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Online Energy Management Strategy Based on Adaptive Model Predictive Control for Microgrid with Hydrogen Storage

Jun Ma *‡, Mustafa Baysal *

* Department of Electrical Engineering, Faculty of Electrical and Electronics, Yildiz Technical University, Istanbul, Turkey

(junma_1991@hotmail.com, baysal@yildiz.edu.tr)

‡ Corresponding Author; Jun Ma, Istanbul, Turkey, PIN: 34403

Tel: +90 536 731 0895, junma_1991@hotmail.com

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Abstract- Energy management optimization is still a big challenge for Microgrid, which includes Renewable Energy and Hydrogen Fuel Cell. In this paper, an online Adaptive Model Predictive Control (AMPC) based Energy Management Strategy (EMS) is proposed to increase the energy sources lifetime of the microgrid while minimizing hydrogen consumption. The EMS problem is simplified according to the control structure of microgrid system and the cost function of system is built and transferred to standard format of the Quadratic Programming problem to solve. Moreover, adaptive algorithm is used to automatically adjust the weights of different targets according to the states of system. It is shown by simulation results for different cases from MATLAB-Simulink™ that proposed EMS has significant effects on controlling State-of-Charge (SoC) of battery and a noticeable improvement on extension of Hydrogen Fuel Cell lifetime and battery charge-sustainability.

Keywords Adaptive Model Predictive Control; Hydrogen Fuel Cell; Microgrid; Online Energy Management Strategy.

1. Nomenclature

$Nser$ Number of solar panel in series

$Npar$ Number of solar panel in parallel

Um Voltage at the maximum power point of solar panel [V]

Im Current at the maximum power point of solar panel [A]

T Surface temperature of solar panel [℃]

S The solar irradiation [kW/m^2]

Δ The difference between real and standard condition

$\dot{m}_{H2}$ the H2 mass flow speed [g/s]

i_{fc} The output current of Fuel Cell [A]

SoC_{bat} The State-of-Charge of battery

SoC_{init} The initial SoC of battery

SoC_r The ideal value of SoC_{bat}

Q_{bat} The battery capacity [Ah]

i_{bat} The output current of battery [A]

m_{hfc} The modulation ratio of Fuel Cell chopper

P_{hfc} The output power of chopper [kW]

P_{ts} The demand power from system [kW]

η_{hfc} The average efficiency of the chopper

n_C The number of electrolyzer cells in series

η_F The Faraday efficiency;

n_{H2} The produced hydrogen speed [mol/s]

i_e The electrolyzer current [A]

ω_f The penalty weight of fuel consumption

ω_{ef} The equivalent factor of battery energy consumption

$\omega_{SoC_{bat}}$ The penalty weight of deviation of SoC_{bat} from SoC_r

$\dot{SoC}_{bat}$ The energy consumption rate of battery [%/s]

2. Introduction

As the energy is increasingly depleted and environmental pollution becomes a serious concern, renewable energies are considered as the best choice to replace traditional fossil fuelled energy resources. However, the volatility and intermittent of renewable energy has brought many adverse effects, such as stability of output power in stand-alone microgrid with Solar Energy and Wind [1]. In order to improve the stability and efficiency of renewable energy, the Energy Storage System (ESS) has been proposed and applied in several systems [2]. Normally the batteries and supercapacitors are the main component of ESS because of the good transient response, but their low energy density is not suitable to long-term energy storage and the short lifetime makes high cost [3]. As the technic of hydrogen production, storage and Hydrogen Fuel Cell develop quickly, high energy density of hydrogen as an energy carrier will play an important role in the long-term energy storage. However, the weak robust performance under transient conditions and slow response are the main barriers for its technological implantation [4]. Therefore, it is commonly necessary to combine different types of storage tools to ensure both long-term and short-term energy storage [5]. The energy management of combined system becomes the key of system efficiency [6].

According to the recent researches, there are mainly two kinds of Energy Management Strategy (EMS): heuristic methods and deterministic methods (see [7] for comprehensive reviews). Considering the uncertainties of forecast, the heuristic methods, such as genetic algorithm, partial swarm optimization, Tabu search algorithm, are required to be adopted [7-9]. Furthermore, heuristic methods could give optimal control target based on predicted information like wind speed, temperature and so on. However as long as the microgrid system involves more components, the control of system requests more complexity, which leads heuristic algorithm results to a thorny issue [5]. For the online EMS, the optimization problem can be solved by deterministic methods if it can be expressed as a series of linear or nonlinear equations [7].

Linear Programming (LP) is a deterministic method for the optimization of linear objective function, which can be solved easier than nonlinear objective function. Battistelli [10] propose a robust linear optimization method for economic optimization of the system composed of renewable power sources and gridable vehicles. Chaouachi [11] present the economic and environment optimization by Iinear - programming-based multi-objective optimization method. However, some economic optimization function cannot be expressed as LP. Fuzzy Logic Control method is also applied to improve the efficiency of microgrid with simple formulation control rules [12-14]. Although the results show that the SoC of battery is kept around a defined SoC, the electrolyzer and the fuel cell is forced to excessive intermittent operation, which has very negative impact on their lifetimes [12,13]. Recently Model Predictive Control (MPC) is considered as the solution of optimization problem of microgrid with hybrid power sources [15-18], because of the integration of forecasting methods, optimal and multi variable control, and the consideration of uncertainties and dead time conditions [19]. In the paper presented by Valverde [5] and Del Real [20], the EMS based on MPC is applied to the microgrid with fuel cell but the degradation issues of the ESS is not considered. Julian Patino [21] proposed an economic MPC approach to minimize the use of the grid-supplied power by using the battery also without considering the lifetime of battery. Garcia [2] considered the degradation of whole system which included wind turbine, solar panel and ESS and the targets of MPC are tuned giving bigger weights to degradation costs of fuel cell and electrolyzer, since these devices are more sensitive to degradation. According to the solution method of MPC, the penalty weight of each target means the importance and priority of target optimization [22]. However, the weights are selected subjectively or according to the experience in all aforementioned studies. Considering the complexity of microgrid, the MPC based EMS could not get the optimal result with the constant penalty weights, moreover, the system will be shut down in some extreme situations. Adaptively changing the weights according to the state of ESS can improve the robustness of the system.

In this paper, an online Adaptive Model Predictive Control (AMPC) based Energy Management Strategy is proposed to increase the energy sources lifetime of the Microgrid while minimizing hydrogen consumption. Firstly, the optimization problem will be simplified according to the structure of hybrid power model. Secondly, the quadratic cost function considering hydrogen consumption, battery recharge equivalent cost and battery charge-sustainability is built and transferred to standard format of the Quadratic Programming problem to estimate the performance of system. The most important contribution of this paper is that adaptive algorithm is applied to dynamically adjust the weights of targets. Finally, simulation results are evaluated to exhibit the performance of the proposed AMPC compared to the conventional MPC method.

The rest of the paper is arranged as follows. Section 3 presents the system configuration and models. An online EMS based on AMPC is proposed in Section 4. Section 5 presents and analyses the simulation results in different situations. Last section concludes the paper.

3. Microgrid System

3.1. System configuration

The microgrid under study is shown in Fig.1. The microgrid is autonomous (means not supplied by main grid) and its main power supply is photovoltaic (PV) source. During daytime, PV produces energy to supply the load and excess energy is stored in the battery or hydrogen tank by Electrolyzer for later use. During the night or non-sunny day, that is to say, PV cannot deliver enough energy to load, then the Energy Storage System (Hydrogen Fuel Cell and battery) will supply the energy to the load. As mentioned before, because of the high round-trip efficiency, the battery is used for short-term energy storage and to take care of the effects caused by instantaneous load ripples/spikes [23]. The ESS model is taken from the IEEE VTS Motor Vehicles Challenge 2017, including the Proton Exchange Membrane (PEM) fuel cell (FC) system and LiFePO4 battery. A compressor ensures the supply of oxygen for FC and it is considered as a voltage source using its static polarization curve. Converters are used as power interfaces allowing energy transfer between the different devices. The voltage of system is held by the ESS. The studied microgrid parameters are presented in Table 1.

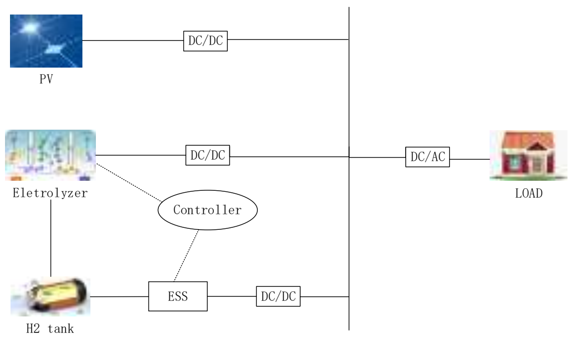

Fig. 1. Test microgrid with PV and Hydrogen Fuel Cell.

3.2. Modelling of Microgrid Components

3.2.1 PV

In this paper, the SunPower SPR-305 solar panel is chosen as the renewable energy source. The V-I and V-P solar cell curves are showed in Fig. 2 [24].

The power generated by the solar panel from the irradiance and temperature input is given by

$$P = mnU_m I_m (1+\alpha\Delta T)(1\text{-}\gamma\Delta T)(1+\beta\Delta S)\frac{S}{S_{STC}} \qquad (1)$$

where *Um* and *Im* are the voltage and current at the maximum power point, respectively; T is temperature and S is irradiation, Δ means difference between real and standard condition [25].

Table 1. Parameters of Microgrid under study

Fuel cell	system	PEMFC
	voltage	40-60 V
	Rated power	16 kW
	maximum current	400A
H2 tank	5.5kg 350bar	
Smoothing inductors	5.5 mΩ, 0.25 mH	
Lithium Iron Phosphate (LiFePO4) battery (*2)	80 V, 40 Ah	
PV	81*SunPower SPR-305, (Nser=9 Npar=9)	
Electroyzer	10kW, 0.14g/s	

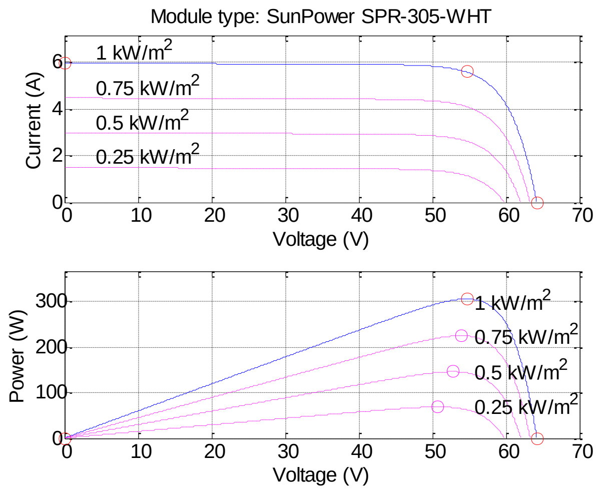

Fig. 2. Solar cell V-I and V-P curves for different irradiance values generated using the model

3.2.2 Fuel Cell

Energy Storage System (ESS) is consisted of Fuel Cell system (FC) and battery, as shown in Fig.3. The FC system is consisted of the fuel cell, a smoothing inductor, a boost chopper and other ancillaries which are not modelled in this paper. The fuel cell having an experimentally validated quasi-static model is used as a voltage source, H2 mass flow is also considered as a static characteristic expressed in equation (2) [26].

$$\dot{m}_{H2} = g_2 i_{fc} + h_2 \tag{2}$$

where g_2, h_2 are the constants obtained from experiments [27].

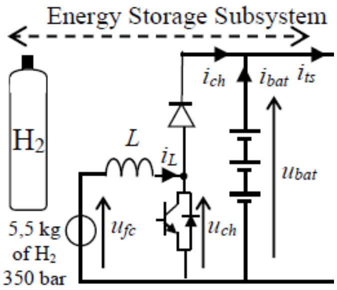

Fig.3. The structure of the ESS

3.2.3 Battery

The battery is modelled using an open-circuit voltage u0 with a series resistance Rc_0 and a parallel combination of resistance capacitance Rc_0 , Cc [27]. The SoC of the battery (SoC_{bat}) is formulated as:

$$SoC_{bat} = SoC_{init} - \int \frac{100 i_{bat}}{3600 Q_{bat}} dt \tag{3}$$

where SoC_{init} is the initial SoC of the battery, Q_{bat} is the battery capacity and i_{bat} is the battery current.

From Fig.3,

$$P_{bat} = P_{ts} - P_{hfc} \tag{4}$$

$$i_{hfc} = m_{hfc} \eta_{hfc}^{k} i_{fc}, k = \begin{cases} 1, \text{if } P > 0 \\ -1, \text{if } P < 0 \end{cases} \tag{5}$$

where m_{hfc} is the modulation ratio of the FC chopper; $\eta_{hfc} = 95\%$ is the average efficiency of the chopper [27]; P_{hfc} , P_{ts} is the output power of chopper and demand power from the system, respectively.

3.2.4 Eletrolyzer

The electrochemical reaction of water electrolysis is given by [28]

$$H_2O_{(\text{liquid})} + \text{electricity energy} \Rightarrow O_{2(gas)} + H_{2(gas)} \tag{6}$$

According to Faraday's law, hydrogen production rate of an electrolyzer cell is directly proportional to the electrical current in the equivalent electrolyzer circuit [29], given by

$$n_{H2} = \frac{\eta_F n_C i_e}{2} \tag{7}$$

where n_C is the number of electrolyzer cells in series; η_F is the Faraday efficiency; n_{H2} is the produced hydrogen moles per second; i_e is the electrolyzer current

4. Proposed Energy Management Strategy

4.1. Problem statement

Based on the structure of microgrid, PV as the main power source delivers energy to the load. The excess power will be saved in battery or H2 tank. When PV cannot supply the load, ESS will provide energy for the system [30]. Therefore, the power balance should be kept all the time, given by

$$P_{net} = P_{load} - P_{PV} \tag{8}$$

$$P_{net} = P_{FC} + P_{bat} + P_{ele} \tag{9}$$

where P_{net} is the power which ESS need to supply; the efficiency of inverter and converter is already considered in all the output power of energy sources.

In this paper, the main purpose is to test the performance of proposed EMS in reducing degradation of fuel cell and battery while considering the hydrogen consumption. Because of the small capacity of the battery, it is preferred as a first choice for excess energy storage. Thus, the load sharing between FC and battery will be the main optimization problem, which also can be expressed as current sharing because the parallel structure.

For the optimization problem of the ESS, there are three items which are taken into consideration:

- Hydrogen consumption and degradation of FC (related to FC output current)

- Energy consumption and degradation of battery (related to battery output current)
- Battery-sustainability (keep close to the ideal SoC_{bat})

Therefore, a quadratic cost function considering all these targets is given to minimize the total cost of system and AMPC method is proposed to solve it as follows:

$$\min_{\{i_{fc}(t),i_{bat}(t)\}} J=\int_{t}^{t+\Delta t}(\omega_f \bullet(\dot{m}_f(\tau))^2+\omega_{ef}\bullet(\dot{SoC}_{bat}(\tau))^2+\omega_{SoC_{bat}}\bullet(SoC_{bat}(\tau)-SoC_r)^2)d\tau \tag{10}$$

$$\begin{cases} SoC_{bat.\min}\le SoC_{bat}(t)\le SoC_{bat.\max} \\ 0\le i_{fc}(t)\le i_{fc.\max} \\ \Delta i_{fc.\min}\le \Delta i_{fc}(t)\le \Delta i_{fc.\max} \end{cases}$$

where Δt is the prediction horizon, ω_f , ω_{ef} , $\omega_{SoC_{bat}}$ are penalty weights of fuel consumption, equivalent factor of battery energy consumption and deviation of SoC_{bat} from the ideal value SoC_r ,respectively; $\dot{SoC}_{bat}(t)$ is the energy consumption rate of battery; $\dot{m}_f(t)$ is the hydrogen consumption rate ; $\Delta i_{fc.\min}$, $\Delta i_{fc.\max}$ represent the limitations of fuel cell current generation which reduce stack faults and degradation [27].

4.2. MPC model

MPC optimization problem can be transferred to quadratic programming (QP) with linear inequality constraints, the standard format is [31]:

$$\Delta U^*=arg\min_{\Delta U}\Delta U^T H\Delta U+2\Delta U^T f \qquad st: A\Delta U\le b \tag{11}$$

where H , f are the constant matrix; A is constraint coefficient matrix; b is the column vector; ΔU^* is the optimal input sequence. The optimal control input sequence can be defined by

$$u(k)=u(k-1)+\Delta u(k) \tag{12}$$

The optimization problem and energy storage system state equation can be formulated in discrete-time as

$$\begin{aligned} min\ \ & \omega_f\sum_{k=0}^{p-1}\dot{m}_f(k)^2+\omega_{ef}\sum_{k=0}^{p}\Delta SoC_{bat}(k)^2+ \\ & \omega_{SoC_{bat}}\sum_{k=1}^{p}(SoC_{bat}(k)-SoC_r)^2 \end{aligned} \tag{13}$$

$s.t.$

$$\begin{cases} SoC_{bat.\min}\le SoC_{bat}(k)\le SoC_{bat.\max}, & k=1,\cdots,\ p \\ 0\le i_{fc}(k)\le i_{fc.\max}, & k=0,1,\cdots,\ p-1 \\ \Delta i_{fc.\min}\le \Delta i_{fc}(k)\le \Delta i_{fc.\max}, & k=0,1,\cdots,\ p-1 \end{cases}$$

$$\begin{cases} I_{fc}=I_{fc0}+M\Delta I_{fc} \\ I_{bat}=I_{ts}-m_{hfc}\eta_{hfc}I_{fc} \\ Y=Y_0+\sigma M(m_{hfc}\eta_{hfc}I_{fc}-I_{ts})/(3600Q_{bat}) \end{cases}$$

$st:$

$$\begin{aligned} & I_{fc0}=\left[i_{fc}(-1)\ \cdots\ i_{fc}(-1)\right]^T;\ Y_0=\left[SoC_{bat}(0)\ \cdots\ SoC_{bat}(0)\right]^T; \\ & I_{bat}=\left[i_{bat}(0)\ i_{bat}(1)\cdots\ i_{bats}(p-1)\right]^T;\ I_{ts}=\left[i_{ts}(0)\ i_{ts}(1)\cdots\ i_{ts}(p-1)\right]^T; \\ & Y=\left[SoC(1)\ \cdots\ SoC(p)\right]^T \end{aligned} \tag{14}$$

where p is the step of prediction horizon; σ is the interval of each prediction step; M is the lower triangular matrix; $i_{fc}(-1)$ is the measured fuel cell current before optimization.

The equation (13) can be rewritten in matrix and then comparing with equation (15), the coefficients of QP problem, H and f can be obtained as shown in equation (15). It is easy to find A and b by using same method.

$$\begin{cases} H=\omega_{SoC_{bat}}\left(\dfrac{m_{hfc}\eta_{hfc}}{3600Q_{bat}}\right)^2 M^T M^T MM+\left[\omega_{ef}\left(\dfrac{m_{hfc}\eta_{hfc}}{3600Q_{bat}}\right)^2+\omega_f g_2{}^2\right]* \\ M^T M \\ f=\omega_f g_2 M^T(g_2 I_{fc0}+B)+\omega_{ef}\dfrac{m_{hfc}\eta_{hfc}}{(3600Q_{bat})^2}M^T(m_{hfc}\eta_{hfc}I_{fc0}-I_{ts}) \\ +\omega_{SoC_{bat}}\begin{bmatrix} \dfrac{m_{hfc}\eta_{hfc}}{3600Q_{bat}}M^T M^T(Y_0-L) \\ +\dfrac{m_{hfc}\eta_{hfc}}{(3600Q_{bat})^2}M^T M^T M(m_{hfc}\eta_{hfc}I_{fc0}-I_{ts}) \end{bmatrix} \\ A=[M;-M;I;-I;-M^2;M^2] \\ b=[C_1-I_{fc0};I_{fc0};C_2;C_2;\dfrac{3600Q_{bat}}{m_{hfc}\eta_{hfc}}(Y_0-C_4)-\dfrac{MR}{m_{hfc}\eta_{hfc}}+MI_{fc0}; \\ \dfrac{3600Q_{bat}}{m_{hfc}\eta_{hfc}}(C_5-Y_0)+\dfrac{MR}{m_{hfc}\eta_{hfc}}-MI_{fc0}] \end{cases} \tag{15}$$

where B and L are constant matrixes representing $h_2, SoC_r; C_1, C_2, C_3, C_4, C_5$ are constraints matrixes; I is identity matrix.

4.3. AMPC based Energy Management Strategy

The on-line energy management optimization problem presented in this paper is formulated as a repeated solution of a finite horizon optimal control problem considering system dynamics, input and state constraints [32].

In the proposed AMPC method, the penalty weight $\omega_{SoC_{bat}}$ will be adjusted according to the deviation of SoC_{bat} which shows the system dynamics. Then the formulated MPC model is applied to obtain the control inputs with measured data of system at each sampling time. Moreover, the stability and disturbance rejection properties of MPC were tested in [33]. The specific actions of the AMPC based EMS are performed at each sampling time as shown in Fig.4.

Step 1: The system state information is measured, including SoC_{bat} ,fuel cell current, current demand, the chopper modulation ratio m_{hfc} and so on.

Step 2: Based on the historical data, demand power is predicted over a short finite horizon in the future.

Step 3: The model and parameters of AMPC is prepared. Firstly, the penalty weights are adjusted with PI controller, according to the deviation of SoC_{bat} (16); secondly other parameters such as *H*, *f* and constraints are updated

$$\omega_{SoC_{bat}}(t) = \omega_0 + K_p\left|SoC_{bat}(t) - SoC_r\right| + K_i\int_{t0}^{t}(SoC_{bat}(\tau) - SoC_r)d\tau \tag{16}$$

Step 4: Using MATLAB function to solve the standard MPC problem and getting the optimal control sequence, then just implementing the first optimal control input. Horizon control recedes just one-time step and MPC repeats the algorithm by going back to step 1.

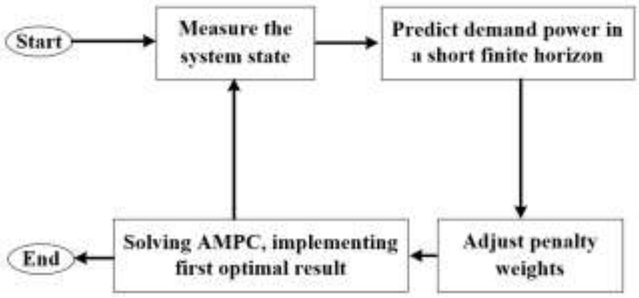

Fig.4. Flowchart of AMPC based EMS

In this method, although $\omega_{SoC_{bat}}$ is adjusted by equation (16), based on the rule-based control some principles are also set to limit it such as increasing the penalty weight $\omega_{SoC_{bat}}$ to huge value when SoC is less than safe range 0.4, due to the extreme situations which can result in over discharging of battery.

5. Simulation Results

The model for testing proposed method is developed in MATLAB-Simulink™ which runs on a computer with 2.3GHz working frequency and 8GB RAM. The general domestic load profile modelled by multiple Gaussian Distribution method is taken from [34] and the solar irradiance and temperature are obtained from the Istanbul University Observatory and Meteorology Station to obtain PV output power (see Fig.5). Using these two general energy source models can effectively reduce the effects of other factors and estimate the performance of AMPC. Additionally, the different initial SoC of battery is applied to show the control effects of AMPC based EMS. Two classic scenarios are presented here:

1) normal case: SoC of battery is 0.5;

2) extreme case: SoC of battery reaches the minimum limit 0.4, but the ESS needs to deliver energy to the network.

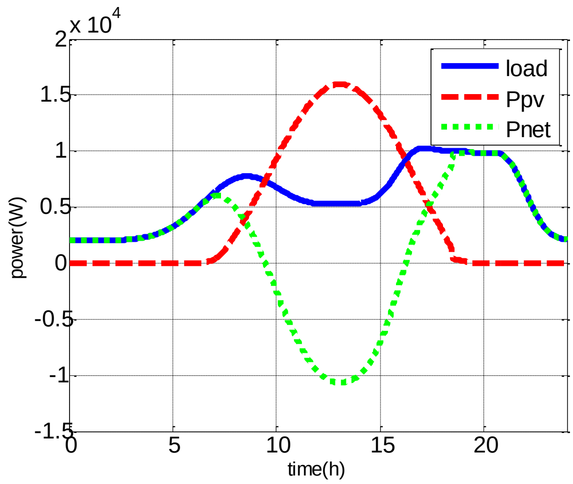

Fig.5. The power of load, PV and network

The proposed EMS could not obtain the data directly from the historical record for predicting the power demand in the future, because it is on-line method [35]. In [2], the Artificial Neural Network (ANN) is applied to predict wind power, solar power and load separately. However, this method will make the prediction error double or more in some situations. Therefore, in this paper, a linear analytical method is proposed by

$$\gamma = \begin{cases} \Delta i_{ts},\ if \quad 0 \le \left|\Delta i_{ts}\right| \le 1 \\ 0.5\Delta i_{ts},\ if \quad 1 < \left|\Delta i_{ts}\right| \le 2 \\ 0.1\Delta i_{ts},\ if \quad 2 < \left|\Delta i_{ts}\right| \le 3 \\ 0,\ if \quad 3 < \left|\Delta i_{ts}\right| \end{cases} \tag{17}$$

The changing rate of current demand is computed via various simulations and observations. The simulation performance obtained is shown in Fig.6.

Then the current demand in the prediction horizon is calculated as equation (18) [37]

$$i_{ts}(k) = i_{ts}(k-1) + \gamma,\quad k = 0,1\ldots p-1 \tag{18}$$

5.1. AMPC based Energy Management Strategy

In this paper, some parameters of MPC model are chosen as follows: the length of prediction horizon is 500s; the sample time is 50s, so p is 10, which can be considered as tuning parameter but not discussed here. The range of SoC_{bat} is from 0.4 to 0.7, ideal State-of-Charge of battery $SoCr$ is 0.6 [36]. It has to be reminded that in order to compare different method fairly, the battery will be charged to the maximum SoC of battery at the best efficiency point after simulation finished. And some parameters about the fuel cell system can be found in [27]. To adjust the with PI controller, the parameters are chosen to be $\omega_0 = 0.1, K_p = 10, K_i = 0.01$; based on the experiments, ω_{ef} and ω_{fc} are chosen as $0.1\alpha^2$,1 respectively (α is the EF at the best efficiency point, $\alpha = 259.55$)

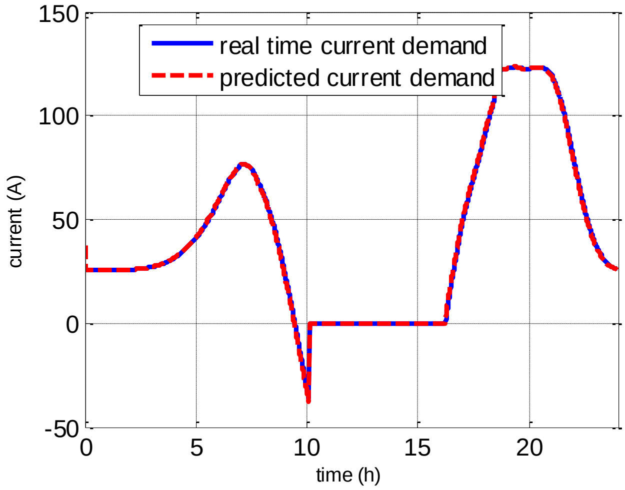

Fig. 6. Comparison of predicted and real-time current demand

5.2. Simulation Results and Observations

Simulation results for proposed AMPC and MPC methods in extreme case are presented in Fig.7 and Fig.8. When the SoC of battery is reaching minimum limitation at the start point, the AMPC based EMS adjusts its penalty weight to huge value, which means the optimization priority of battery-sustainability is higher than other targets, correspondingly the SoC of battery in AMPC method increases faster than that in MPC method. After it reaches the safe range, the $\omega_{SoC_{bat}}$ also decreases. Around 06:00-07:00, as the power demand increases, the SoC_{bat} of MPC passes the minimum limit but the SoC_{bat} of AMPC avoids this situation successfully, which means battery can provide energy sustainably.

Although the degradation of battery in AMPC is higher than in MPC before 10:00 as shown in Fig.7, which because battery is not charged during 00:00-08:00, it increases faster than that of AMPC starting from the 08:00 and is higher after 10:00. At the end of day, the degradation of battery controlled by AMPC is decreased 8.55% as compared with MPC. The degradation of FC is also decreased almost 2.4%.

In the normal case, the result is similar to the extreme case; the SoC_{bat} of AMPC is close to ideal value quickly and also the degradation of battery and FC decreases 18.1% and 1.53% compared to MPC based EMS, respectively. Simulation results are given as whole in Table 2.

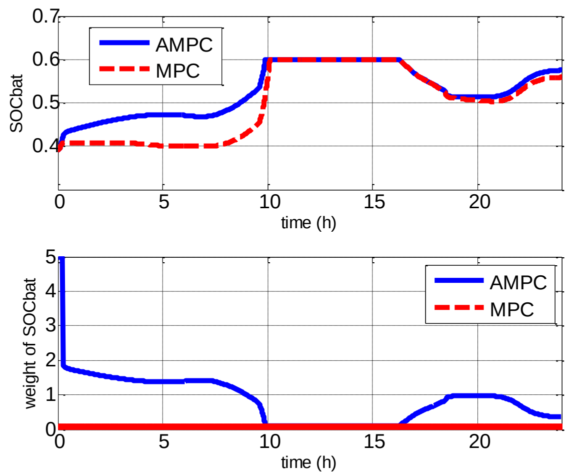

Fig. 7. SoC_{bat} and weight of SoC_{bat} for both method in extreme case

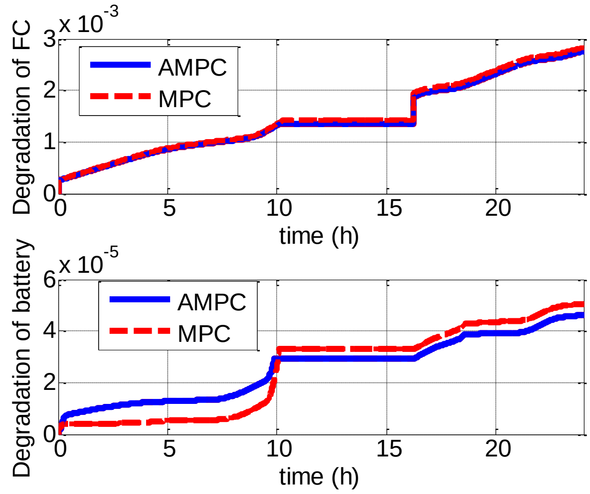

Fig. 8. Degradation of battery and fuel cell for extreme case

Although improvements are realized on performance of SoC_{bat} and degradation, the consumption of hydrogen in AMPC method increases compared to MPC for both scenarios. This is because the FC works at the beginning to charge battery based on AMPC (by increasing the $\omega_{SoC_{bat}}$ to a huge value), which increases the SoC_{bat} from the minimum limit. But in this extreme situation, EMS based on MPC could not dynamically change the penalty weight and makes SoC_{bat} close to minimum limit. If the load increases during this period, the SoC_{bat} will be lower than 0.4, which makes big damage to battery and decreases the stability of system. When the initial SoC_{bat} equals to 0.6, the total hydrogen consumption is close to MPC.

Therefore, while minimizing hydrogen consumption, proposed EMS can reduce the degradation of both FC and battery, and increase the stability of system by adaptively adjust the weights of SoC_{bat} according to the deviation to ideal value, especially in some extreme scenarios. The increased hydrogen consumption can be neglected in this situation.

Table 2. Simulation results of AMPC and MPC

Initial SoC	Performance index	MPC	AMPC	Improvement (%)
0.4	SoC_end	0.56	0.58	N
	Battery Degradation* 10^4	0. 5031	0.4601	-8.55
	FC Degradation* 10^3	2.8290	2.7614	-2.39
	Hydrogen cost (g)	6549.9	6564.2	0.21
0.5	SoC_end	0.56	0.58	N
	Battery Degradation* 10^4	0.435	0.3563	-18.1
	FC Degradation* 10^3	2.8120	2.7689	-1.53
	Hydrogen cost (g)	6519.83	6534.0	0.21

Note: The degradation is calculated based on the equations presented in [24], from 1 (means still new, never be used) to 0(means cannot work anymore), no unit.

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Therefore, while minimizing hydrogen consumption, proposed EMS can reduce the degradation of both FC and battery, and increase the stability of system by adaptively adjust the weights of SoC_{bat} according to the deviation to ideal value, especially in some extreme scenarios. The increased hydrogen consumption can be neglected in this situation.

6. Conclusion

In this paper, Adaptive Model Predictive Control based online energy management strategy for microgrid with renewable source and hydrogen fuel cell is proposed to extend the system lifetime while considering the fuel economy. As the complexity of microgrid increases, the common Model Predictive Control based EMS is hard to adapt to all the situations. With dynamically changing the penalty weights of optimization target by a simple PI controller, not only the adaptivity of MPC is improved but also the robustness of EMS and the stability of microgrid system are increased. Furthermore, this AMPC method also can be applied to different fields using MPC, such as EMS for Electric Vehicles. Based on the simulation results, this paper gives a better understanding of MPC. However, the adjustment of penalty weights need to obtain from the experiments. More researches will be realized by studying on prediction horizon, prediction method and adjustment method of penalty weights in the future.

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