Model Predictive Control: A Survey of Dynamic Energy Management

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Abstract: This paper presents the structure of the model predictive control (MPC), its development and application through optimal energy system. The MPC is one of the algorithms that are used in a computer controlled environment to predict the future behaviour of an explicit process model. It is devised by computing and adjusting the next sequence of the input variables at each control interval. The MPC is an algorithm in which the challenge is to optimize the behaviour of a future plant. The optimization sequence starts by sending the first input into the plant and then at each subsequent control interval the entire computation is repeated to reach the performance index function to follow. MPC offers a variety of applications in a wide range of industries. This is due to its robustness in the optimal control design of a process. MPC is also widely used in aerospace, automotive, chemical and food processing applications. This study describes the implementation of the energy management scheme through the use of MPC design.

1 INTRODUCTION

Managing the energy system has transformed the configuration of a conventional power grid in terms of coordinating the optimal power flow, minimising the system power losses and voltage stability on the electrical network (Abdi et al., 2017a; Siti et al., 2019; Abdi et al., 2017b; Mbungu et al., 2019a; Adefarati et al., 2019; Foley et al., 2020). Currently, several research works try to look for the alternative approaches of dealing with different grid's challenges, which consists of analysing the system protection of the electrical system and optimal integration and coordination of energy mix system. The objective of these approaches aims to improve the efficiency of the power system, which must be based on dynamic modelling strategy.

MPC is frequently used in the industry as an optimal control strategy due to its ability to handle hard system constraints. MPC system design offers the possibility of controlling the input system and the output constraints (Mesbah, 2016; Mbungu et al., 2018; Kale and Chipperfield, 2005) as well as the incremental constraints of the control signal (Mbungu et al., 2020). Manufacturing process has been widely influenced by developing the implementation of MPC due to its approach to resolve and manage the uncertainty of a processing system. It predicts the future behaviour and keeps the input and output signal in the acceptable optimal operation level.

Through the MPC strategy, a controller of a given system can handle multiple inputs, multiple outputs plant model that are subject to diverse constraints. The MPC algorithm is also valued for its robustness in handling unexpected process and system behaviour. Therefore, this research works contributes on implementation strategy of a system behavior based on MPC design. The approach aims to analyse the dynamic performance of the energy management under the smart grid environment.

2 SYSTEM MODELLING

2.1 State-space Model

Consider a given function $f(x,u)$ with its internal system, in which the vector space is known as the state-space. If this structure is also lumped together and has finite state-space, then, the state-space equations

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can describe the system. It is essential to note that modelling of this type of structure in a state-space model must satisfy the three superposition of the state and the output equations and the linearity propriety of state-space (Holkar and Waghmare, 2010; Seborg et al., 2010; Bishop, 2007; Lee, 2009; Mayne et al., 2000; Dahleh et al., 2004; Rossiter, 2003; Maciejowski, 2002; Rawlings and Mayne, 2009). The state of the system is the basis of the state-space representation. It also considers the value of updating internal elements of the system. This procedure can change independently from the system output. The function $f(x,u)$ in the state-space model is constituted of three components, namely input variables (u) or manipulated variables (MVs), output variables (y) or controlled variables (CVs), and the state variables (x) (Mbungu et al., 2016; Mbungu et al., 2017b; Wang, 2009; Holkar and Waghmare, 2010; Seborg et al., 2010; Bishop, 2007; Lee, 2009; Mayne et al., 2000; Dahleh et al., 2004; Rossiter, 2003; Maciejowski, 2002; Rawlings and Mayne, 2009). The vectors below describe these components as:

$$u(t) = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_m \end{bmatrix}, y(t) = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_q \end{bmatrix}, x(t) = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \tag{1}$$

where m the number of input into the system, q the number of output of the plant mode, and n the number of state that defines the system or order of state-space.

2.1.1 Continuous-time System

If the function $f(x,u,t)$ is considered as the state evolution equation of a given system, and the output vector $y(t)$ can be described by the function of the state variable and MVs over a given time t as $g(x,u,t)$, which is the instantaneous output equation (Dahleh et al., 2004; Rossiter, 2003; Maciejowski, 2002; Rawlings and Mayne, 2009). Therefore, the relation below can describe the system in a continuous time model as:

$$\dot{x}(t) = f(x(t),u(t),t) \tag{2a}$$

$$y(t) = g(x(t),u(t),t) \tag{2b}$$

where $t \in \mathbb{R}$ or $\mathbb{R}^+$, and $\dot{x}(t)$ is the rate of change of the state variables. Equation 2 can be simplified in compact linear and time-invariant relations, which describe the continuous state space model of a given system as:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{3a}$$

$$y(t) = Cx(t) + Du(t) \tag{3b}$$

where A, B,C, and D are respectively, the state matrix of dimension, input matrix, output matrix, and feed forward matrix. For $t \geq 0$, $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^m$, and $y \in \mathbb{R}^p$ these involve that $\dim[A] = n \times n$, $\dim[B] = n \times m$, $\dim[C] = q \times n$, and $\dim[D] = q \times m$. Due to the absence of direct feed through on the system model developed in (Mbungu et al., 2016; Wang, 2009; Mbungu et al., 2017b), it is assumed that the feed forward matrix is zero.

2.1.2 Discrete-time System

The discrete-time system model is considered a standard state-space model. Nowadays, all modern applications in control systems are discretised or digitalised for more accurate evaluation and robustness of the design. The discrete time system offers the possibility of determining the output of the system in real time by using past information of the input. The technical approach should be followed regarding the amount of input information which defines the present output. From Eq. 3a, the discrete time system in a state-space model is developed. This consists of using Euler's forward approximation method (Mbungu et al., 2016; Mbungu et al., 2017b; Dahleh et al., 2004). Suppose that the system is operated at a given period T, the discretization of state evolution in that time for (x,u,t) can be determined as (Mbungu et al., 2016; Mbungu et al., 2017b; Dahleh et al., 2004; Rossiter, 2003; Maciejowski, 2002; Rawlings and Mayne, 2009).

$$\frac{x((t+1)T) - x(tT)}{T} = Ax(tT) + Bu(tT) \tag{4}$$

If it is supposed that the parameters (tT) can be replaced by (k), where $k \in \mathbb{Z}$ denotes the time sample, Eq. 4 can therefore be rewritten as follows

$$x(k+1) = (I + TA)x(k) + TBu(k) = A_d x(k) + B_d u(k) \tag{5}$$

By combining Eq. 5 with the output function of continuous state space model Eq. 3b which is supposed to be discretised by Euler's forward approximation like Eq. 43a, the linear discrete state space model can be described as

$$x(k+1) = A_d x(k) + TB_d u(k) \tag{6a}$$

$$y(k) = C_d x(k) + D_d u(k) \tag{6b}$$

where A_d is the discrete state matrix, B_d is discrete input matrix, C_d is discrete output matrix, and D_d is the discrete feedforward matrix. It is also important to notice that all discrete time matrices of Eq. 6 have the same dimension with the continuous matrices that are defined in Eq 3. However, in most cases, for example, in predictive control, it can sometimes be assumed that the feed-forward matrix D_d equals to zero (Mbungu et al., 2016; Mbungu et al., 2017b; Zhang et al., 2014; Wang, 2009; Rossiter, 2003; Maciejowski, 2002; Rawlings and Mayne, 2009; Ma et al., 2011; Xie et al., 2007). This is dependent on the system design due to the principle of receding horizon (Wang, 2009). In this study, the linear discrete state space model is used to design the system.

2.2 Augmented State Space Model

Suppose that at a given MV with sample k, finding the relationship between the sample k and the instant before it, i.e., $k-1$, this relation could describe the augmented state space model. Equation 6a could, therefore, be rewritten as (Mbungu et al., 2017b; Wang, 2009)

$$x(k+1)-x(k) = A_d(x(k)-x(k-1)) + B_d(u(k)-u(1-1)) \tag{7}$$

Through Eq. 7, the increment of state variables and the MV can be rewritten respectively by $\Delta x(k+1) = x(k+1)-x(k)$, $\Delta x(k) = x(k)-x(k-1)$ and $\Delta u(k) = u(k)-u(k-1)$. By considering these incremental function and Eq. 7, the increment of the state-space equation is therefore expressed as

$$\Delta x(k+1) = A_d \Delta x(k) + B_d \Delta u(k) \tag{8}$$

As the system input is changed to the increment of MV, it is, therefore, a question of connecting the increment of state vector to the CV. This method introduces a new state vector of the system that is developed as follows.

$$x_a(k) = \begin{bmatrix} \Delta x(k) \\ \Delta y(k) \end{bmatrix} \tag{9}$$

where x_a denotes the augmented state vector.

From Eqs. 8 and 9, the output vector at the sample $(k+1)$ needs to be determined for the stability of the system. If, at a given sample k of a CV, the designed model can predict a future CV at the sample $(k+1)$. By using the developed strategy of Eq. 7, which can be identified with the effect of CV in Eq. 9, thus, Eq. 6a as a function of current and future CV with $D_d = 0$ is expressed as follows.

$$y(k+1)-y(k) = C_d(x(k+1)-x(k)) = C_d \Delta x(k+1) \tag{10}$$

By substituting Eq. 8 in Eq. 10, the relationship between the current and predicted CV can be expressed as follows.

$$y(k+1)-y(k) = C_d A_d \Delta x(k) + C_d B_d \Delta u(k) \tag{11}$$

Equations 12a and 12b define the compact format of the augmented state-space model, which derives from Eqs. 8, 9, and 11 as follows.

$$x_a(k+1) = A_a x_a(k) + B_a \Delta u(k) \tag{12a}$$

$$y(k) = C_a x_a \tag{12b}$$

where $A_a = \begin{bmatrix} A_d & 0_d^T \\ C_d^d & 1 \end{bmatrix}$, $B_a = \begin{bmatrix} B_d \\ C_d B_d \end{bmatrix}$, $C_a = \begin{bmatrix} 0_d \\ C_d 1 \end{bmatrix}$, $x_a(k+1) = \begin{bmatrix} \Delta x_d \\ y(k) \end{bmatrix}$, and $0_d = \begin{bmatrix} 0 & 0 & \dots & 0 \end{bmatrix}$ with 0_d^T as a zero column vector of n dimension. The augmented state space system is also used in MPC design (Wang, 2009).

3 PREDICTIVE CONTROL

The MPC approach is the composition of three base components of the predictive controller. These are the prediction, optimisation and receding horizon implementation. The advantages of predictive control strategy are its stability of driver for constrained systems. Moreover, due to the opportunity of real-time computation and the improvement of the predictive controller efficiency, the application predictive control has extended many controller structures that include high-speed sampling systems (Cannon, 2015).

3.1 Prediction

By considering the dynamic model of discrete-time linear state-space model Eq. 6a and the MPC sample time strategy, to generate the predicted behaviour of a given plant system consists of assuming that at sampling instant kth, the future state vector is in a relationship with the next input. This strategy is executed for N sampling intervals. If only at each given predicted MV sequence when the model is simulated forward over a given prediction horizon, the corresponding sequence of predicted state is, therefore, generated to describe the future sequence behaviour of the system. The vector state and below input define the predicted sequence of the discrete-time dynamic model.

$$x(k) = \begin{bmatrix} x(k+1|K) \\ x(k+2|K) \\ x(k+3|K) \\ \vdots \\ x(k+N|K) \end{bmatrix}, u(k) = \begin{bmatrix} u(k|K) \\ u(k+1|K) \\ u(k+2|K) \\ \vdots \\ x(k+N-1|K) \end{bmatrix} \tag{13}$$

where $x(k+i|K)$ and $u(k+i|K)$ are respectively the state vector and MV at a time $(k+i)$ and the parameter k of each variable denotes the predicted sampling instant. Through Eq. 13, the demonic model of linear discrete state-space is rewritten in predictive environment as:

$$x(k+i+1|k) = A_d x(k+1|k) + B_d u(k+1|k) \quad (14)$$

with $i = 0, 1, ..., N$, and for the initial condition i.e. $i = 0$ the state vector is $x(k|k) = x(k)$.

3.2 Optimisation

References (Wang, 2009; Holkar and Waghmare, 2010; Seborg et al., 2010) describe the predicted control law computation framework. The optimisation strategy of MPC is based on minimising anticipated performance cost. The predicted sequence of state and MV play an influential role in the optimisation strategy. Equation 15 defines the optimal approach to predictive control as:

$$J(K) = \sum_{i=0}^{N} [x^T(k+i|k)Qx(k+i|k) + u^T(k+i|k)Ru(k+i|k)] \quad (15)$$

where $J(k)$ denotes the performance index of predicted sequences, and Q and R are the positive definite weighting matrices. But Q or R can also be a positive semi-definite matrix. It is also important to notice that Q and R are diagonal matrices that contain only the positive elements. It has been noted that the performance index is a function of state and MV at each instant k. During the optimization strategy of predicted input sequence which consists of minimizing Eq. 15 to find the minimum argument of the input sequence, at each instant the optimal MV can be calculated as:

$$u^*(k) = \arg \min_u J(k) \quad (16)$$

It is also important to note that finding the minimum MV can be subject to the input, state, and output constraints. Therefore, these can be included in the optimization strategy to determine the optimal solution. The structure of the restrictions in MPC design will be established further in section 4.

3.3 Receding Horizon Implementations

Once the initial value is computed, i.e. at $i = 0$ by using Eqs. 13 and 16 under a finite horizon, the optimal predicted MV sequence that is introduced into the plant through the MPC control law is determined as follows.

$$u(k) = u^*(k|k) \quad (17)$$

For $k = 0, 1, ..., N$, at each sampling instant as described in (Wang, 2009; Holkar and Waghmare, 2010; Seborg et al., 2010) the same process that is computed for the first element is then repeated at each sampling instant. The effect of repeating the optimisation of future time instants describes the online optimisation strategy of predictive control. This strategy defines the receding horizon approach that keeps the prediction horizon at the same length. The concept of feedback as described in (Holkar and Waghmare, 2010; Seborg et al., 2010) determines the degree of robustness of the system.

4 MPC DESIGN

If the dynamic of state-space design for a given digital mode Eq. 12 can verify either the controllability or the observable laws, this dynamic model can also be implanted in MPC controller. The MPC design entails controlling the optimum approach that the observation sets at each predicted sequence as defined in Eq. 15, which is defined as a quadratic equation. This performance index can develop in terms of MPC gain for the robustness of the designed controller (Wang, 2009). Thus, the performance index can be rewritten in function of CVs and the targets of the system as follows (Mbungu et al., 2016; Mbungu et al., 2017b; Wang, 2009).

$$J(k) = (Y(k) - r_w)^T (Y(k) - r_w R(k)) \quad (18)$$

where $J(k)$, $R(k)$ and r_w are the output system, target to follow, turning parameter respectively. After computation of a given sample k with a given predicted horizon N_p and a given control horizon N_c through an MPC design, the optimum output of system is descried in (Mbungu et al., 2018; Tungadio et al., 2018; Mbungu et al., 2017a).

Afterwards, optimising the given system by using the MPC design is the effect of implanting a quadratic equation as described in (Mbungu et al., 2016; Mbungu et al., 2017b; Wang, 2009), whuch can compute whether a constraining or unconstraining plant model. This consists of finding the argument of CV in relation with the minimum value of the objective function of the MPC gain.

4.1 Quadratic Programming

A quadratic programming offers several advantages in the industrial environment due to its opportunity of a real-time application. This consists of safely writing a jacket software implementation and the possibility to update and change the code (Holkar and Waghmare, 2010; Seborg et al., 2010; Mbungu et al., 2020). If the objective function of a given plant model in MPC computation is subject to some linear inequality constraints, finding the optimum control solution of the MVs in receding horizon implementation consists of resolving a quadratic programming equation below

$$J(k) = H(k)u(k) + \frac{1}{2}u(k)^T G(k)u(k) \tag{19a}$$

$$Mu(k) \leq \gamma \tag{19b}$$

where M and γ are constraints matrix and vector. Eq. 19b can be either or not combined with the equality constraints (Seborg et al., 2010). This system restriction mostly depends on what the controller has to achieve on the performance of a given model.

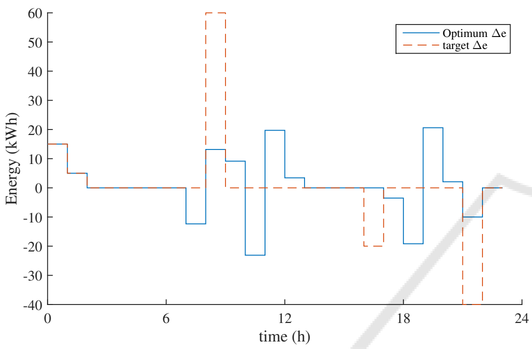

Figure 1: Daily TOU-MPC cost of electricity vs target of electricity cost.

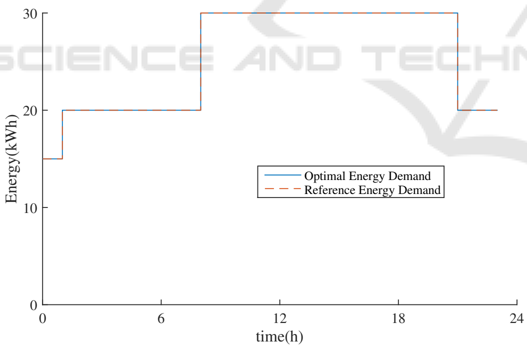

Figure 2: Daily Prepaid-MPC cost of electricity vs target of electricity cost.

5 IMPLEMENTATION ANALYSIS

This section consists of analysing the dynamic behavior of MPC design. The simulation of the results are based on the data developed in (Mbungu et al., 2016; Holkar and Waghmare, 2010) of the energy management system for a commercial load demand. Besides, this research study deals on the possibility of finding the dynamic energy system of the increment of the control variable. The strategy implements the demand response scheme based the energy management in the consumers side (Mbungu et al., 2019b), namely real-time electricity pricing.

5.1 Simulation Analysis

Table 1 provides different biased values that are used to simulate the dynamic behavior of the given data. The system implementation computed different time of use (TOU) and prepaid electricity tariff as described in Table 1. The simulation of the results is presented in Figs. 1 and 2. Figure 1 gives the dynamic behavior of the optimal energy that flows on the system. It is necessary to notice that this model computes only the increment of the control signal as described by the canonic form of state space model in Eqs. 12a and 12b. Besides, the performance index of the MPC design as described in Eq. 18, with its developed strategy which includes constraints and simplified model of the objective function (Eqs. 19a and 19b) are computed in the fashion of the increment model. It is also important to notice that Fig. 2 is not computed by the augmented model.

5.2 Discussion Analysis

Tables 2 and 3 present different values of the energy cost and the saving energy. When it is about to compare the results of the optimal input signal with target input as described in Figs. 1 and 2, it is clearly shown that this result is roughly running close to one another for the increment signal during TOU computation, and both signals (target and optimal energy demand) are close in prepaid mode. However, at some time, the optimal result does not follow the target energy. This interpretation can be controversial in the context of energy-saving and optimal computation. Nevertheless, the total cost of energy and the percentage of the energy cost saving as described in Table 2 gives another profile of the system performance. Besides, Table 3 and Fig. 2 present perfect results which are not often guaranteed during the computation process. Based on this approach of interpreting the simulations results, it can be seen that the system dynamics of the proposed MPC scheme provides satisfactory results to the consumer side. This is due to the important value of the optimal energy cost and the significant percentage rate of the cost-saving.

6 CONCLUSION

The MPC is an optimisation strategy because it offers the opportunity of computing the control vari-

Table 1: Turning parameter and Energy tariffs.

Tariff scheme	Weighted coefficient	Energy prices (R/kWh)
Off-peak (TOU)	1	0.6150
Standard (TOU)	1 and 5	1.073
Peak(TOU)	1.0526 and 1.143	4.115
Prepaid	2	1.2774

Table 2: TOU Cost of energy and percent of costs analysis.

Type of strategy	Cost (Rand)	Parameters	Saving analysis (%)
Cost to pay	2254.3	Cost-target	48.1818
Target cost	1086.2	MPC cost	38.1196
Optimal cost	895.3235	Cost-saving	61.8804

Table 3: Prepaid Cost of energy and percent of costs analysis.

Type of strategy	Cost (Rand)	Parameters	Saving analysis (%)
Cost to pay	1475.4	Cost-target	52.3810
Target cost	772.8270	MPC cost	52.3810
Optimal cost	772.8270	Cost-saving	47.6190

ables based on a given target. This optimal control method aimed to minimising the cost of electricity for a given electrical system. It was found that the model is robust in conjunction with consumers′ actions. It involves creation of an optimal strategy where the user can custom the amount of electricity to use. The optimisation tactics of the MVs for an MPC is an online algorithm that can compute any linear model in the real-time environment. The MPC approach is also considered as a suitable strategy algorithm to be implemented in smart grid technology due to its robustness in the optimal control solution. The MPC can also perform a control problem as an optimisation problem that is made by an on-line optimisation with receding horizon implementation. Thus, the real-time optimisation through the quadratic programming strategy in the framework of the MPC performs a suitable scheme between data transfer and optimisation calculation. It also aims to resolve at each sampling time the optimal controller within the given set-point. Besides, the system provides satisfactory performance in terms of energy-saving and cost optimisation. Therefore, future research work can look at different implementation strategy of the MPC design through a dynamic energy metering based on sensors networking within the applications of the smart technologies.

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