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Energy dispatch strategy for a photovoltaic–wind–diesel–battery hybrid power system

Henerica Tazvinga *, Bing Zhu, Xiaohua Xia

Center of New Energy Systems, Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria 0002, South Africa

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Abstract

In this paper, an energy dispatch model that satisfies the load demand, taking into account the intermittent nature of the solar and wind energy sources and variations in demand, is presented for a solar photovoltaic–wind–diesel–battery hybrid power supply system. Model predictive control techniques are applied in the management and control of such a power supply system. The emphasis in this work is on the co-ordinated management of energy flow from the battery, wind, photovoltaic and diesel generators when the system is subject to disturbances. The results show that the advantages of the approach become apparent in its capability to attenuate and its robustness against uncertainties and external disturbances. When compared with the open loop model, the closed-loop model is shown to be more superior owing to its ability to predict future system behavior and compute appropriate corrective control actions required to meet variations in demand and radiation. Diesel consumption is generally shown to be more in winter than in summer. This work thus presents a more practical solution to the energy dispatch problem.
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Keywords: Energy management; Disturbance; Intermittent nature; Hybrid energy system; Optimization scheme

1. Introduction

Renewable energy (RE) and autonomous hybrid energy systems have become attractive energy supply options in many countries because of global environmental concerns and access to electricity, as well as the depletion and rising cost of fossil fuel resources (Deshmukh and Deshmukh, 2008). Diesel generators (DGs) have traditionally been favored solutions for off-grid applications because of their low initial capital cost. They however exhibit high operational and maintenance costs and have negative environmental impacts. Solar photovoltaic(PV) and wind supplies are free and environmentally friendly, but because of their intermittent nature they cannot provide continuous uninterrupted power. Incorporation of battery storage can improve supply reliability but it is often necessary to oversize both the storage and RE systems excessively, resulting in high capital costs and inefficient use of the system. PV–wind–diesel–battery (PWDB) hybrid power systems offer great opportunities by overcoming the above problems, providing environmentally friendly, reliable systems that reduce DG running costs and are considered as a cost-effective way to meet energy requirements of areas not easily accessible for grid connection (Elhadidy and Shaahid, 1999; Datta et al., 2009).

Hybrid energy systems have been used to power satellite earth stations, rural communities, radio telecommunications and other off-grid applications (Belfkira et al., 2011). In Central Africa, in countries such as the Congo,

* Corresponding author. Tel.: +27 12 420 2068.
E-mail address: henerica.tazvinga@up.ac.za (H. Tazvinga).

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Nomenclature

$P_1(k)$ control variable representing energy flow from the diesel generator to the load at the kth hour [kW]
$P_2(k)$ control variable representing energy flow to and from the battery at the kth hour [kW]
$P_3(k)$ control variable representing energy flow from the PV array at the kth hour [kW]
$P_4(k)$ control variable representing energy flow from the wind generator at the kth hour [kW]
$P_L(k)$ control variable representing the load at the kth hour [kW]
A_c the PV array area [m^2]
$P_{pv}(k)$ the hourly energy output from a PV generator of a given array area at the kth hour[kW h/m^2]
$P_{wind}(k)$ the hourly energy output from a wind generator at the kth hour [kW]
η_{pv} the PV generator efficiency
η_{pv} the PV generator efficiency
η_{WG} the wind generator efficiency
η_B the battery round trip efficiency
$SOC(k)$ the current state of charge of the battery bank

many mines are operating on DGs and RE hybrid systems can be useful in such industrial applications. The main challenge is the design of an optimal energy management system that satisfies the load demand, considering the variable nature of the RE energy sources and the real-time variations in demand. Considerable research effort has been made to optimize hybrid system components and operations, using various methods (Dufo-Lopez et al., 2011; Barley and Winn, 1996; Kamaruzzaman et al., 2008; Elaiw et al., 2012). However, these do not solve the problem in real-time in order to analyze the actual performance of the system, hence the application of a receding horizon strategy in the performance analysis of the hybrid system in this work. Unlike most similar works, this work focuses on the optimal dispatch of the various powers while minimizing operation cost and maximizing the utilization of renewable energy sources while considering battery life improvement by minimizing the charge–discharge cycles of the battery. Model predictive control (MPC) is employed in this work owing to its advantages over the open loop approach and its capability to handle constraints of the system explicitly using a user-defined cost function (Lee and Yu, 1994). Closed-loop models automatically adjust to changes in the outputs due to external disturbance, measures states and give feed back to the optimization model repeatedly and hence the optimal solution is updated accordingly (Kaabeche and Ibtiouen, 2014; Vahidi et al., 2006). The open loop model is unable to compensate for disturbances occurring from external sources owing to the absence of a feedback mechanism. When compared with the open loop optimization approaches, MPC results in reduced dimensions, easier computation, convergence and robustness which are well demonstrated by its application to power economic dispatching problems with a six-unit system (Kaabeche and Ibtiouen, 2014; Xia et al., 2011; Zhang and Xia, 2011). The MPC approach has been applied to a building heating system in order to analyze the energy savings that can be achieved (Siroky et al., 2011). Implementation of the receding horizon in controlling a single conventional power plant output to balance the demand has been explored by Gallestey et al. (2002). However, the work done so far does not specifically apply the on-line methodology to PWDB hybrid power supply options. A few researchers have applied this approach to the analysis of electric energy systems that incorporate intermittent resources (Xie and Ilic, 2008).

This work follows up on previous work presented in Tazvinga et al. (2013). The major addition is the wind generator and the application of the receding horizon technique to the optimal energy management strategy of a PWDB hybrid power supply system. The paper presents a more practical model when compared with the open loop model making it more favorable for real-time applications. The optimal control model for the PWDB hybrid system is an open loop approach and there is no feedback of system states. Absence of feedback might render the system vulnerable to disturbances in both load demand and RE (solar and wind) energy. In this paper, the MPC technique is applied to the open loop model for a PWDB hybrid power supply system with the aim of minimizing fuel costs, minimizing use of the battery and maximizing use of RE generators. The paper considers the effect of daily energy consumption and RE variations on the system by introducing disturbances in the demand profiles and RE output for both winter and summer seasons. The multi-objective optimization used in this work enables designers, performance analyzers, control agents and decision-makers who are faced with multiple objectives to make appropriate tradeoffs, compromises or choices. Although an MPC strategy might be too sophisticated for individual domestic applications, it is certainly useful for institutional and industrial applications. The paper is organized as follows: in Section 2, the hybrid system configuration is briefly described. In Section 3, the MPC formulation for the PWDB hybrid system is described. In Section 4, the simulation results are discussed and the last section is the conclusion.

2. Hybrid system configuration

The PWDB hybrid power supply system considered in this paper consists of the PV system, wind generator (WG) system, battery storage system and the DG, as

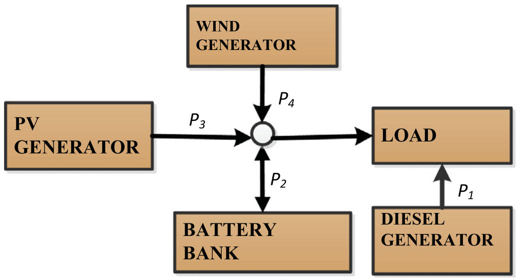

Fig. 1. Schematic layout of the PV–wind–diesel–battery hybrid power supply system.

shown in Fig. 1. The supply priority is such that the load is initially met by the RE generators (PV and wind) and the battery comes in when the RE generators' output is not enough to meet the load, provided it is within its operating limits. The DG comes in when the RE and/or the battery cannot meet the load. The battery is charged when the total generated power is above the load requirements. The RE supplies the load and/or battery, depending on the instantaneous magnitude of the load and the battery bank state of charge. Control variables P_1, P_3 and P_4 respectively, represent the energy flows from the DG, PV and WG to the load at any hour (k), while P_2 represents the energy flow to and from the battery.

2.1. Sub-models

The PV, DG and battery models are described in detail in our previous paper, in which the hourly energy output from the PV array of a given area is given by Tazvinga et al. (2013):

$$P_{pv}(k) = \eta_{pv} A_c I_{pv}(k), \tag{1}$$

where η_{pv} is the efficiency of the PV array, $I_{pv}(k)$ (kW h/m^2) is the hourly solar irradiation incident on the PV array, A_c is the PV array area and $P_{pv}(k)$ is the hourly energy output from a PV generator (Hove and Tazvinga, 2012). The battery state of charge (SOC) is given by the expression:

$$SOC(k+1) = SOC(k) - \alpha(P_2(k)), \tag{2}$$

in which, $\alpha = \eta_B / B_C^{max}$ and η_B is the battery round trip efficiency while B_C^{max} is the maximum battery capacity. $SOC(k)$ is the current SOC of the battery. A variable speed DG is employed in this work because of its lower fuel consumption compared to the constant speed type and its ability to use optimum speed for a particular output power, resulting in higher efficiency of the generator operation. In this way, the engine is able to operate at relatively low speed for low power demand and vice versa (Seeling-Hochmuth, 2012).

The power output of a wind turbine depends on the wind speed pattern at the specific location, air density, rotor swept area and energy conversion efficiency from wind to electrical energy. The wind speed at the tower height can be calculated by using the power law equation as follows:

$$v_{hub}(k) = v_{ref}(k)\left(\frac{h_{hub}}{h_{ref}}\right)^{\beta}, \tag{3}$$

where $v_{hub}(k)$ is the hourly wind speed at the desired height h_{hub}, $v_{ref}(k)$ is the hourly wind speed at the reference height h_{ref} and β is the power law exponent that ranges from $\frac{1}{7}$ to $\frac{1}{4}$. $\frac{1}{7}$ is used in this work which is typical for open land. Various models are used to simulate the wind turbine power output and in this work, the mathematical model used to convert hourly wind speed to electrical power is as follows (Ashok, 2007):

$$P_{wind} = 0.5\eta_w \rho_{air} C_p A V^3, \tag{4}$$

where V is the wind velocity at hub height, ρ_{air} the air density, Cp the power coefficient of the wind turbine, which depends on the design, A the wind turbine rotor swept area, and η_w the WG efficiency as obtained from the manufacturer's data.

2.2. Open loop optimal control model

In this paper, the WG and PV module are modeled as variable power sources controllable in the range of zero to the maximum available power for a 24-h interval. No operating costs are incorporated for the renewable energy sources. The DG is also modeled as a controllable variable power source with minimum and maximum output power. The battery bank is modeled as a storage entity with minimum and maximum available capacity levels. No battery operating costs are incorporated. Fuel consumption costs are modeled as a non-linear function of generator output power (Muselli et al., 1999). The optimization problem is solved using the "quadprog" function in MATLAB.

The multi-objective function is given by the expression:

$$\min \sum_{k=1}^{N} (w_1(C_f(aP_1^2(k) + bP_1(k))) + w_2 P_2(k) - w_3 P_3(k) - w_4 P_4(k)), \tag{5}$$

subject to the following constraints:

$$P_1(k) + P_2(k) + P_3(k) + P_4(k) = P_L(k), \tag{6}$$
$$P_i^{min} \leqslant P_i(k) \leqslant P_i^{max}, \tag{7}$$
$$0 \leqslant P_1(k) \leqslant DG^{rated}, \tag{8}$$
$$P_2^{min} \leqslant P_2(k) \leqslant P_2^{max}, \tag{9}$$
$$0 \leqslant P_3(k) \leqslant P_{pv}(k), \tag{10}$$
$$0 \leqslant P_4(k) \leqslant P_{wind}(k), \tag{11}$$

$$SOC^{min} \leqslant SOC(0) - \alpha \sum_{\tau=1}^{k} P_2(\tau) \leqslant SOC^{max}, \tag{12}$$

for all $k = 1, \ldots, N$, where N is 24 and C_f is the fuel price. $w_1 - w_4$ are weight coefficients whose sum is 1. Daily operational costs are considered, as they enable customers to make informed decisions before buying a given system, as stated earlier. The daily operational cost can then be extrapolated to get the weekly, monthly or yearly cost but this is not within the scope of this work. $SOC(0)$ is the initial SOC of the battery.

$\alpha\sum_{\tau=1}^{k}P_2(\tau)$ is the power accepted and discharged by the battery at time k. P_i^{min} and P_i^{max} are the minimum and maximum limits for each variable.

2.3. Model parameters and data

The solar radiation data used in this study are calculated from stochastically generated values of hourly global and diffuse irradiation using the simplified tilted-plane model of (Collares-Pereira and Rabl, 1979). This is calculated for a Zimbabwean site, Harare (latitude 17.80 °S). Wind speed data measured at 10 m height at the site over a period of two years is used in this work. Two typical summer and winter load demand profiles for institutional applications based on an energy demand survey carried out in rural communities in Zimbabwe are used and the methodology for calculating the load demand profile is as described in Tazvinga and Hove (2010). These are as shown in Table 1.

The model parameters and PV output data are as used in Hove and Tazvinga (2012). The generator cost coefficients are specified by the manufacturer while the DG, PV and battery bank capacities are chosen based on a sizing model developed by Hove and Tazvinga (2012). The system is designed such that demand is met at any given time. A small system means demand will not always be met while an oversized system means the demand will be met but the system will be unnecessarily costly and energy will be wasted. This work focuses mainly on the optimal energy management of any given system. The sizing is also within "Rule of thumb" provisions, for example PV array area for 1 kWp varies from 7 m^2 to 20 m^2 depending on cell material used. A 5 kW Evoco endurance wind turbine is employed in this study. The energy generated by the PV, WG and the DG is consumed by the load, and the PV and wind generators also charge the battery, depending on the instantaneous magnitude of the load and SOC of the storage battery. The switching on or off times of the DG depend on the DG energy dispatch strategy employed which is herein referred to as the load following strategy. The DG switches on when the combined hourly output of PV and WG is lower than the hourly load and the combined output of the battery, WG and PV cannot meet the load.

3. Model predictive control for the photovoltaic–wind–diesel–battery hybrid system.

The optimal control for the PWDB hybrid system described above is an open loop approach, and there exists no feedback of system states. Absence of feedback might render the system vulnerable to disturbances (in both load demand, PV and wind energy).

In this section, a closed-loop linear MPC is proposed for the PWDB hybrid system, such that: (1) load demand at each sampling time is satisfied, (2) power provided by the DG is minimized, and (3) the closed-loop system is robust with respect to disturbances in both load demand and RE output.

3.1. Brief introduction of discrete linear MPC

Discrete linear MPC is a control approach for a given system expressed as follows:

$$x(k+1) = Ax(k) + Bu(k), \tag{13}$$

$$y(k) = Cx(k), \tag{14}$$

where $x \in R^n$, $u \in R^m$ and $y \in R^l$ are states, inputs and outputs, respectively. The MPC approach can minimize the cost function

$$J = \sum_{i=1}^{N_p}(y(k+i-1|k) - r(k+i-1))^2 = (Y-R)^T(Y-R), \tag{15}$$

subject to constraint

$$Mu \leqslant \gamma, \tag{16}$$

Table 1
Summer and winter demand profiles.

Time	Winter load (kW)	Summer load (kW)	Time	Winter load (kW)	Summer load (kW)
00:30	2.5	2.5	12:30	2.95	2.25
01:30	2.5	2.5	13:30	2.95	2.32
02:30	2.5	2.85	14:30	2.95	2.35
03:30	2.5	2.95	15:30	2.95	2.35
04:30	2.5	2.85	16:30	2.65	2.45
05:30	2.65	2.5	17:30	2.65	3.15
06:30	2.65	2.15	18:30	4.25	3.31
07:30	2.35	2.25	19:30	4.25	4.25
08:30	2.35	2.3	20:30	3.31	4.25
09:30	4.0	2.32	21:30	3.15	3.0
10:30	4.0	2.35	22:30	3.15	2.95
11:30	2.95	0.32	23:30	2.35	2.65

where $Y(k) = [y^T(k), y^T(k+1|k), \ldots, y^T(k+N_p-1|k)]^T$, and $y(k+i|k)$ denotes the predicted value of y at step $i(i=1,\ldots,N_p)$ from sampling time k; $R(k) = [r(k), r(k+1), \ldots, r(k+N_p-1)]$ is the predicted reference value for Y; N_p denotes the predicted horizon; and M and γ are matrices and vector with proper dimensions.

In this paper, the control horizon is selected equal to the predicted horizon. Predicted states can be calculated by

$$\begin{aligned}
&x(k+1|k) = Ax(k) + Bu(k),\ y(k) = Cx(k),\\
&x(k+2|k) = Ax(k+1|k) + Bu(k+1|k)\\
&\quad = A^2x(k) + ABu(k) + Bu(k+1|k),\\
&\vdots\\
&x(k+N_p-1|k) = \ldots = A^{N_p-1}x(k)\\
&\quad + \sum_{i=1}^{N_p-1} A^{N_p-1-i}Bu(k+i-1|k),
\end{aligned}$$

and predicted outputs can be calculated by

$$Y(k) = [C, C, \ldots, C]X(k) = Fx(k) + \Phi U \tag{17}$$

where $X(k) = [x^T(k), x^T(k+1|k), \ldots, x^T(k+N_p-1|k)]^T$, $U(k) = [u^T(k), u^T(k+1|k), \ldots, u^T(k+N_p-1|k)]^T$, and

$$F = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{N_p} \end{bmatrix}, \Phi = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & & 0 \\ \vdots & & \ddots & \vdots \\ CA^{N_p-1}B & CA^{N_p-2}B & \cdots & CA^{N_p-N_c}B \end{bmatrix}. \tag{18}$$

Substitute (17) into (15). It can be deduced that minimizing (15) is equivalent to minimizing $\widehat{J} = U^TEU + FU$, where

$$E = \Phi^T\Phi, \quad H = (Fx(k) - R(k))^T\Phi. \tag{19}$$

Numerical tools can be used to solve the optimization problem:

$$U = \arg\min_U U^TEU + FU, \quad s.t. \quad \overline{M}U \leqslant \overline{\gamma}, \tag{20}$$

where the constraint is derived from (16).

The MPC is implemented by using receding horizontal control

$$u(k) = [I, 0, \ldots, 0]U, \tag{21}$$

where I is the identity matrix with proper dimension.

The key concept of MPC is that, in each time k, the control series $U(k)$ is calculated by using optimal control technique, but only the first mth (the dimension of $u(k)$) element of $U(k)$ is implemented. Feedback is incorporated by minimizing the cost function. In the next time $k+1$, performances of the closed-loop system can be assessed, and the control is recalculated and re-implemented based on updated information, such that unpredicted disturbances can be addressed.

3.2. Model transformation for MPC design

For typical MPC design, the PWDB model should be transformed into a linear state-space form, as are given by (13) and (14). In this paper, charging (or discharging) rate of the battery ($P_2(k)$), the energy flow from PV ($P_3(k)$) and wind turbine ($P_4(k)$) are considered as the control inputs. Energy flow from the DG ($P_1(k) = P_L(k) - P_2(k) - P_3(k) - P_4(k)$) and the practical use of RE ($P_3(k) + P_4(k)$) are regarded as the outputs, where $P_L(k)$ denotes the load demands at kth sampling time. The transformation process is carried out as outlined below.

Define $x_m(k) = SOC(k)$ and $u(k) = [P_2(k), P_3(k), P_4(k)]^T$. Transformation process can be started by considering the dynamic model of the battery:

$$x_m(k) = x_m(k-1) + b_mu(k-1), \tag{22}$$

where $b_m = [-\alpha, 0, 0]$. Define

$$y_m(k) = P_L(k) - P_1(k) = P_2(k) + P3(k) + P_4(k), \tag{23}$$

such that

$$y_m(k) = c_mx_m(k) + d_mu(k), \tag{24}$$

where $c_m = 0$ and $d_m = [1, 1, 1]$. From the definition of y_m, it can be seen that minimizing $\sum P_1$ ($P_1 > 0$) is equal to minimizing $\sum (P_L(k) - y_m(k))$.

Define an auxiliary output $y_a(k) = P_3(k) + P_4(k) = c_ax_m(k) + d_au(k)$, where $c_a = 0$ and $d_a = [0, 1, 1]$. Usage of PV can be encouraged by minimizing $\sum (P_{pv}(k) + P_{wind} - y_a(k))$.

Define the augmented system states $x(k) = [x_m(k), y_m(k), y_a(k)]^T$ and the augmented output $y(k) = [y_m(k), y_a(k)]^T$. An augmented linear state space model can be obtained in the form of (13) and (14), where

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} -\alpha & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{25}$$

The augmented linear state-space equations are considered as the plant to be controlled by MPC approach.

3.3. Objective function

The main objectives of the MPC control system are to minimize the use of the DG and to encourage the use of renewable energy. To this end, the objective function (or cost function) can be assigned as the sum of two parts:

1. $\min J_1 = \min \sum_k^{k+N_p} P_1^2(k) = \min \sum_k^{k+N_p} (P_L(k) - y_m(k))^2$, which indicates that usage of the DG should be minimized;
2. $\min J_2 = \min \sum_k^{k+N_p} (P_{pv}(k) + P_{wind}(k) - y_a(k))^2$, which implies that usage of renewable energy is encouraged.

Define the reference value $R(k) = [P_L(k), P_{pv}(k) + P_{wind}(k), P_L(k+1), P_{pv}(k+1) + P_{wind}(k+1), \ldots, P_L(k+N_p-1), P_{pv}(k+N_p-1) + P_{wind}(k+N_p-1)]^T$. The overall objective function is then given by

$$\begin{aligned}\min J &= \min(J_1 + J_2) \\ &= \min\,(Y(k) - R(k))^T(Y(k) - R(k)).\end{aligned} \tag{26}$$

3.4. Constraints

Several types of constraints exist in this hybrid system:

1. Energy flows from generators and battery are non-negative values and are subjected to their maximum values: $0 \leqslant P_1(k) = P_L(k) - y_m(k) \leqslant P_1^{max}, 0 \leqslant P_i(k) \leqslant P_i^{max} (i = 3,4), -P_2^{max} \leqslant P_2(k) \leqslant P_2^{max}$, where $P_i^{max} (i = 1,2,3,4)$ denote the maximum values of energy flows.
2. Energy flow from the PV generator ($P_{pv}(k)$) is no less than PV energy directly used on the load ($P_3(k)$): $P_{pv}(k) \geqslant P_3(k)$. Energy flow from the Wind turbine ($P_{wind}(k)$) should be no less than the wind energy directly used on the load ($P_4(k)$): $P_{wind}(k) \geqslant P_4(k)$.
3. Battery capacity is subject to its minimum and maximum values: $B_C^{min} \leqslant x_m(k) \leqslant B_C^{max}$.

Constraints 1 and 2 can be rewritten into a compact form:

$$M_1 u(k) \leqslant \gamma_1, \tag{27}$$

where

$$M_1 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1 & 0 & -1 \end{bmatrix}, \quad \gamma_1 = \begin{bmatrix} P_2^{max} \\ 0 \\ 0 \\ P_L(k) \\ P_{pv}(k) \\ P_{wind}(k) \\ P_2^{max} \\ P_3^{max} \\ P_4^{max} \\ P_1^{max} - P_L(k) \end{bmatrix}. \tag{28}$$

And they can be rewritten by using the control series

$$\overline{M}_1 U(k) \leqslant \bar{\gamma}_1, \tag{29}$$

where

$$\overline{M}_1 = \begin{bmatrix} M_1 & & \\ & \ddots & \\ & & M_1 \end{bmatrix}, \quad \bar{\gamma}_1 = \begin{bmatrix} \gamma_1 \\ \vdots \\ \gamma_1 \end{bmatrix}. \tag{30}$$

For constraint 3, consider the battery dynamic Eq. (22), which can be written into

$$x_m(k+i|k) = x_m(k) + b_m \sum_{j=k}^{j \leqslant k+i} u(j), \tag{31}$$

or

$$X_m(k) = x_m(k)[1, 1, \cdots, 1]^T + B_m U(k), \tag{32}$$

where $X_m(k) = [x_m(k), x_m(k+1|k), \cdots, x_m(k+N_c-1|k)]^T$, and $x_m(k+i|k)$ denotes the predicted value of x_m from sampling time k; the matrix B_m has the following form:

$$B_m = \begin{bmatrix} b_m & 0 & \cdots & 0 \\ b_m & b_m & \ddots & \vdots \\ \vdots & & \ddots & 0 \\ b_m & b_m & \cdots & b_m \end{bmatrix}. \tag{33}$$

Consider the constraint for the battery. It then follows that

$$\begin{aligned} B_C^{min}[1, 1, \ldots, 1]^T &\leqslant x_m(k)[1, 1, \ldots, 1]^T + B_m U(k) \\ &\leqslant B_C^{max}[1, 1, \ldots, 1]^T, \end{aligned} \tag{34}$$

which can be further expressed by

$$\overline{M}_2 U(k) \leqslant \bar{\gamma}_2, \tag{35}$$

where

$$\overline{M}_2 = \begin{bmatrix} -B_m \\ B_m \end{bmatrix}, \bar{\gamma}_2 = \begin{bmatrix} \left(x_m(k) - B_C^{min}\right)[1, 1, \ldots, 1]^T \\ \left(B_C^{max} - x_m(k)\right)[1, 1, \ldots, 1]^T \end{bmatrix}. \tag{36}$$

Combining constraints (29) and (35) yields constraints in the form of (16), where

$$\overline{M} = [\overline{M}_1^T, \overline{M}_2^T]^T, \quad \bar{\gamma} = [\bar{\gamma}_1^T, \bar{\gamma}_2^T]^T. \tag{37}$$

3.5. MPC algorithm

With the linear state-space equations, the objective function and the constraints, a standard MPC algorithm can be applied to the PWDB hybrid system:

1. Calculate MPC gains E and H by using (18) and (19).
2. Conduct the optimization with objective function given by (15) subject to constraints (16), where $\overline{M}$ and $\bar{\gamma}$ are given by (37).
3. Calculate and implement the receding horizontal control by using (21).
4. Set $k = k + 1$, and update system information with the control $u(k)$; repeat steps 1–5 until k reaches its predefined value.

Basic principles of MPC are given in Section 3.1. Detailed explanations and proofs concerning constrained model predictive control are outlined in Wang (2009).

Based on the proposed MPC algorithm, the closed-loop system could be illustrated by Fig. 2. Energy flows from the PV panel, the wind generator and the battery are dispatched by the proposed MPC, based on the information of diesel consumption. The inclined line implies that the

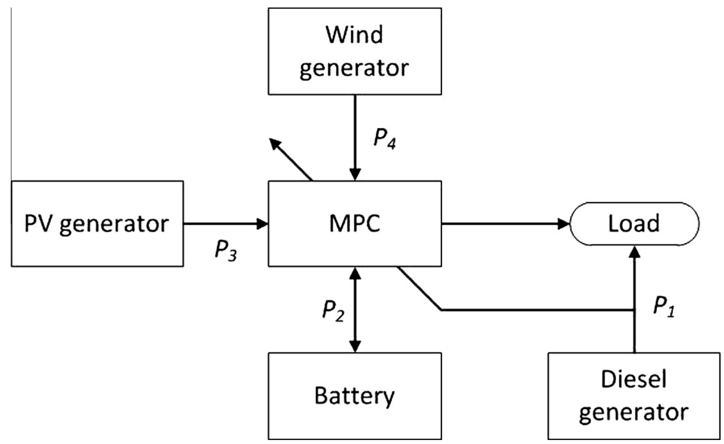

Fig. 2. The closed-loop system for the PWDB hybrid system.

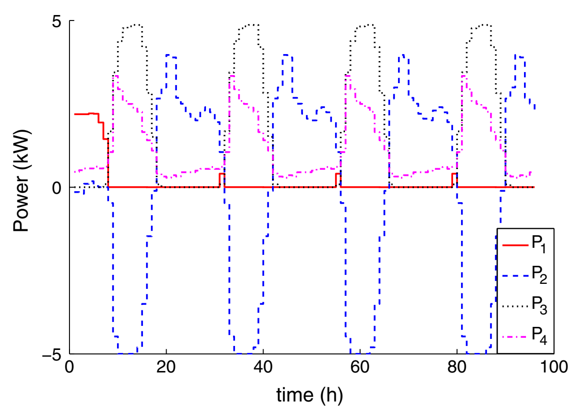

Fig. 3. Simulation result of the closed-loop system without disturbances (in summer).

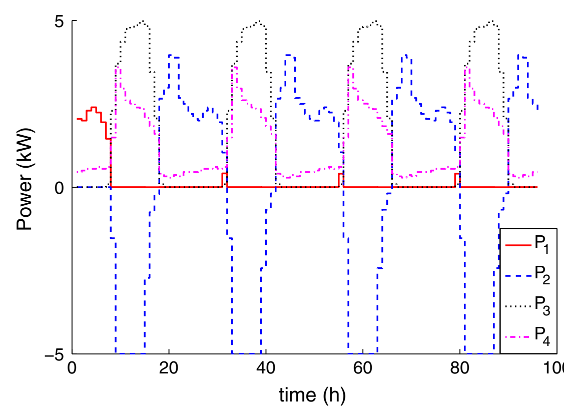

Fig. 5. Simulation result of the open loop system without disturbances (in summer).

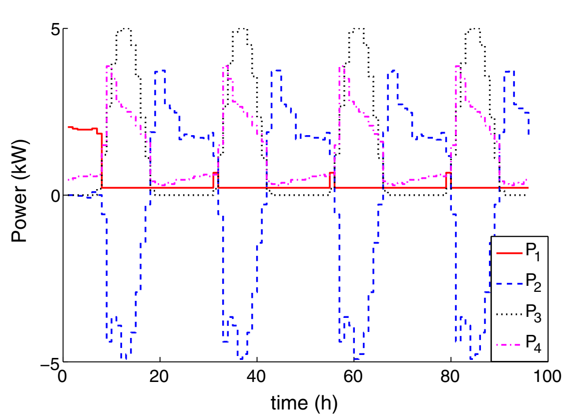

Fig. 4. Simulation result of the closed-loop system without disturbances (in winter).

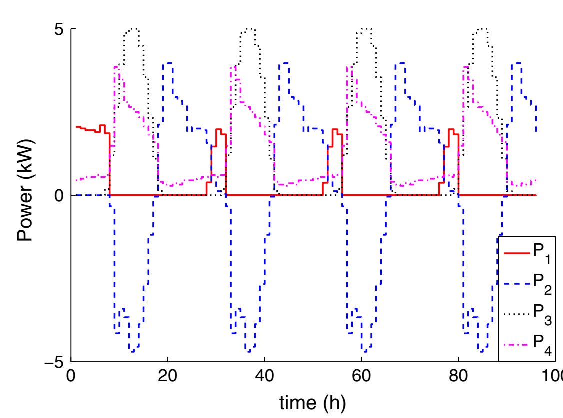

Fig. 6. Simulation result of the open loop system without disturbances (in winter).

real-time information of diesel consumption is fed-back to MPC for decision making, but P_1 is not dispatched directly by MPC.

4. Simulation results and discussion

In this section, simulation results of the PWDB hybrid system in different situations are presented. Data concerning the daily load demand and system parameters of the PWDB system for a Zimbabwean site are presented in Section 2.3. The initial values of $P_i(k)(i = 1, 2, 3, 4)$ are set to zeros. The initial values of the SOC are set to $x_m(1) = 0.5B_c^{max}$. The time spans of simulation cases are assigned to four days (96 h).

Table 2
Diesel energy consumption (kW h) of PWDB hybrid system without disturbances.

	Closed-loop system	Open loop system
Summer	15.61	15.66
Winter	34.63	30.92

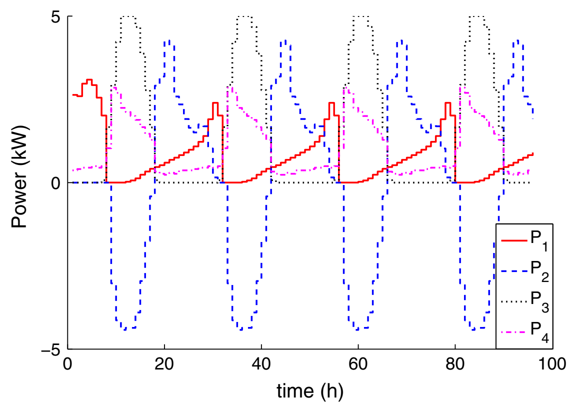

Fig. 7. Simulation result of the closed-loop system with disturbances (in summer).

4.1. Simulation results of the PWDB hybrid system without disturbances

In this simulation case, MPC is simply applied to the ideal PWDB hybrid system without any disturbances. The results of the closed-loop system are displayed in Fig. 3 and Fig. 4.

From the figures, it can be seen that the closed-loop system can automatically schedule the use of the different generators to satisfy the demand load. With the effect of MPC, the hybrid system uses P_3 and P_4 as a priority when there is enough energy from PV and WG. At the same time, the surplus energy from PV and WG is utilized to charge the battery (negative P_2). In case of insufficient PV energy, the discharge of the battery (positive P_2) is used as a priority to meet the demand load. The DG (P_1) is operated as the final choice.

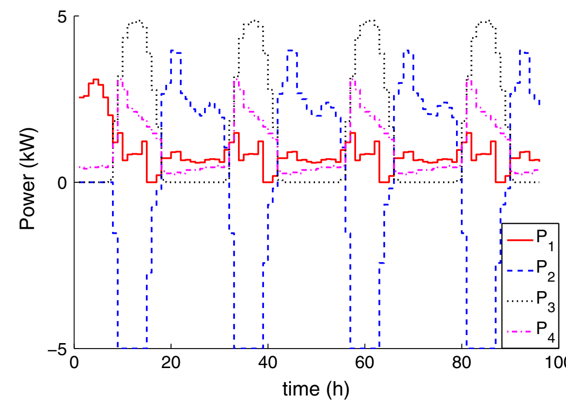

Fig. 9. Simulation result of the open loop system with disturbances (in summer).

For comparison purposes, results of the open loop system without MPC are presented in Figs. 5 and 6. In open loop control, the optimization scheme is identical to that of the closed-loop MPC control, but without receding horizon control. It can be seen from the figures that, without disturbances, performances of both controllers are fairly similar.

The consumption of diesel energy is indicated in Table 2. From the table, it seems that performances of the open loop system and the closed-loop system are almost the same in terms of diesel consumption.

4.2. Results of the PWDB hybrid system with disturbances

The load demand and RE energy presented in Section 2.3 are only expectations based on previous experiences, and there are always disturbances resulting from weather conditions, disasters and migration. In this subsection, it is supposed that the hybrid system encounters a particularly bad condition: actual load demand is 20% greater than expected, and the energy provided by PV and wind turbine is 20% less than expected.

Performances of the closed-loop system with disturbances are displayed in Fig. 7 and Fig. 8, and performances

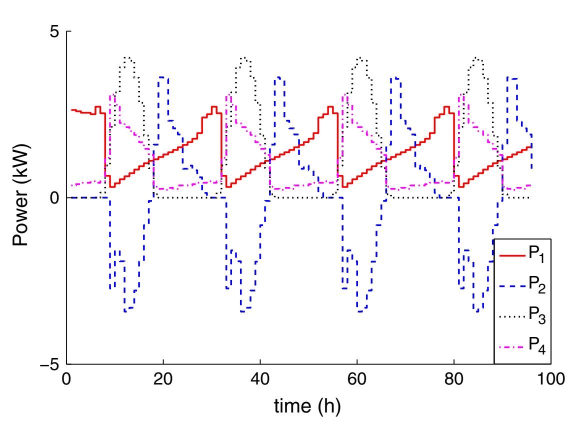

Fig. 8. Simulation result of the closed-loop system with disturbances (in winter).

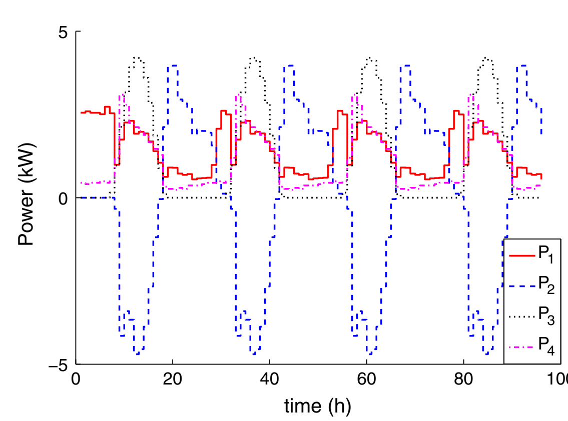

Fig. 10. Simulation result of the open loop system with disturbances (in winter).

Table 3
Diesel energy consumption (kWh) of PWDB hybrid system with disturbances.

	Closed-loop system	open loop system
Summer	75.62	83.17
Winter	132.11	137.32

of the open loop system with disturbances are illustrated by Fig. 9 and Fig. 10. It can be seen from the figures that performances of the closed-loop system are generally better, indicating that its robustness with respect to disturbances is superior to that of the open loop system. The reason is that MPC is capable of predicting future states based on feedback of current states (which are influenced by disturbances). In contrast, open loop control is unable to respond to unpredictable disturbances, and it simply starts the DG when the load demand is greater than expected.

Diesel energy consumption is listed in Table 3 and also indicates that the performance and robustness of the closed-loop system are superior.

5. Conclusion

In this paper, the MPC technique has been applied to the energy management of a PV–diesel–wind–battery power supply system. Comparisons have been made on the performances of the open loop model and the MPC model without disturbances and with disturbances for both winter and summer times. The performances of the closed-loop system have been found to be generally better, indicating that its robustness with respect to disturbances is superior to that of the open loop system. The simulation results show promising applications of MPC approach in the energy dispatch problem. Although an MPC technique might be sophisticated for individual domestic applications, it can be beneficial for institutional and industrial applications. Future work will include further development of the model to cater for thermal loads as well as comparison of model and actual experimental results.

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