Residential Household Electrical Appliance Management Using Model Predictive Control of a Grid Connected Photovoltaic-Battery System

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Abstract

Grid-connected photovoltaic (PV) based power generation technology is being pushed to the forefront as a viable alternative source of renewable energy, particularly in small-scale domestic applications. Due to the variable nature of solar energy, PV usually works well with battery storage to provide continuous and stable energy. However, by incorporating storage with such systems there is a need to develop controllers that allow the owners to maximize the benefit of such systems and so require sophisticated control strategies.

In this work a multiple-input multiple-output (MIMO) state space model of a PV array, load energy demand, battery bank and utility grid was used to develop a model predictive control setup for a grid connected photovoltaic-battery power generation system. Artificial neural network (ANN) based energy demand prediction was used as the output measured disturbance for the MPC. Switched constraints were used for the MIMO state space model to mimic the dynamic behavior of the storage system. Simulation results show that the proposed MPC would activate non-critical electrical appliances usage at periods when excess PV energy was available from the PV array. Further, it would also allocate energy to the battery storage when this was available, and, when load energy demand was more than the PV array produced would deactivate non-critical appliances (dish washer, washing machine and dryer) and use battery energy if necessary.

1. Introduction

The employment of passive technologies such as building insulation or more energy efficient appliances for heating and cooling offer a path towards the energy efficient operation of buildings. Another approach is to improve building automation by using advanced control concepts (Laustsen, 2008). Current control systems in buildings employ rule-based approaches combined with proportional–integral–derivative (PID) controllers. A shortcoming of these PID controllers is that they operate on a feedback arrangement and are prone to calibration errors and cannot handle unpredicted time delays. Moreover, they cannot handle nonlinearities in the control process and operate only for the predetermined time horizons.

Typically building dynamics are slow and the building is subject to intermittent disturbances that gives rise to a constrained control problem. In many modern buildings the goal is to use on-site generations systems such as photovoltaics (PV) and battery storage systems, but still maintain a connection to the utility grid. To be able to make use of the energy generated and stored by such systems a controller that incorporates weather and energy demand predictions would be desirable. However, in order to best utilize the on-site generation, it is also necessary to make appropriate use of the thermal storage capacity of a building, electrical appliances and energy dispatch strategies. As such, the concept of Model Predictive Control (MPC) provides an ideal framework to tackle this problem (Oldewurtel, et al., 2012).

In this respect, control of large-scale solar energy systems has received some attention and most researchers have considered energy management and demand response for large-scale integration of renewable energy at the utility side (Moura and de-Almeida, 2010 and Huang, et al., 2012). Also, uncertainties within forecast errors of renewable energy and load energy demand have been studied for large-scale integration of renewable energy (Makarov, et al., 2011), but uncertainties at the demand side are not well evaluated. Further, most of the related optimal scheduling methods cannot handle complicated cases when hybrid systems experience external disturbances, and only a few closed-loop control methods have been designed (Palma, et al., 2013) and (Zervas, et al., 2008). However, there is lack of work in consideration on the optimal planning and control of small-scale grid-tied PV systems with battery storage, such as those used in residential houses. Recently, a controller developed by Power Genius for residential houses is able to delay usage of hot water cylinders, water pumps, and washing machines to periods when spare solar energy is available from the PV array but cannot predict periods of low sunshine or periods of high energy demand. Therefore, there is a need to model the behavior of such power systems to comprehensively study the optimal schedule, with demand side management, and to analyze the uncertainty and robustness for an MPC system.

2. Methodology

The basic premise of MPC is to predict future behavior using a system model, given measurements or estimates of the current state of the system and a hypothetical future input trajectory. In this framework future inputs are characterized by a finite number of degrees of freedom that are used to optimize a cost function depending on the predictions. Only the first control input of the optimal control sequence is implemented, and, to introduce feedback into this strategy, the process is repeated at the next time instant using newly available information on the system state. This repetition is instrumental in reducing the gap between the predicted and the actual system response (in closed-loop operation). It also provides a certain degree of inherent robustness to the uncertainty that can arise from imperfect knowledge or unknown variations in the model parameters (referred to as multiplicative uncertainty), as well as to model uncertainty in the form of disturbances appearing additively in the system dynamics (Kouvaritakis and Cannon, 2015).

As such, in this work an MPC system was examined in which an Artificial Neural Network (ANN) based load energy demand prediction (Ahmad and Anderson, 2014) was used as a disturbance for a closed-loop MPC. Figure 1 shows the overall structure of the photovoltaic-battery-grid (PBG) system. Broadly speaking the MPC utilises energy consumption as a measured disturbance, while output from the PV array and the load data for a residential house were used as reference signals for the adaptive switched MPC.

In developing the MPC a multiple-input multiple-output (MIMO) state-space model was developed to mimic the dynamic behavior of the system, and switched constraints were used to simplify the MPC design. Additionally, the AC loads for the household are divided into critical and non-critical loads, as shown in Figure 1. When predicted consumption was greater than generation, non-critical loads were switched off and turned back on when excess electricity was available from the PV array.

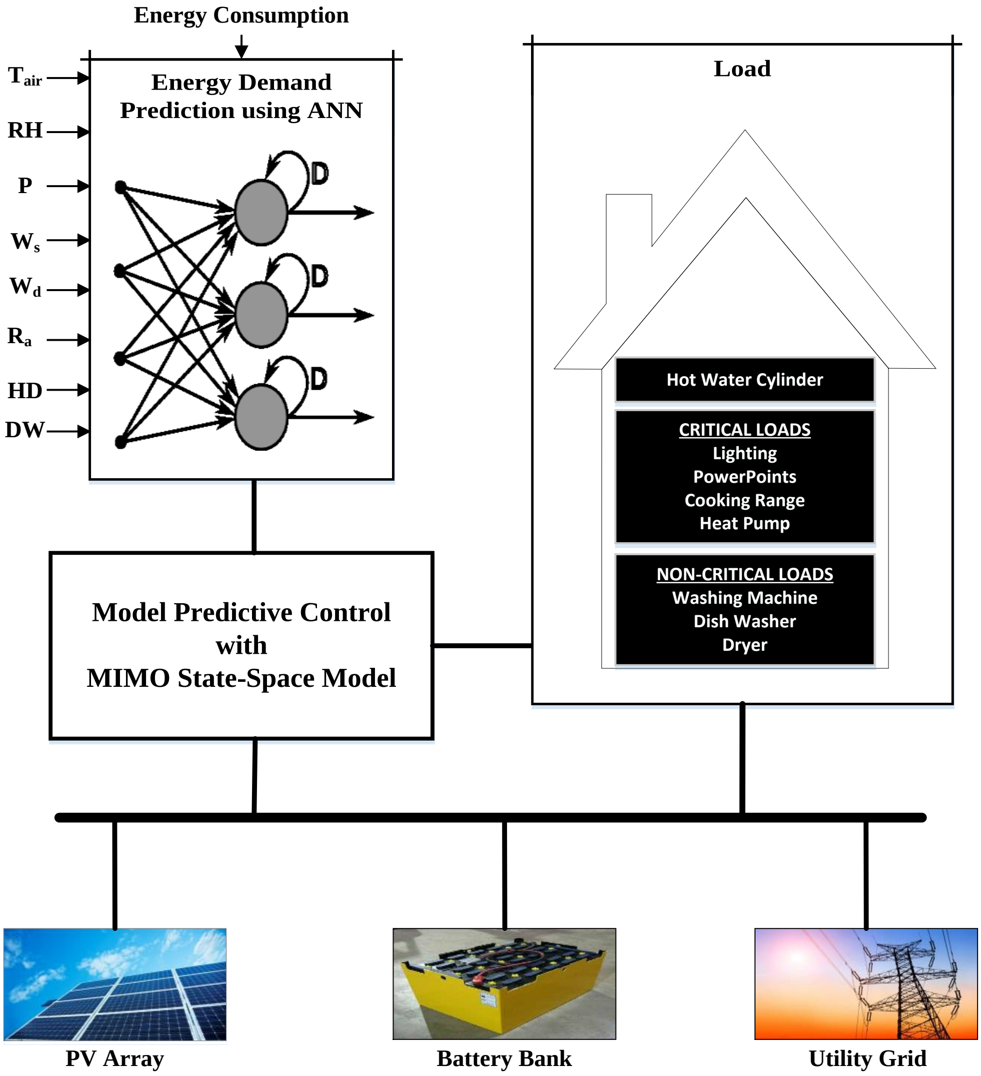

Figure 1. Structure of the photovoltaic-battery-grid system for a residential house with ANN prediction

2.1. Model Predictive Control Design

Model predictive control systems are designed based on a mathematical model of the plant. In this work, a MIMO state-space model was used and was evaluated with the system disturbance being the load energy demand. The linear state-space model can be deduced from the photovoltaic-battery-grid system model shown in Figure 1, such that the control input, at any time (t), is given by Equation (1)

$$u(t) \triangleq [P_{PVL}(t), P_{PVB}(t), P_B(t), P_G(t)]^T \tag{1}$$

where $P_B(t)$ and $P_G(t)$ are the energy drawn from the battery bank and the energy delivered to the grid respectively, and $P_{PVL}(t)$ and $P_{PVB}(t)$ are the energy from the PV array to the load, and to the battery bank respectively.

Now, in an ideal situation all the energy generated by the PV system would be consumed by the household, though in reality this is not always possible. As such, for the system in this study, it was assumed that electricity generated by the PV array would be used to satisfy demand and charge the battery bank with priorities of 80% and 20% respectively. In doing this it is assumed that when demand is satisfied, and the battery is fully charged, excess electricity is exported to the grid. Hence the PV array is subject to the following constraints:

$$0 \leq P_{PVL}(t) \leq P_{PVL}^{max}$$

$$0 \leq P_{PVB}(t) \leq P_{PVB}^{max}$$

$$0 \leq P_{PVL}(t) + P_{PVB}(t) \leq P_{PV}(t)$$

where P_{PVL}^{max} and P_{PVB}^{max} are the maximum amount of electricity that can be delivered to the load and battery bank respectively, during one hour.

Considering the battery storage system further, the charging and discharging equations for the proposed battery bank are given by Equations (2) and (3).

$$V_{batt} = E_0 - R \times i - K \frac{Q}{it - 0.1Q} i^* - K \frac{Q}{Q - it} it + Exp(t) \tag{2}$$

$$V_{batt} = E_0 - R \times i - K \frac{Q}{Q - it} (it + i^*) + Exp(t) \tag{3}$$

where E_0 is the battery constant voltage (V), $Exp(t)$ is the exponential zone dynamics (V), K is the polarization constant (Ah^{-1}), i^* is the low frequency current dynamics (A), i is the battery current (A), it is the extracted capacity (Ah) and Q is the maximum battery capacity (Ah).

Furthermore, the state-of-charge (SOC) of the battery can be calculated using Equation (4).

$$SOC = 100\left(1 - \frac{1}{Q}\int_0^t i(t)dt\right) \tag{4}$$

Now with respect to controlling the operation of the battery storage system, the charging and discharging model of the battery for the MPC computation is given by Equation (5)

$$S(t+1) = S(t) + \eta_c P_{PVB}(t) - \eta_d P_B(t) \tag{5}$$

where $S(t)$ is the SOC at sampling time t and $S(t+1)$ is the SOC at the next hour, P_{PVB} and P_B are the charging and discharging energies respectively, and η_c and η_d are charging and discharging efficiencies (in saying this, η_c and η_d are uncertain constant parameters, that are estimated online in the MPC design). Furthermore, in Equation (5), the current SOC ($S(t)$) can be expressed by referring to the initial SOC ($S(0)$) of a day as shown in Equation (6).

$$S(t) = S(0) + \eta_c \sum_{t=0}^{t+N_c-1} P_{PVB}(t) - \eta_d \sum_{t=0}^{t+N_c-1} P_B(t) \tag{6}$$

Obviously the SOC of the battery is subject to several constraints including, the maximum allowable charge limit and the minimum allowable discharge limit, referred to as the depth of discharge (DOD). Therefore, the lower and upper bounds of SOC are subject to the following constraint

$$S^{min} \leq S(t) \leq S^{max}$$

where S^{min} and S^{max} are the minimum and maximum allowable SOC of the battery bank respectively. The lower bound of SOC (S^{min}) can be expressed in terms of the DOD (D)

$$S^{min} = (1 - D)S^{max}$$

Given that the batteries are charged only during day time, when PV energy is available, and mainly discharged during night time, simultaneous charging and discharging is avoided using Equation (7) as an additional constraint.

$$P_{PVB}(t)P_B(t) = 0 \tag{7}$$

Hence, when PV production exceeds the total demand of the household, the battery bank is set in charging mode. When the demand of the house exceeds PV production, the battery bank is set in discharging mode. Zhou et. al (2015) used a battery bank that was charged by the grid during off-peak times and discharged during peak time when electricity prices were high. However, in this work excessive charging and discharging of the battery bank was avoided to extend battery life.

Now, as mentioned previously, electricity from the grid is used only as a last resort by the MPC, as the main objective of the controller is to minimize grid imports and maximize the usage of the PV array by shifting non-critical loads to periods when excess PV electricity is available. In doing this the grid electricity P_G is bidirectional and is used to cover the imbalance when the energy provided by the PV and battery are not sufficient to meet the demand. Positive values of P_G represent grid imports and negative values of P_g represent grid exports.

On this basis the demand of the household at any given time should satisfy the condition set out in Equation (8):

$$P_{PVL}(t) + P_B(t) + P_G(t) \geq P_L(t) \tag{8}$$

Where $P_L(t)$ represents the household demand at any given hour.

As such, when implementing the MPC, the system state $x(t)$ and the augmented output $y(t)$ are given by Equations (9) and (10).

$$x(t) \triangleq [S(t), y(t-1)]^T \tag{9}$$

$$y(t) = w_1 P_{PVL}(t) + w_1 P_B(t) + w_2 P_{PVL}(t) + w_2 P_{PVB}(t) \tag{10}$$

where $S(t)$ is the state-of-charge (SOC) of the battery bank and w_1 and w_2 are the positive weight coefficients.

The linear state-space model is given by Equation (11)

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ \quad y(t) = Cx(t) + D(t) \end{cases} \tag{11}$$

where *A*, *B*, *C* and *D* are the linear state-space system matrices of which $D(t)$ is the ANN based demand prediction used as the measured output disturbance matrix.

Now, the MPC was developed for closed-loop control in which the objective function of the PV-battery-grid system model was optimized over a prediction horizon. In saying this the objective function J is given by Equation (12)

$$\min J(t) = min \sum_{t=k}^{k+N_p-1} [w_1 P_{PVL}(t) + w_1 P_B(t) + w_2 P_{PVL}(t) + w_2 P_{PVB}(t)] \tag{12}$$

where N_p is hours over the prediction horizon.

In doing this, the MPC is undertaking what amounts to an optimal dispatching problem, hence it is modelled into a control problem and solved by using the MIMO state-space model. Where the constraints on the MPC are expressed by Equation (13)

$$\begin{cases} 0 \le P_{PVL}(t) \le P_{PVL}^{max} \\ 0 \le P_{PVB}(t) \le P_{PVB}^{max} \\ 0 \le P_B(t) \le P_B^{max} \\ S^{min} \le S(t) \le S^{max} \\ P_{PVL}(t) + P_{PVB}(t) \le P_{PV}(t) \\ P_{PVL}(t) + P_{PVB}(t) + P_B(t) = P_L(t) \\ S(0) \le S(N) \end{cases} \quad (13)$$

where N is hours over the overall scheduling period.

In summary, a MIMO MPC is developed for the photovoltaic-battery-grid system of Figure 1. MPC is utilized to solve the control problem at each sampling period. An optimal control problem over the prediction horizon is repeatedly solved ($t = 0, \ldots, N - N_p$) with the linear state-space Equation (11), the objective function (12) and the constraints (13). The optimization variable is the power distribution sequence at each sampling period. At the t^{th} sample, an optimal solution $[U(t), U(t+1), \ldots. U(t + N_p - 1]^T$ can be obtained after solving the optimal problem. Only the first part of the solution, i.e., $U(t)$, is used in the current period and subsequently, at each instant t is set to $t + 1$ and the system states, inputs and outputs are updated.

3. Results

In order to examine the behaviour of the MPC a simulation of a photovoltaic-battery-grid system was undertaken using a week's measurements of PV array production and energy demand taken from a real house, as shown in Figure 2.

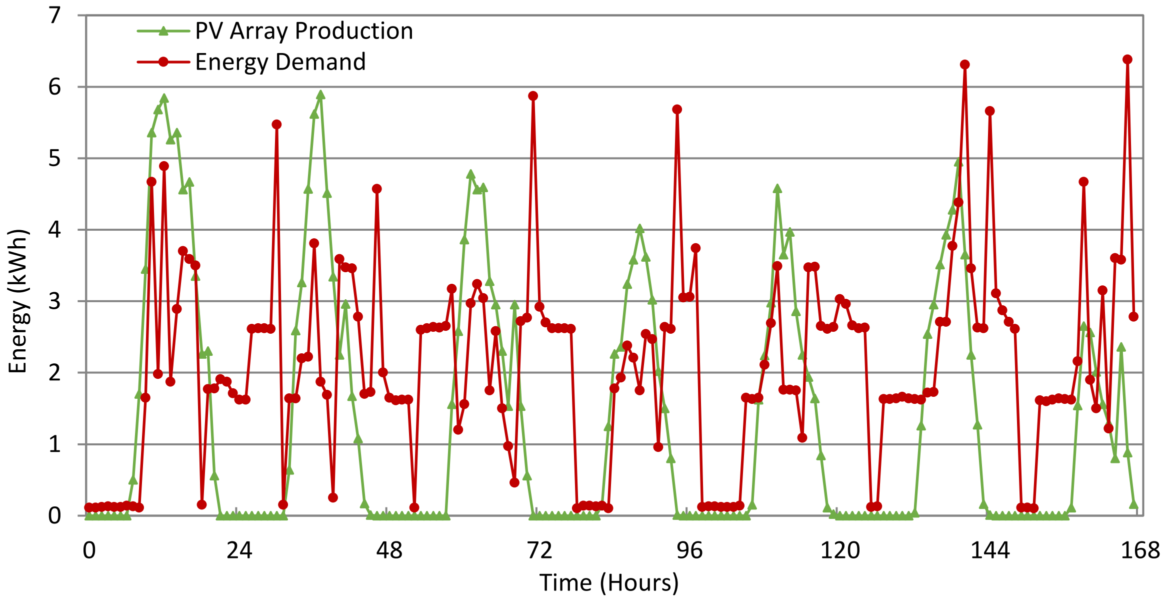

Figure 2. PV array production and energy demand of the house

Figure 3 shows how the MPC would behave for this particular week, as such, whenever the PV array production is less than the demand, usage of the non-critical loads is deferred until periods when excess PV energy is available. By doing so, grid imports are reduced and PV energy is utilized within the house, also exporting locally generated energy to the grid is discouraged. As such, it can be seen in that non-critical loads in the house would be used mainly during the day, when energy is available from the PV array.

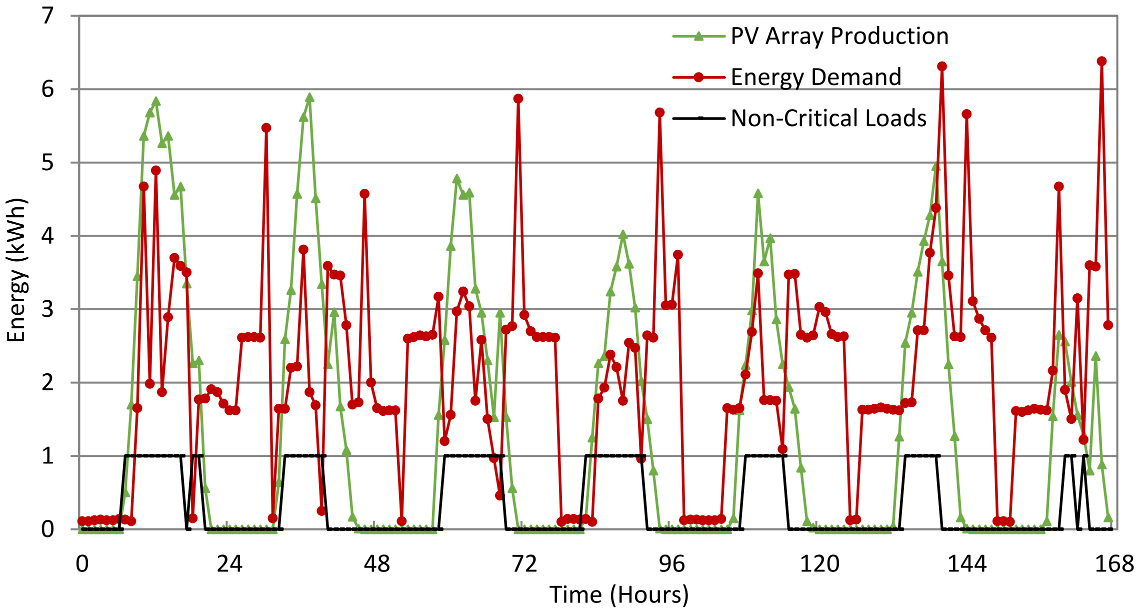

Figure 3. Switching behaviour of the MPC (On=1, Off=0)

Exploring this further, Figure 4 shows how energy would be moved to and from the battery bank. As such, excess energy is used to charge the battery bank during the day-time and energy is supplied by the battery to loads during periods when the PV array alone cannot satisfy load energy demand (where for the proposed MPC with online estimation, initial values of the estimated parameters are given by $\hat{\eta}_c(0) = 1.0$ and $\hat{\eta}_d(0) = 1.0$). Further, it can be seen that during the last three days energy demand is high and PV production is lower than the previous days, therefore, more PV energy is assigned to satisfy demand and less PV energy is available to charge the battery bank.

Finally, the performance of the proposed MPC was tested by analysing how closely the output of the controller followed the reference signal. In Figure 5 it can be seen that the MPC is attempting to minimize the difference between the controller output signal and the reference signal. This is equivalent to maximizing the usage of the PV array energy and consequently helping reduce grid imports.

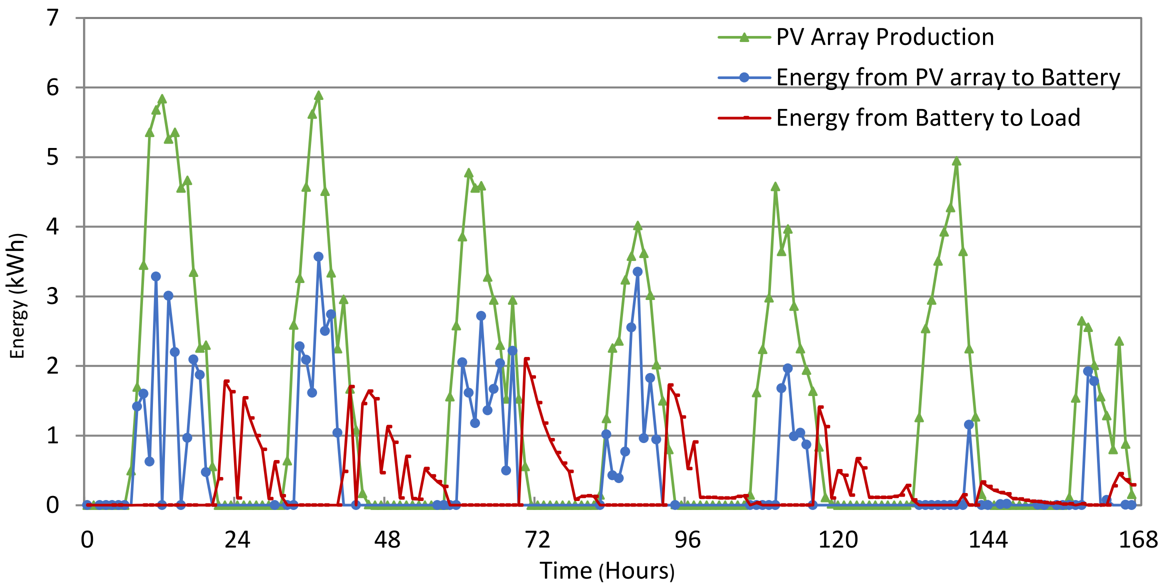

Figure 4. Energy flow from the PV array to battery and battery to satisfy load

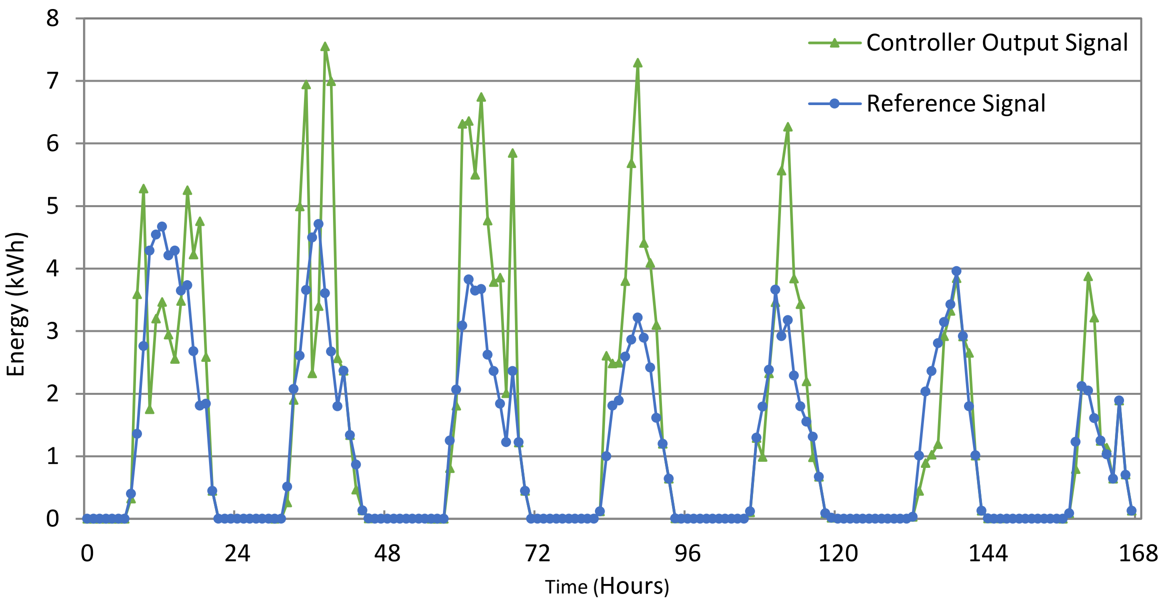

Figure 5. Reference signal vs controller output signal

4. Conclusion

In this work artificial neural network based energy consumption was used as an output disturbance for the development of an adaptive model predictive control system, to plan in advance for periods of high energy demand in a residential house. Using this, a switched MPC strategy was developed for energy dispatching of the photovoltaic-battery-grid system. The model predictive controller was found to be capable of operating non-critical loads when excess PV energy was available and also to dispatching energy to and from the battery storage system.

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