PVs. This strategy can be used for heat pumps (HPs) as the heating/cooling suppliers to meet the space heating/cooling requirements.

Many researchers have presented various strategies to minimize peak demand for residential buildings with the integrations of rooftop PVs. Sichilalu et al. [3] focused on HP water heaters to reduce energy cost based on time-of-use (TOU) tariff, by presenting an optimal scheduling model. Wanjiru et al. [4] presented an optimal model to minimize energy and water consumptions. The authors controlled an HP water heater and an instant heater which are integrated with a wind turbine, PV system, and diesel generator. However, space heating/cooling was not considered in both papers. In [5], an optimal DR methodology presented to decrease the electrical water heating costs based on TOU tariff. The authors considered the advantage of thermal energy storage (TES) by assuming the hot water consumption for one day. Reference [6] developed a day-ahead optimization of TES based on DR. The aim was to utilize TES for hot water and thermal mass of 50 residential buildings, by considering the expected energy and discomfort costs. A scheduling approach for an energy system with a battery was proposed in [7]. This approach is employed to control the demand response for HVAC systems. The authors in [8] introduced a cost-optimal schedule method. A Mixed Integer Linear Programming optimization technique is used for the better utilization of solar energy in buildings. The demand caused by heating and partial thermal storage was investigated in [9]. An optimal thermal storage energy was determined by predicting the heat demand of the building.

A potential approach to take advantage of the pre-cooling and pre-heating energies is to adopt temperature set-point based on real-time pricing (RTP) tariffs. References [10] and [11]] propose two variable temperature set-point strategies for changing the set-point temperature when the electricity price is higher than a threshold price which is determined based on consumers preferences. However, neither of these two strategies can considerably shift the HVAC loads. Braun [12] presented a literature review on the application of building thermal mass (BTM) for shifting and reducing peak cooling loads in commercial buildings based on TOU tariff. Henze et al. [13] extended this idea to the usage of both BTM and TES by presenting an optimal control based on common TOU rate differentials. A price based DR strategy for an office building to optimize energy costs of HVAC units and thermal discomfort levels of occupants is proposed in [14]. The TOU tariffs are used to generate day-ahead pre-cooling schedules for early morning hours to reduce the peak load demand. However, the real-time pre-cooling/pre-heating strategies are proven to be more effective than the conventionally scheduled pre-cooling operations. Therefore, in this paper, the proposed RTB is designed to shift up to 100% of HVAC loads from peak-load hours while taking advantage of a TES. It is more effective to develop a control strategy for heat pumps coupled with TES to respond to DRP.

Among all proposed control methodologies for controlling indoor temperature, the model predictive control (MPC) approach can effectively predict the future behavior of the system to minimize energy consumption while considering thermal comfort [11], [15]–[17]. Avci et al. [11] proposed a practical cost and energy efficient MPC method for HVAC load under real-time day-ahead electricity pricing tariff. A state-space model was developed to model the impact of inputs (outside temperature, HVAC operation, etc.) on the output (inside building temperature) at each control interval. Based on RTP tariff, around 8% reduction in overall energy consumption and 13% cost savings, were achieved by this MPC controller. An MPC controller to optimize the thermal comfort level and energy efficiency in a commercial building is applied in [15]. However, the authors do not take advantage of pre-heating/pre-cooling for electricity cost reduction.

This paper presents an approach to resolve the issues associated with variations in rooftop PV power by minimizing the peak demand of smart buildings. This is done by integrating a HP-PV system model that consists of a rooftop PV and a HP which is used as a controllable load. The implemented residential thermal energy management strategy consists of a model predictive control (MPC) to minimize the operation cost of HP, and a real-time temperature boundary (RTB) strategy based on real-time pricing (RTP) tariff. Furthermore the occupants' thermal comfort is also taken into account while shifting the HP electricity load.

The paper is organized as follows. Section II describes the system model. Section III formulates the proposed MPC . Sections IV and V present simulation results and discussion. Finally, the conclusions are outlined in Section VI.

II. System Model

A. Building thermal load prediction modeling

For a constructed building with given materials, design and equipment, the most important parameters impacting the cooling/heating load are: the ambient temperature, humidity and solar radiation. Therefore, these parameters are considered as the input parameters of the building cooling/heating load prediction model. In addition, considering the impacts of delay of air temperature and solar radiation intensity's on the dynamic cooling/heating load, the recorded values are also selected as input parameters.

B. Thermal energy storage (TES) model

The adopted TES model for heating and cooling modes is based on a stratified two-layer tank separated by the thermocline layer as proposed in [18]. In this paper, TES is used in the cooling mode to simplify the description of the model. This is done by placing the return water from the radiator at temperature (T_w), at the top of TES, while the chilled water produced by the HP at temperature T_{HP} are directed to the bottom of TES. The volume of the stored water (m) in TES is always constant and equal to the sum of the volumes of return water (m_w) and chilled water (m_c) which is $m = m_w + m_c$. Therefore, the SOC of TES model based on the heat and mass flow balance can be described as:

$$SOC_i^{TES} = SOC_{i-1}^{TES} + \sum_i \frac{\dot{m}_{HP} - \dot{m}_r}{m} \times 100 \tag{1}$$

where $\dot{m}_r$ is the mass water flow rate through the radiator and $\dot{m}_{HP}$ is the mass water flow rate of HP. The cooling energy stored in the TES can be calculated by:

$$Q_{TES} = m_c c_p (T_w - T_{HP}) \tag{2}$$

C. PV model

The PV power generation is calculated based on ambient temperature (T_o) ans the solar irradiation data (I_s) [19], [20].

$$P_{PV} = I_s A_{PV} N_{PV} \eta_{PV} (1 - 0.005(T_o - 25)) \tag{3}$$

where A_{PV} is the area of PV module and N_{PV} is the number of PV module. η_{PV} is the efficiency of PV system which is dependent on T_o and I_s.

III. MPC-based for HP

A. Real-time temperature boundary (RTB) based on RTP

Real-time indoor temperature boundary $\chi(t)$ enables the DR to efficiently take advantage of the building pre-cooling and pre-heating. Most of the heat distributors such as radiators and fan coil units regulate the room temperature utilizing thermostats [21]. The state of an on/off relay can be determined by the hysteresis control rule as follow [21]

$$\chi(t+1) = \begin{cases} 0 & \text{if } T_{in}(t) \leq \underline{T}_{in} + \mathcal{U} \\ 1 & \text{if } T_{in}(t) \geq \overline{T}_{in} + \mathcal{U} \\ \chi(t) & \text{otherwise,} \end{cases} \tag{4}$$

where the continuous state T_{in} is the building temperature and the discrete state χ is the state of the relay, which switches the heat distributor on and off according to the hysteresis control rule. The set-point offset $\mathcal{U}$ is a control signal which is determined by the proposed RTB strategy based on DR signal as follows:

$$\mathcal{U} = \begin{cases} -1.5 & \text{if } P_{PV} \geq 0 \\ 0 & \text{if } NRTP(t) \leq 0.5 \\ (NRTP - 0.5) \times 2\, \mathcal{U}_{max} & \text{otherwise,} \end{cases} \tag{5}$$

where $\mathcal{U}_{max}$ represents the maximum set-point offset which can be determined by customers or based on thermal comfort zone. $NRTP$ represents the normalized real-time price.

B. MPC

The MPC uses the system model to predict the future evolution of the plant to generate the control action on receding control strategy [17], [22]. The goal of this controller is to switch the HP on/off in order to shift HP power consumption based on DRP while producing sufficient chilled/hot water. For

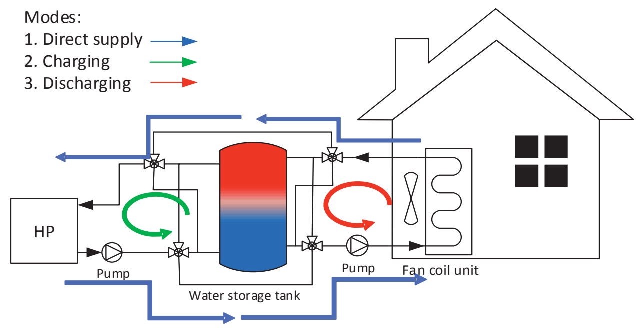

Fig. 1: Residential air-conditioning system with and without a storage tank.

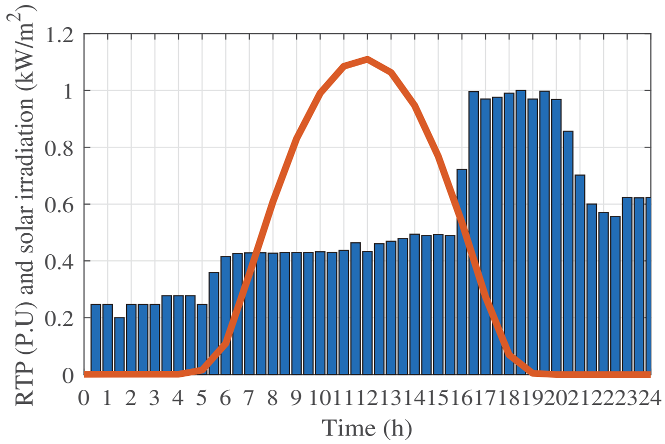

Fig. 2: Normalized wholesale electricity market and solar irradiation for a day in summer.

this purpose, we designed a cost function for the MPC of HP based on RTP tariffs and availability of PV power. The stored chilled/hot water in TES should be produced and consumed on the same day to prevent thermal losses. To consider this constraint, MPC is implemented to predict thermal demand based on weather condition and building thermal model. The objective function is a trade-off between minimizing the total electricity cost and producing enough chilled/hot water subject to dynamic constraints:

$$\min_{u_k} \sum_{j=k}^{k+N-1} (NRTP(j|k)(HP(j|k)) \tag{6}$$

subject to

$$x(j+1|k) = f(x(j|k), u(j|k), d(j|k)), \quad \forall j = k, k+1, \ldots, k+N-1 \tag{7}$$

$$y(j|k) = g(x(j|k), u(j|k), d(j|k)), \quad \forall j = k, k+1, \ldots, k+N \tag{8}$$

$$T_{HP}^{min} \leq T_{HP}(j) \leq T_{HP}^{max} \tag{9}$$

$$SOC_{TES}^{min} \leq SOC_{TES}(j) \leq SOC_{TES}^{max}, \tag{10}$$

$$SOC_{TES}(k+N) = SOC_{TES}(k) \tag{11}$$

where N is the prediction horizon. $NRTP$ is the normalized electricity tariff at time step j, HP is the binary decision variable $u = \{HP\}$ while state variable is $x = \{SOC_{TES}, T_c\}$ and disturbance is $d = \{\dot{m}_r\}$. HP is defined by

$$HP(j) = \begin{cases} 1, & \text{if the A/C is on} \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

IV. Simulation Results

In this paper, the thermal system consists of a 1000 litre storage tank and water source HP with 7.1 kW cooling capacity (1.92 kW power consumption) and 10.3 kW heating capacity. The electrical system consists of 18 series mono-crystalline PV modules rated at 285 W each which is 5.1 kWp.

In this section, we show the detailed system operation for two typical days in summer and winter. Figure 1 shows a water source HP system for a residential building. This system can directly supply thermal demand and the load can be supplied by the thermal storage tank. The thermal demand is calculated based on the weather condition and thermal building model [18]. The proposed strategy changes the RTB based on the forecasted PV generation and RTP to minimize the price by shifting the AC load. Figure 2 shows the wholesale electricity market in Western Australia [23] and solar irradiation for a typical day in summer. Figure 3 shows the AC operation without a water storage tank. The AC load is shifted by RTB strategy. MPC is also implemented to operate HP online based on RTP to control the state of charge of the storage tank. This section shows the system operation for a typical day in summer and winter. The simulations are carried out for the following there scenarios.

A. Residential air-conditioning system without storage tank

Typical air-conditioning system operates based on thermostat control. Figure 3 shows temperature control and A/C power consumption for a day in summer. The temperature sets on 22^oC-24^oC. The A/C runs during peak-price to keep the indoor temperature within determined set-points.

B. Residential air-conditioning system with RTB

In this section, RTB is implemented in typical air-conditioning system to reduce A/C power from peak-load hours and consequently it helps to reduce the electricity bill. Meanwhile, the indoor temperature is kept within thermal comfort zone. Figure 4 shows temperature control and A/C power consumption for a day in summer with the implementation of RTB. The maximum temperature offset ($\mathcal{U}_{max}$) is set on 4.5 $^\circ C$.

C. Residential air-conditioning system with storage tank and RTB

Houses with PV system require storage systems to reduce the electricity bill. The battery storage systems is not cost-

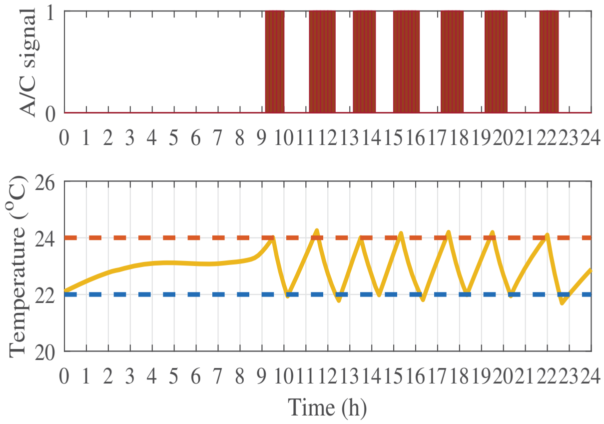

Fig. 3: AC operation and indoor temperature for a day in summer.

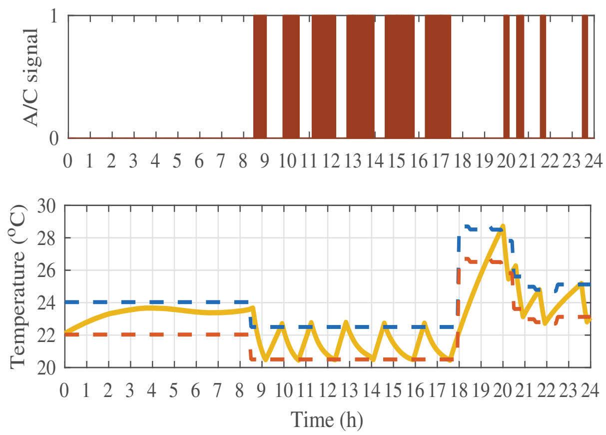

Fig. 4: AC operation and indoor temperature for a day in summer.

effective, whereas, adding a thermal energy storage to typical A/C system can reduce significant A/C load from peak-load hours. However, adding a TES to A/C system requires an accurate controller to prevent wasting thermal energy. In this section, we implemented MPC controller to store enough chilled water in TES to supply thermal load during peak-load period based on predicting weather condition. Figure 5 shows A/C power consumption coupled with TES for a day in summer with the implementation of RTB. As it can be seen, all A/C load shifted in PV power generation period. Figure 6 shows the percentage of stored chilled water in TES. To minimize thermal losses, the TES is charged in midday when PV power is sufficient to run A/C. TES is then discharged to supply thermal load during high electricity price period.

V. Discussions

Simulation results including electrical energy cost, peak-load shifting, and average indoor temperature are summarized in Table I. It is worth mentioning that the proposed

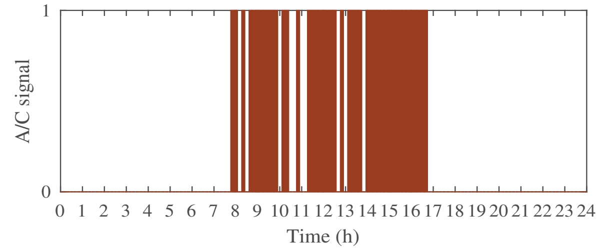

Fig. 5: A/C operation coupled with TES for a day in summer.

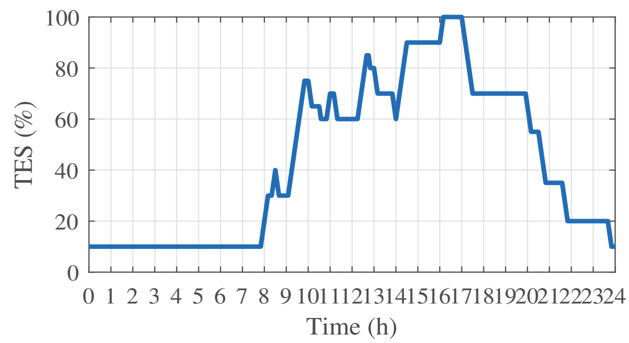

Fig. 6: Percentage of thermal energy storage in TES.

controller takes full advantage of TES coupled with A/C in terms of reducing the overall energy cost and shifting energy consumption from peak-load hours. The proposed RTB with MPC controller based on RTP enables the end-users to efficiently increase PV power consumption. Based on the detailed simulations of Figs. 3-6 and Table I:

- The proposed RTB reduces the total energy cost by 55%. The RTB reduced the HP load from peak-price period significantly, by taking advantage of building pre-cooling during PV power generation. However, only the proposed RTB reduced the electricity cost by 55%.
- The MPC effectively shifted 100% of HVAC load from the peak-load hours. In addition, TES supplied the thermal load during peak-load period and TES is totally discharged as shown in Fig. 6. The proposed method minimizes thermal losses by charging and discharging TES in same day. It might be not needed thermal energy for the next day.

VI. Conclusion

This paper demonstrates a practical approach to resolve the issues associated with variations in rooftop PV power causing a mismatch between generation and load demand in smart residential buildings. A real-time temperature boundary (RTB) strategy based on real-time pricing (RTP) tariff is used to shift heat pump load to minimize the operation cost of a smart building and reduce the export energy to the utility. Simulations are performed for residential air-conditioning systems without storage tank, with RTB, and with both storage tank and RTB.

TABLE I: Comparison of results (Figs. 3-6) with the percentage of improvement.

Cases	Electrical energy cost		Power consumption in peak hours		Average temperature	Results
	$	%*	kWh	%*	°C	
A/C without TES (Base case)	1.91	-	1.75	-	23.08	Fig. 3
A/C with RTB and without TES	0.86	55	0.87	50	22.92	Fig. 4
A/C with RTB and TES	0	100	0	100	22.92	Figs. 5,6

* Percentage of improvement with respect to base case.

REFERENCES

[1] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy and buildings*, vol. 40, no. 3, pp. 394–398, 2008.

[2] R. Tang, S. Wang, K. Shan, and H. Cheung, "Optimal control strategy of central air-conditioning systems of buildings at morning start period for enhanced energy efficiency and peak demand limiting," *Energy*, vol. 151, pp. 771–781, 2018.

[3] S. M. Sichilalu and X. Xia, "Optimal power dispatch of a grid tied-battery-photovoltaic system supplying heat pump water heaters," *Energy Conversion and Management*, vol. 102, pp. 81–91, 2015.

[4] E. M. Wanjiru, S. M. Sichilalu, and X. Xia, "Model predictive control of heat pump water heater-instantaneous shower powered with integrated renewable-grid energy systems," *Applied Energy*, vol. 204, pp. 1333–1346, 2017.

[5] J. J. Shah, M. C. Nielsen, T. S. Shaffer, and R. L. Fittro, "Cost-optimal consumption-aware electric water heating via thermal storage under time-of-use pricing," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 592–599, 2016.

[6] N. Good, E. Karangelos, A. Navarro-Espinosa, and P. Mancarella, "Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users discomfort," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2333–2342, 2015.

[7] F. Jabari, S. Nojavan, B. M. Ivatloo, and M. B. Sharifian, "Optimal short-term scheduling of a novel tri-generation system in the presence of demand response programs and battery storage system," *Energy conversion and management*, vol. 122, pp. 95–108, 2016.

[8] S. Baldi, A. Karagevrekis, I. T. Michailidis, and E. B. Kosmatopoulos, "Joint energy demand and thermal comfort optimization in photovoltaic-equipped interconnected microgrids," *Energy Conversion and Management*, vol. 101, pp. 352–363, 2015.

[9] M. Ali, J. Jokisalo, K. Siren, and M. Lehtonen, "Combining the demand response of direct electric space heating and partial thermal storage using lp optimization," *Electric Power Systems Research*, vol. 106, pp. 160–167, 2014.

[10] J. H. Yoon, R. Baldick, and A. Novoselac, "Dynamic demand response controller based on real-time retail price for residential buildings," *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 121–129, 2014.

[11] M. Avci, M. Erkoc, A. Rahmani, and S. Asfour, "Model predictive hvac load control in buildings using real-time electricity pricing," *Energy and Buildings*, vol. 60, pp. 199–209, 2013.

[16] D. Molina, C. Lu, V. Sherman, and R. G. Harley, "Model predictive and genetic algorithm-based optimization of residential temperature control

[12] J. E. Braun, "Load control using building thermal mass," *Journal of solar energy engineering*, vol. 125, no. 3, pp. 292–301, 2003.

[13] G. P. Henze, C. Felsmann, and G. Knabe, "Evaluation of optimal control for active and passive building thermal storage," *International Journal of Thermal Sciences*, vol. 43, no. 2, pp. 173–183, 2004.

[14] Y. Kim, "Optimal price-based demand response of hvac systems in multi-zone office buildings considering thermal preferences of individual occupants," *IEEE Transactions on Industrial Informatics*, DOI 10.1109/TII.2018.2790429, pp. 1–1, 2018.

[15] G. Mantovani and L. Ferrarini, "Temperature control of a commercial building with model predictive control techniques," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 4, pp. 2651–2660, 2015.

in the presence of time-varying electricity prices," *IEEE Transactions on Industry Applications*, vol. 49, no. 3, pp. 1137–1145, 2013.

[17] Y. Ma, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, and P. Haves, "Model predictive control for the operation of building cooling systems," *IEEE Transactions on control systems technology*, vol. 20, no. 3, pp. 796–803, 2012.

[18] A. Baniasadi, D. Habibi, O. Bass, and M. A. S. Masoum, "Optimal real-time residential thermal energy management for peak-load shifting with experimental verification," *IEEE Transactions on Smart Grid*, DOI 10.1109/TSG.2018.2887232, pp. 1–1, 2018.

[19] S. Chen, H. B. Gooi, and M. Wang, "Sizing of energy storage for microgrids," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 142–151, 2012.

[20] K. Khadka, H. Pourgharibshahi, and H. Zargarzadeh, "Comparative analysis of mppt methods for pv system with dc-dc three-level converter," in *2018 Clemson University Power Systems Conference (PSC)*, pp. 1–6. IEEE, 2018.

[21] C. Perfumo, E. Kofman, J. H. Braslavsky, and J. K. Ward, "Load management: Model-based control of aggregate power for populations of thermostatically controlled loads," *Energy Conversion and Management*, vol. 55, pp. 36–48, 2012.

[22] J. Vasilj, S. Gros, D. Jakus, and M. Zanon, "Day-ahead scheduling and real-time economic mpc of chp unit in microgrid with smart buildings," *IEEE Transactions on Smart Grid*, DOI 10.1109/TSG.2017.2785500, pp. 1–1, 2017.

[23] "Australian energy market operator," https://www.aemo.com.au/Electricity/Wholesale-Electricity-Market-WEM/Data-dashboard, accessed: 2018-12-20.