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

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 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.

Keywords: energy management, disturbance, intermittent nature, hybrid energy system, optimization scheme

Email address: henerica.tazvinga@up.ac.za. Tel.:+27 12 420 2068 (Henerica Tazvinga)

Nomenclature	
$P_1(k)$	control variable representing energy flow from the diesel generator to the load at the k^{th} hour $[kW]$
$P_2(k)$	control variable representing energy flow to and from the battery at the k^{th} hour$[kW]$
$P_3(k)$	control variable representing energy flow from the PV array at the k^{th} hour $[kW]$
$P_4(k)$	control variable representing energy flow from the wind generator at the k^{th} hour $[kW]$
$P_L(k)$	control variable representing the load at the k^{th} 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 k^{th} hour$[kWh/m^2]$
$P_{WG}(k)$	the hourly energy output from a wind generator at the k^{th} 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

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). Economic optimisation of the energy supply also plays an important role in the use of RE options, especially in areas where access is difficult or where it is uneconomic to extent the grid. In cases where countries import fossil fuels, use of RE sources reduces dependency on imports and increases the security of the energy supply. In terms of social benefits, introduction of RE options generates both direct and indirect employment in the manufacturing, installation and maintenance of the plant. 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 (PV) and wind (W) 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 over-size both the storage and RE systems excessively, resulting in high capital costs and inefficient use of the system. A combination of PV, W, DG and battery storage in a hybrid system overcomes the above problems and provides an economic, environmentally friendly, reliable system that reduces DG run time, number of start/stop cycles and diesel running costs (Elhadidy and Shaahid, 1999).

Hybrid energy systems have been used to power satellite earth stations, rural communities, radio telecommunications and other off-grid applications (Belfkira et al., 2011). The same authors presented a deterministic algorithm to minimize the total system cost of a hybrid wind/PV/diesel energy system while satisfying the load requirements. The results demonstrate the need to use the sizing methodology and the impact of the battery storage on the total hybrid system cost. PV–wind–diesel–battery (PWDB) hybrid power systems offer great opportunities and are considered as a cost-effective way to meet energy requirements of isolated locations and areas not easily accessible for grid connection (Datta et al., 2009). In Central Africa, in countries such as the Congo, many mines are operating on DGs and RE hybrid systems can be useful in such industrial applications. However, the main challenge is the design of an optimal energy management system that satisfies the load demand, considering the intermittent 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). The application of generic algorithm in the optimization of a hybrid system comprised of pico hydro, PV, diesel and battery system has been analysed by (Kamaruzzaman et al., 2008). Dufo-Lopez et al. (2011) apply multi-objective optimization to a PV-wind-diesel system with battery storage focussing on the minimization of the levelized cost of energy and the equivalent carbon dioxide life cycle emissions. It is also suggested in literature that optimal configuration for hybrid systems should be determined by the minimization of the kWh cost (Muselli et al., 1999). (Elaiw et al., 2012) presents an optimal sizing model based on an iterative approach to optimize the capacity sizes of various stand-alone PV/wind/diesel/battery hybrid system components for zero load energy deficit taking into account the total energy deficit, the total net present cost and the energy cost. 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. In addition we employ model predictive control (MPC) owing to its advantages over the open loop approach. The capability to handle constraints of the system explicitly is one of the merits of using this approach to solve this problem. The receding horizon approach is capable of computing a sequence of manipulated variable adjustments through the utilization of a system model to optimize forecasts of system behaviour. The open loop model is unable to compensate for disturbances occurring from external sources owing to the absence of a feedback mechanism. Closed-loop models, on the other hand, automatically adjust to changes in the outputs due to external disturbance. The rationale for introducing MPC is that unlike the open loop predictions, this approach measures states and gives feed back to the optimization model repeatedly and hence the optimal solution is updated accordingly (Kaabeche and Ibtiouen, 2014; Vahidi et al., 2006). Such on-line methods have been applied to dynamic dispatch problems in both regulated and deregulated systems. The advantages of using this approach over open loop optimization approaches include reduced dimensions, resulting in easier computation. Some of the major advantages of MPC are convergence and robustness and these are well demonstrated by the application of MPC to power economic dispatching problems with a six-unit system (Kaabeche and Ibtiouen, 2014; Xia et al., 2011; Zhang and Xia, 2011).

On-line optimization approaches have been implemented in various industrial and process control applications incorporating multiple inputs and outputs (Prett and Garcia, 1998). The MPC technique allows the use of a user-defined cost function and has the capability to explicitly handle system constraints (Lee and Yu, 1994). The on-line approach has been applied to a building heating system in order to analyze the energy savings that can be achieved (Siroky et al., 2011). A heating system optimization model is used to predict the future building behavior following the selected operational strategy and the weather and occupancy forecasts. 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). A few researchers have applied this approach to the analysis of electric energy systems that incorporate intermittent resources (Xie and Ilic , 2008). However, the work done so far does not specifically apply the on-line methodology to PWDB hybrid power supply options.

This work follows up on our 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. 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 energy. In this paper, we apply the MPC technique 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 multi-objective optimisation used in this work enables designers, performance analyzers, control agents and decision-makers who are faced with multiple objectives to make appropriate trade-offs, compromises or choices. The on-line optimal energy management system takes into account the variable nature of RE (solar and wind) and changes in demand, thus enabling customers to make informed decisions before buying a given system. 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 on-line approach is shown to be more favorable for real-time applications. We therefore propose a closed-loop model for the PWDB hybrid system that satisfies the load demand at each sampling time, minimizes power provided by the DG, maximizes use of RE and is robust with respect to disturbances in the load demand, PV and wind energy. 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, we briefly describe the hybrid system configuration. In section 3, we describe the MPC formulation for the PWDB hybrid system. In Section 4, we discuss the simulation results 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 shown in Figure 1. The supply priority is such that the load is initially met by the renewable generators (PV and wind) and the battery comes in when the renewable 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

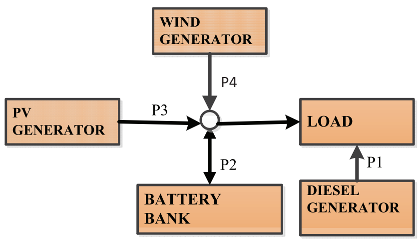

Figure 1: Schematic layout of the PV-wind-diesel-battery hybrid power supply system

the load and/or battery, depending on the instantaneous magnitude of the load and the battery bank state of charge. Control variables $P1$, $P3$ and $P4$ respectively, represent the energy flows from the DG, PV and WG to the load at any hour (k), while $P2$ 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) :

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

where η_{pv} is the efficiency of the PV array, I_{pv} (kWh/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:

$$SOC(k+1) = SOC(k) - \alpha_{.} P2(k), \tag{2}$$

in which, $\alpha = \eta_B / E^{max}$ and η_B is the battery round trip efficiency. $SOC(k)$ is the current SOC of the battery. A variable speed diesel generator 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:

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

where $v_{hub}(t)$ is the hourly wind speed at the desired height h_{hub}, $v_{ref}(t)$ 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):

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

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 wind generator 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-hour 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 optimisation problem is solved using the "quadprog" function in MATLAB.

The multi-objective function is given by the expression:

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

subject to the following constraints:

$$P_1(k) + P_2(k) + P_3(k) + P_4(k) = P_L(k), \quad (6)$$
$$P_i^{min} \leq P_i(k) \leq P_i^{max}, \quad (7)$$
$$0 \leq P_1(k) \leq DG^{rated}, \quad (8)$$
$$P_2^{min} \leq P_2(k) \leq P_2^{max}, \quad (9)$$
$$0 \leq P_3(k) \leq P_{pv}(k), \quad (10)$$
$$0 \leq P_4(k) \leq P_{WG}(k), \quad (11)$$
$$SOC^{min} \leq SOC(0) - \alpha \sum_{\tau=1}^{k} P_2(\tau) \leq SOC^{max}, \quad (12)$$

for all $k = 1, \cdots, N$, 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.

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

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 $1kWp$ varies from $7m^2$ to $20m^2$ 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 PWDB hybrid system is described above is an open loop approach, and there exist 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 model predictive control (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 energy.

3.1. Brief introduction of discrete linear MPC

Discrete linear MPC is a control approach for system

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

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

where $x \in R^n$, $u \in R^m$ and $y \in R^l$ are states, inputs and outputs, respectively. The MPC approach could 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

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

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

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

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 with minimizing $\hat{J} = U^TEU + FU$, 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:

$$U = \arg\min_{U} U^T E U + F U, \quad s.t. \;\; \bar{M} U \leq \bar{\gamma}, \tag{20}$$

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 renewable energy ($P_3(k) + P_4(k)$) 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:

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

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

$$y_m(k) = c_m x_m(k) + d_m u(k), \tag{24}$$

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 $y_a(k) = P_3(k) + P_4(k) = c_a x_m(k) + d_a u(k)$, 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

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} -\alpha & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}, \; C = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (25)$$

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

$$\min J = \min(J_1 + J_2) = \min (Y(k) - R(k))^T (Y(k) - R(k)). \quad (26)$$

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: $0 \le P_1(k) = P_L(k) - y_m(k) \le P_1^{max}$, $0 \le P_i(k) \le P_i^{max}$ $(i = 3, 4)$, $-P_2^{max} \le P_2(k) \le P_2^{max}$, 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 ($P_3(k)$): $P_{pv}(k) \ge P_3(k)$. Energy flow from the Wind turbine ($P_{wind}(k)$) should be no less than the wind energy directly used on the load ($P_4(k)$): $P_{wind}(k) \ge P_4(k)$

3. State of charge of the battery is subjected to its minimum and maximum values: $B_C^{min} \leq x_m(k) \leq B_C^{max}$.

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

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

where

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

And they can be rewritten by using the control series

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

where

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

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

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

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

$$B_C^{min}[1,1,\cdots,1]^T \leq x_m(k)[1,1,\cdots,1]^T + B_m U(k) \leq B_C^{max}[1,1,\cdots,1]^T, \tag{34}$$

which can be further expressed by

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

where

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

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

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

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 PDB 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 $\bar{M}$ 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. For more detailed explanations and proofs concerning constrained model predictive control, the readers can refer to some classic textbooks (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 real-time information of diesel consumption is fed-back to MPC for decision making, but P_1 is not dispatched directly by MPC.

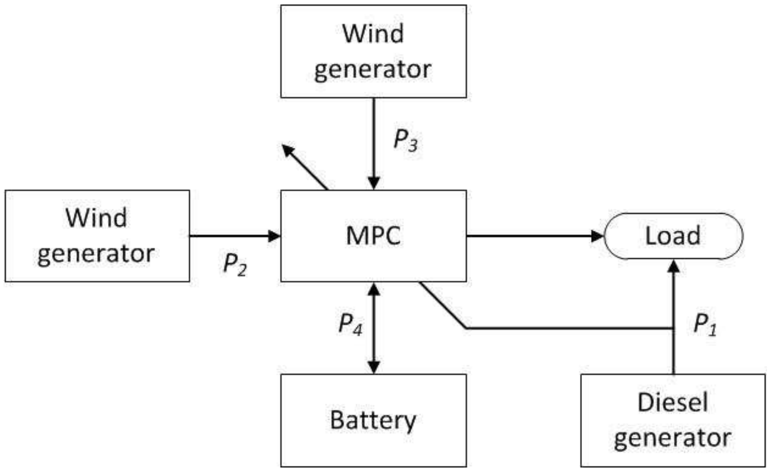

Figure 2: The closed-loop system for the PDB hybrid system

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 hours).

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 wind turbine. At the same time, the surplus energy from PV and wind turbine 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.

For comparison purposes, results of the open loop system without MPC are presented in Fig. 5 and Fig. 6. In open loop control, the optimization

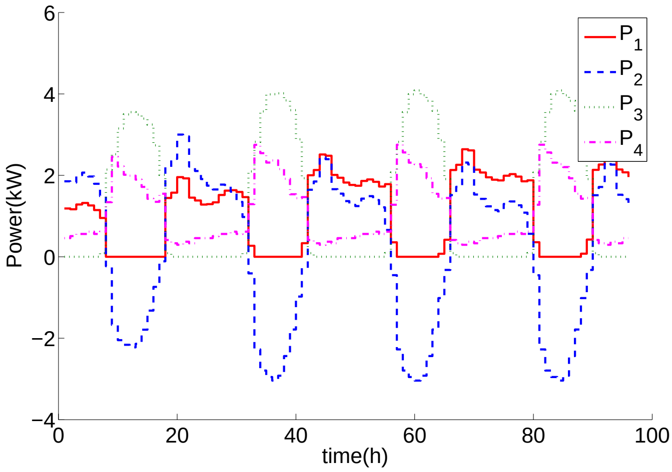

Figure 3: Simulation result of the closed-loop system without disturbances (in summer)

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.

Table 2: Diesel energy consumption (kWh) of PWDB hybrid system without disturbances

	Closed-loop system	open loop system
Summer	15.61	15.66
Winter	30.63	30.92

4.2. Results of the PWDB hybrid system with disturbances

The load demand and PV 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.

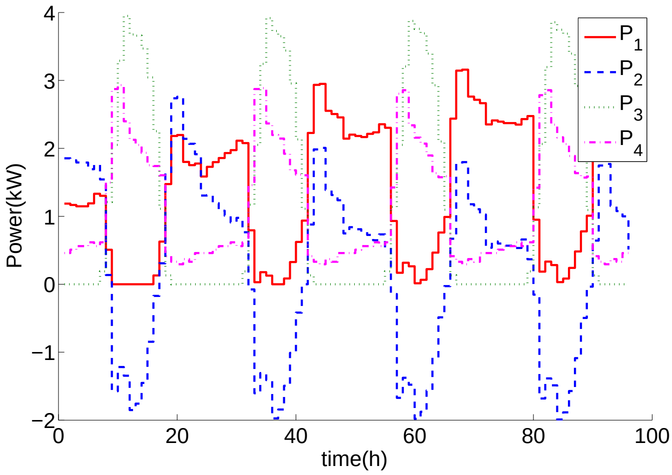

Figure 4: Simulation result of the closed-loop system without disturbances (in winter)

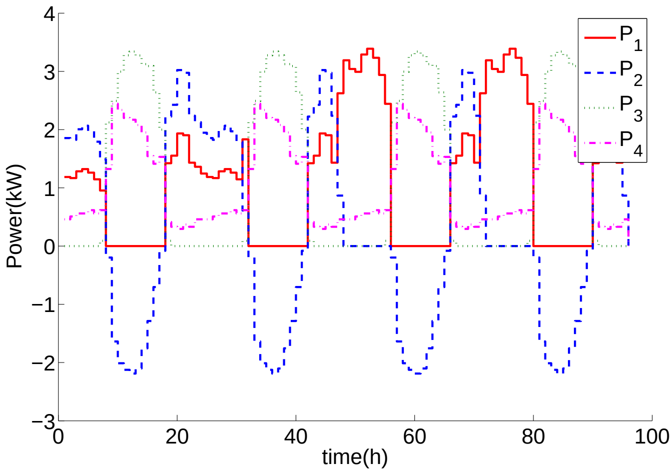

Figure 5: Simulation result of the open loop system without disturbances (in summer)

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

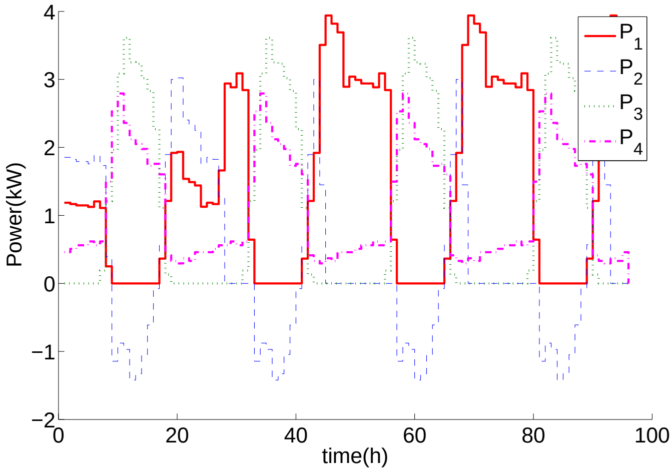

Figure 6: Simulation result of the open loop system without disturbances (in winter)

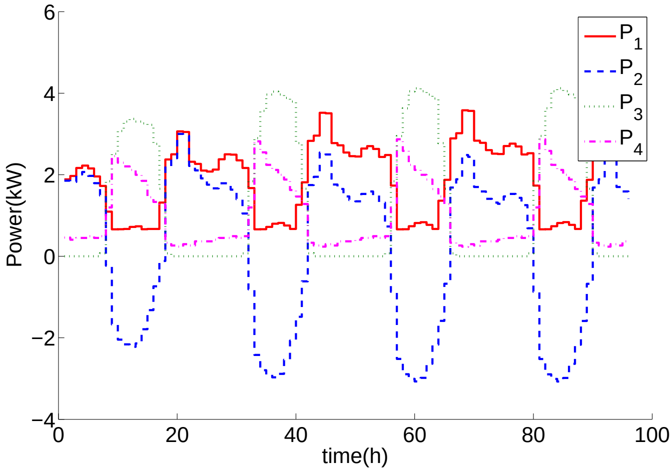

Figure 7: Simulation result of the closed-loop system with disturbances (in summer)

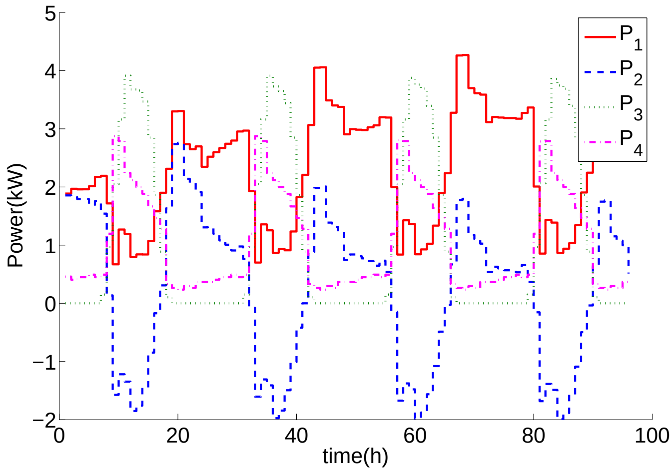

Figure 8: Simulation result of the closed-loop system with disturbances (in winter)

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.

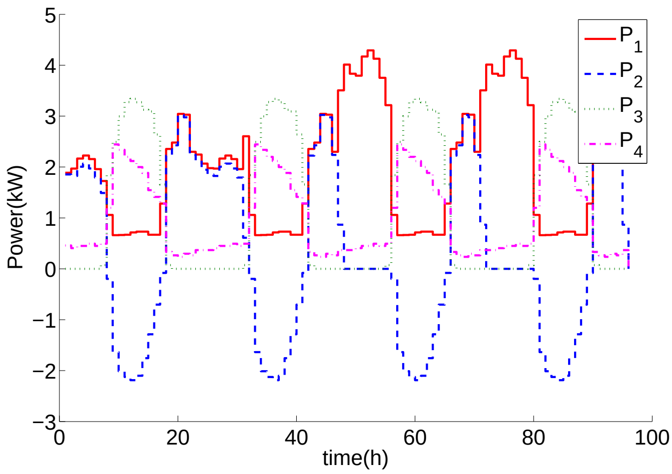

Figure 9: Simulation result of the open loop system with disturbances (in summer)

Diesel energy consumption is listed in Table 3 and also indicates that the

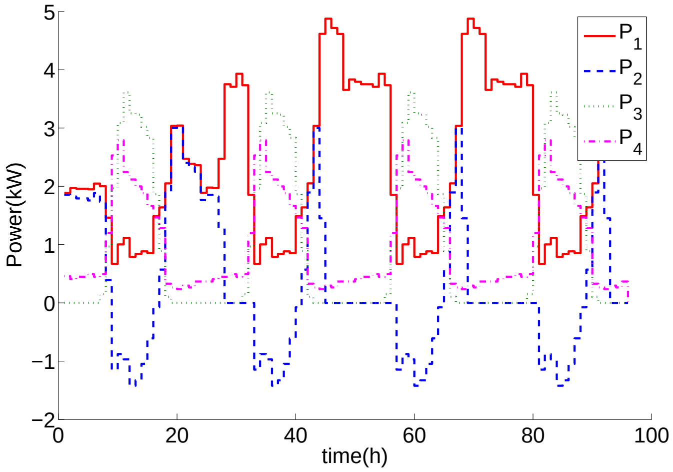

Figure 10: Simulation result of the open loop system with disturbances (in winter)

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

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. It has been observed that the optimal solutions obtained can help decision-makers, designers, performance analyzers and control agents who are faced with multiple objectives to make appropriate trade-offs. For the system considered, it has been shown that for the same load, both the open loop model and the MPC model without disturbances produce similar results in terms of fuel cost. It has also been shown in this work that the advantages of MPC become apparent when the system is subject to uncertainties. The results have shown 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 MPC model is shown to be able to predict future system behavior and compute the necessary control actions while satisfying the system constraints. The results thus reveal that closed-loop control is capable of predicting future states based on feedback of current states while open loop control is unable to respond to unpredictable disturbances. The results of this work generally shows that diesel energy is consumed more in winter than in summer thus revealing the importance of taking into account seasonal variations of both RE output and load demand. From the simulation results, it can be concluded that the proposed MPC model can handle significant system-model mismatch and disturbances while offering robust performance. Although an MPC technique might be too sophisticated for individual domestic applications, it is certainly useful for institutional and industrial applications. Future work will include further development of the model to cater for heating and cooling loads as well as comparison of model and experimental results.

6. Acknowledgements

The authors acknowledge the support for this work provided by the National Research Foundation of South Africa and the Energy Efficiency and Demand Side Management Hub.

Deshmukh, M. K., Deshmukh, S. S., 2008. Modelling of hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 12: 235-249.

Elhadidy, M. A., Shaahid, S.M., 1999. Optimal sizing of battery storage for hybrid (wind/diesel) power systems. Renew Energy 18: 77-86.

Belfkira, R., Zhang, L., Baraka, G., 2011. Optimal sizing study of hybrid Wind/PV/diesel power generation unit. Solar Energy 85: 100-110.

Datta, M., Senjyu, T., Yona, A., Funabashi, T., Kim, C. H., 2009. A coordinated control method for leveling PV output power fluctuations of PV-diesel hybrid systems connected to isolated power utility. Energy Conversion. IEEE Transactions 24(1): 153-162.

Dufo-Lopez, R., Bernal-Agustin, J. L., Yusta-Loyo, J. M., Domnguez-Navarro, J.A., Ramrez-Rosado, I. J., Lujano, J., Aso, I., 2011. Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV-wind-diesel systems with batteries storage. Applied Energy 88(11): 4033-4041.

Barley, C. D., Winn, C.B., 1996. Optimal dispatch strategy in remote hybrid power systems. Solar Energy 58(4-6): 165-179.

Kamaruzzaman, S., Azami, Z., Yusoff, A., Zulkifli, M. N., 2008. Optimal operational strategy for hybrid renewable energy system using genetic algorithms. WSEAS Transactions on Mathematics 4(7): 130-140

Muselli, M., Notton, G., Louche, A., 1999. Design of hybrid-photovoltaic power generator, with optimization of energy management. Solar Energy 65(3), 143-57.

Elaiw, A. M., Xia, X., Shehata, A. M., 2012. Application of model predictive control to optimal dynamic dispatch of generation with emission limitations. Electric Power Systems Research 84(1): 31-44.

Kaabeche, A., Ibtiouen, R., 2014. Techno-economic optimization of hybrid photovoltaic/wind/diesel/battery generation in a stand-alone power system. Solar Energy 103: 171-182.

Vahidi, A., Stefanopoulou, A., Huei, P., 2006. Current management in a hybrid fuel cell power system: A model-predictive control approach. Control Systems Technology, IEEE Transactions 14(6): 1047-1057.

Xia, X., Zhang, J., Elaiw, A., 2011. An application of model predictive control to the dynamic economic dispatch of power generation. Control Engineering Practice 19(6): 638-648.

Zhang, J., Xia, X., 2011. A model predictive control approach to the periodic im- plementation of the solutions of the optimal dynamic resource allocation problem. Automatica 47: 358-362.

Prett, D. M., Garcia, C. E., 1998. Fundamental Process Control. Butterworths series in Chemical Engineering. Butterworths, Stoneham, Massachusetts.

Lee, J. H., Yu, Z. H., 1994. Tuning of model predictive controllers for robust performance. Computers and Chemical Engineering 8(1):15-37.

Siroky, J., Olderwurtel, F., Cigler, J., Privara, S., 2011. Experimental analysis of model predictive control for an energy efficient building heating system. Applied Energy 88:3079-3087.

Gallestey, E., Stothert, A., Antoin, M., Morton, S., 2002. Model predictive control and the optimization of power plant load while considering lifetime consumption. IEEE Trans. on Power Systems 17(1):186-191.

Xie, L., Ilic, M. D., 2008. Model predictive dispatch in electric power systems with intermittent energy sources. In Proceedings of IEEE Conference on Systems. Man and Cybernatics, Singapore 12-15 October 2008, pp 42-47.

Tazvinga, H., Xia, X., Zhang, J., 2013. Minimum cost solution of photovoltaic-diesel-battery hybrid power systems for remote consumers. Solar Energy 96:292-299.

Hove, T., Tazvinga, H., 2012. A techno-economic model for optimising component sizing and energy dispatch strategy for PV-diesel-battery hybrid power systems. Journal of Energy in Southern Africa 23(4): 18-28.

Seeling-Hochmuth, G. C., 2012. A combined optimization concept for the design and operation strategy of hybrid-PV energy systems. Solar Energy 61(2): 77-87.

Ashok, A., 2007. Optimised model for community-based hybrid energy system. Renewable Energy 32(7): 1155-1164.

Collares-Pereira, M., Rabl, A., 1979. Derivation of method for predicting long term average energy delivery of non-concentrating and concentrating solar collectors. Solar Energy 22 (2): 155-170.

Tazvinga, H., Hove, T., 2010. Photovoltaic / Diesel / Battery hybrid power supply system: Generator component sizing and energy performance analysis. VDM Publishing, Germany.

Wang, L., 2009. Advances in Industrial Control: Model Predictive Control System Design and Implementation Using MATLAB. Springer, London.