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DYNAMIC ENERGY MANAGEMENT STRATEGY UNDER PRICE-BASED DEMAND RESPONSE SCHEME

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ABSTRACT
The intelligent energy system supports the structure of the energy mix that can effectively improve the reliability and autonomy of any given electrical system. This paper assesses an optimal control that monitors in real-time the energy demand with the integration of photovoltaic (PV) system combined with an energy storage system (ESS) connected to the grid. The designed model uses the model predictive control (MPC) framework to create closed-loop behaviour. This is based on the demand response strategy by using real-time electricity pricing schemes. The closed-loop model behaviour consists of limiting the control horizon (CH) to be less than the predicted horizon (PH). This strategy is implemented through the design structure of the performance index. It observed that the optimal results are influenced by selecting a value of CH that is about half less than PH in which the system behaviour of the energy supply must follow a given target of the consumers. It is also found that the proposed strategy is intelligently robust to manage the energy system and brings satisfaction to different stakeholders optimally.

Keywords: building energy system, demand response, model predictive control, renewable energy, smart grid.

NOMENCLATURE

Abbreviations

CH	Control Horizon
ESS	Energy Storage System
DER	Distributed Energy Resources
DSO	Distribution system operator
MPC	Model Predictive Control
PH	Predicted Horizon
PV	Photovoltaic
SOC	State of charge of the battery
TOU	Time of use

Symbols

C	Cost
E	Energy
J	Objective function
η	Efficacity
r	Reference

Indexes

bs	Battery energy storage
ch	Charging state of the battery
dis	Discharging state of the battery
d	Demand (Consumer)
i	Input or output index
nom	Nominal
ut	Utility grid
max	Maximal point
min	Minimal point

1. INTRODUCTION

The energy management behaviour is one the scheme that can change the system energy flow patterns and improve the load frequency of the electricity system [1], [2]. Due to the diversity of consumers and the integration of distributed energy resources (DER), the power system quality can be affected negatively [3]–[7]. Through smart grid technology, the energy management of a given electrical system enhances the efficiency of the power

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system by improving the energy behaviour pattern while resolving a power quality issue. Currently, several pieces of research work design the energy management system using the novel technology and application of the system model to improve the energy system efficiency.

Demand response strategy is one of the approaches that has effectively tackled current energy crises. This strategy deals with electricity pricing dynamical [8] and different techniques of load management [9]. A virtual power plant internal market-based data mining approach is presented in [10] to drive the incentive of demand response scheme. The model coordinates the internal energy systems based on consumptions, generations (conventional and renewable energy), and ESSs. In [5] machine learner data model using demand response program is designed to create a smart algorithm that can optimise the energy system of a building. Eissa [11] has proposed a demand response program through a supplier's smart energy management and consumer's intelligent energy management systems. The proposed approach uses the first real-time time model to handle the different energy resources for the benefits of industrial/commercial users.

Price-based demand response through real-time electricity pricing scheme is currently used in several smart grid applications to create dynamic behaviour of the energy system [12]–[15]. A dynamic strategy based on battery energy storage is designed to optimal coordinate the energy flow of a smart home, which is computed through the use of price-based demand response. This model is considered to be a closed loop strategy [16]. The MPC is found to be one of the most promoting strategies to design an energy management system based on smart grid technology [17]–[22]. A novel strategy of the intelligent metering system using the MPC approach to dynamical manages the energy is proposed in [17]. Additionally, it is recommended for the integration of distributed energy resources (DER) including renewable energy and energy storage system (ESS). The strategies developed in [20]–[22] incorporate a real-time electricity pricing scheme to coordinate the power flow of the hybrid power system for industrial consumer and hybrid electric vehicle. In [19], an adaptive time of use (TOU) based MPC managing system is proposed to achieve the energy system of a commercial building. It is observed that the method using optimal behaviour where the CH has the same value as the PH.

In this paper, a dynamic model of energy management is designed using an MPC controller where the CH has a value less than the PH to manage energy system of PV and ESS connected to the grid. The model is based on closed-loop behaviour that implements a price-based demand response strategy to include a real-time electricity pricing and prepaid tariff scheme. The approach computes the demand response scheme into the system performance index. This model allows the set of targets to manage the different energy patterns optimally. The novelty of the designed model is its ability to handle the system uncertainty regardless of the set target and the difference between CH and PH. Besides, its robustness is demonstrated through simulation analysis of the results, which effectively maximise the use of the DERs so that the utility's energy cost can be minimised.

2. SYSTEM DESIGN

2.1 Model description

Figure 1 presents the system model for commercial usage. In the demand side, the consumer has two kinds of load demands which are divided by the uncontrollable loads and controllable loads. The target of the energy demand is based on unmanageable loads which are feed by the energy from the distributed system operator (DSO) or the utility grid while another load demand is the principal part from the consumer to be supplied by the DER. The system controller, as described in Fig. 1, is based on MPC managing, and it aims to manage the energies from the different systems such as PV, ESS, and DSO according to the energy pattern from the end users.

The model consists of prioritising the controllable load demands based on different energy supplies from DER. This consists of minimising the energy from the utility and maximising the energy supplies for DER.

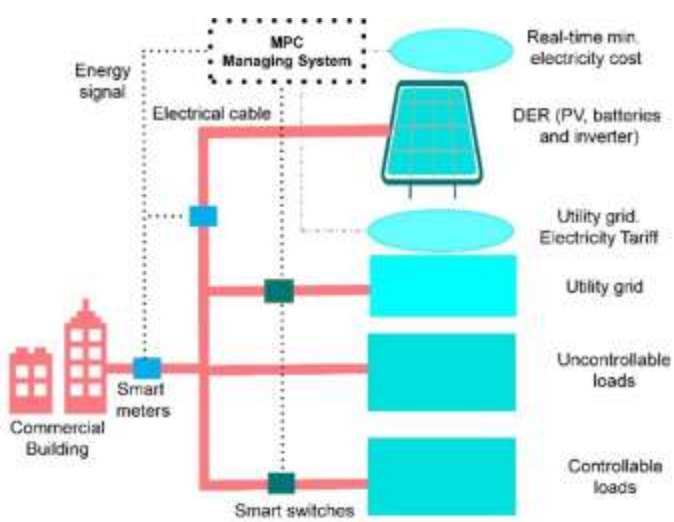

Fig. 1 Dynamic MPC energy managing system.

2.2 System description

Based on the developed model of Fig. 1, it can be assumed that the inverter efficiency does not affect the designed system parameters and it is equal to unity. The system energy flow can, therefore, be expressed as follows

$$E_{ut}(t) + E_{pv}(t) + E_{bs}(t) = E_d(t) \tag{1}$$

Where $E_{ut}(t)$ is the DSO's energy supply, $E_{pv}(t)$ is the PV's energy supply, $E_{bs}(t)$ is the ESS flowing on the battery which depends on charging and discharging period, and $E_d(t)$ is the energy demand. The last two variables can be defined as

$$E_{bs}(t) = \begin{cases} E_{ch}(t) & \text{if } E_{bs}(t) > 0 \\ E_{dis}(t) & \text{if } E_{bs}(t) < 0 \end{cases} \tag{2}$$

$$E_d(t) = E_{ul}(t) + E_{cl}(t) \tag{3}$$

with $E_{ch}(t)$, $E_{dis}(t)$, $E_{ul}(t)$, and $E_{cl}(t)$ are respectively energy during charging and discharging period of the ESS, and energy demand from uncontrollable and controllable loads. Each component of the second term of Eq. (2) can also be identified with the dynamics of battery described in [19].

The dynamic system of the energy flow on ESS is presented in Eqs. (4) and (5). These relations describe the random representation of dynamic models of the battery, which are based on the state of charge (SOC) and the energy flow dynamics.

$$SOC(t) = SOC(t-1) + \frac{1}{E_{nom}}\left(\eta_{ch}E_{ch}(t-1) - \frac{E_{dis}(t-1)}{\eta_{dis}}\right) \tag{4}$$

$$E_{bs}(t) = E_{bs}(t-1) + \eta_{ch}E_{ch}(t-1) - \eta_{dis}E_{dis}(t-1) \tag{5}$$

E_{nom}, η_{ch} and η_{dis} are respectively the nominal energy of the battery, charging and discharging efficiency of the battery.

2.3 MPC design

The system design implements the state space model developed in [19]. However, the implementation structure of the present research study considers the weighted coefficients as invariable parameters which are equal to unity, and it is designed by a closed model according to the MPC strategy and implemented as developed in [12]. This consists of making the CH less than the PH, which is different from other works where the CH is equal to PH.

The performance index function of the MPC managing system is dependent on the system output and the reference signal. The system has four inputs, as described in Eqs. (1) and (2). These inputs are the energy flow from the DSO, PV and ESS (including charging and discharging of a battery). The system outputs are considered as the energy costs which are the function of the inputs system. The cost of energies of the dynamic MPC managing system can be written using real-time electricity scheme as follows

$$C_{ut}(t+1) = p_{ut}(t)E_{ut}(t) \tag{6}$$

$$C_{DER}(t+1) = p_{DER}(t)\begin{cases} E_{pv}(t) \\ E_{ch}(t) \\ E_{dis}(t) \end{cases} \tag{7}$$

where $C_{ut}(t)$ is the energy cost from the DSO, $C_{DER}(t)$ constitutes the cost of energy from DER which depends on PV and ESS (during charging and discharging period). $p_{ut}(t)$ and $p_{DER}(t)$ are the energy supply price from the DSO and DER respectively. It is assumed that the electricity price a constant function at any given time. Therefore, the price of energy in Rand per kWh are set as $p_{ut} = 1.2774$ and $p_{DER} = 0.62$.

From Eqs. (4) and (7) and based on the MPC design, the system performance index can be described as shown in Eq. (8). The implement of the objection is based on a quadratic formulation which computes the dynamic model of Eqs. (4) to (7). The system approach designs a closed dynamic model.

$$J(k) = \sum_{k=1}^{PH}\sum_{k=1}^{CH<PH}(C_k(k) - r_k(k))^T(C_k(k) - r_k(k)) \tag{8}$$

with k is the sampling time which can be equivalent to time t. $r_k(k)$ is the output reference in which the MPC managing system must follow. The reference depends on input and system behaviour. Figure 2 describes the data profile of the system. The reference of utility grid is a function of the target energy demand. For DER, the cost reference of PV is attached to PV generation, battery changing to PV and discharging to the load demand. The system constraints of the objective function as described in Eq. (8) are represented as

$$0 \le E_i \le E_{\max} \tag{9}$$

$$0 \le C_i \le C_{\max} \tag{10}$$

$$SOC_{\min} \le SOC \le SOC_{\max} \tag{11}$$

where i represents a given input or output signal.

2.4 System algorithm

The MPC managing strategy executes the following steps:

1. Compute the system designed model based on state space.

2. Set the system CH and PH
3. Assess the system data as described in Fig. 2 in the function of PH and set the system constraints as shown in Eq. (9) to (11).
4. Set the system reference and Predict the system output based on Eqs. (6) and (7)
5. Find the minimal input of the system by using Eq. 6 through the MPC design strategy
6. Based on set CH and PH as described in step 2, repeat steps 3-5 until the PH is reached.

3. RESULTS AND DISCUSSION

For the system model, as shown in Fig. 1, set the constraints based on the limits of the given data in Fig. 2. Additionally, all minimum values are set to be zero, but the minimum value SOC is different from zero. The implementation model uses the system parameters of PV and ESS specifications as described in Table 1. The system design implements a closed-loop structure which uses the behaviour of Eq. (8). The PH is set to be at the range of data which is 24 hours.

Table 1 Simulations assessment parameters

Parameters	values	Parameters	values
PV system	350	η_{dis}	1
ESS Nominal	150	SOC_{max}	1
η_{ch}	0.8	SOC_{min}	0.1

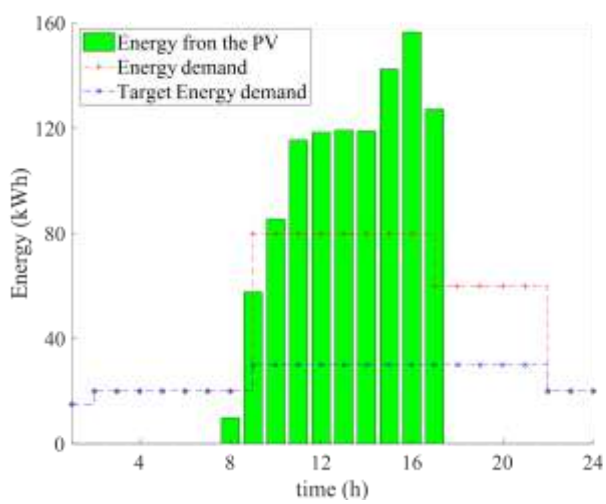

Fig. 2 Data: PV, load demand including uncontrollable and controllable

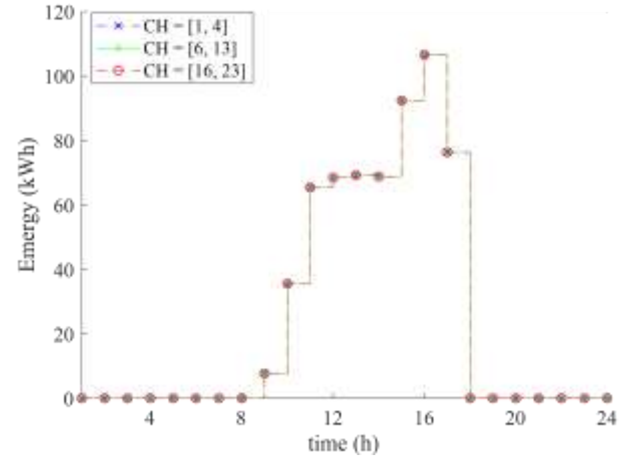

Fig. 3 Energy from PV to the battery (charging)

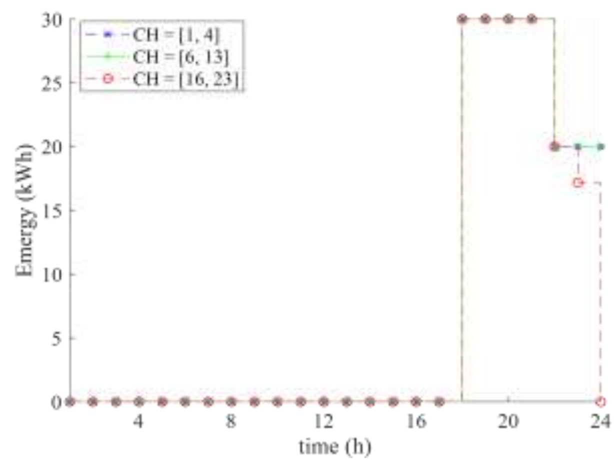

Fig. 4 Energy from the battery to the load (discharging)

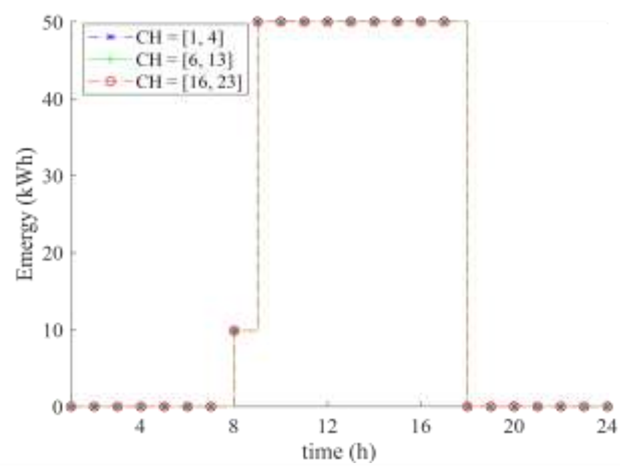

Fig. 5 Energy from PV to the consumer

Figures 3 - 6 present the optimum results of the control variables. These results are assessed based on the variation of CH. Three range schemes of CH are selected to present the results. The selected values of CH are 1 to 4, 6 to 13, and 16 to 23. Figures 3 and 4 describe the optimum results of the energy pattern of the battery. It is essential to notice that this is created based on the dynamic behaviour of the ESS. The optimal energies to supply the end user, compared with data of the consumer (load demand and reference) as described in Fig. 2, are presented in Figures 4-6. The results show the impact of different CH regarding the robustness behaviour of the designed model to follow the given target. It is observed from Figures 3-4 that some isolated values of CH are not selected.

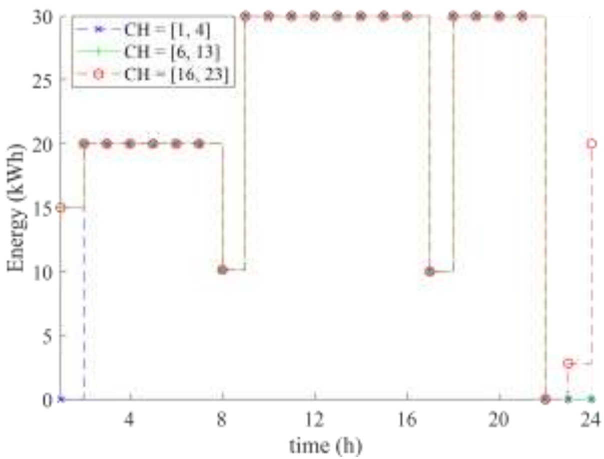

Fig. 6 Energy from the utility grid to the consumer

The system results in the context of minimising the energy from the utility as a result of Figures 4-6 to supply the end users. Table 1 gives a comparison of the results of the energy costs that the consumer can pay the utility grid. There are three values of CH that are added in Table 2, which are 5, 14, and 15. The minimum value in Table 2 is when CH is between 1 and 4. However, as described in Fig. 6, this result is not optimal in term of energy supply because at a sample time the energy supply is zero. The optimal value is between 6 to 13. From 16 to 23, the results approach the reference, but this cannot be an optimal solution to the consumer side. Thus, an optimal selection of the CH should be about the half value of PH.

Table 2 Energy cost analysis

CH: Control horizon	Demand Cost	Reference Cost	Cost: MPC managing
1 to 4	1475.397	772.827	638.8604
5	-	-	652.6431
6 to 13	-	-	658.0210
14	-	-	661.6158
15	-	-	687.1638
16 to 23	-	-	712.7718

Table 3 Energy saving

1 to 5	5	6 to 13	14	15	15 to23
56.7%	55.8%	55.4%	55.1%	53.4%	51.6%

By analysing the cost reference, as described in Table 2, it is seen that this cost is of about 47.6% compared with the demand cost. Table 3 gives the saving percentage of the designed model when considering the different values of the CH.

4. CONCLUSION

A dynamic energy strategy using the MPC design is presented to optimally manage the energy system from commercial usage, including DER connected the utility grid. It is observed that the optimal behaviour of the design system depends on the selecting control horizon. This setting value aims to manage different energy patterns of the designed electrical system. The results present that the model is robust in terms of following the system constraints and inputs system references. Thus, the model can minimise the energy from the utility grid and maximise the DER. It is also observed that there is an excess of the energy from DER, which can consist of a future research study in the context of selling this energy to the primary grid for total energy minimisation.

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