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Richard L. Welch

Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

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HDP based Optimal Control of a Grid Independent PV System

Richard L. Welch and Ganesh Kumar Venayagamoorthy, *Senior Member, IEEE*

Abstract – This paper presents an adaptive optimal control scheme for a grid independent photovoltaic (PV) system consisting of a PV collector array, a storage battery, and loads (critical and non-critical loads). The optimal control algorithm is based on the model-free Heuristic Dynamic Programming (HDP), an adaptive critic design (ACD) technique which optimizes the control performance based on a utility function. The HDP critic network is used in a PV system simulation study to train a neurocontroller to provide optimal control for varying PV system output energy and load demands. The emphasis of the optimal controller is primarily to supply the critical base load demand at all times. Simulation results are presented to compare the performance of the proposed optimal scheme with the conventional priority control scheme. Results show that HDP based control scheme performs better than a conventional priority control scheme.

Index Terms — Adaptive Critic Designs, Battery Storage, Energy Management, Neural Networks, Optimal Control, Photovoltaic System

I. INTRODUCTION

WITH the recent dramatic rise in the prices of fossil fuels, alternative energy sources are an intriguing way to reduce energy costs for heating, cooling, and meeting the general electrical needs of a residence or a facility. There are several alternative energy sources available, such as windmills, solar water heating (both for direct use and space heating), photovoltaic (PV) panels, and hydroelectric sources. Not all of these are as practical as one would hope, however; windmills require a windy location and hydroelectric systems need a large reserve of water stored at higher elevations. Solar energy is much more abundant, and can be harnessed much more easily (unless one lives near the poles or other areas which receive limited amounts of sunlight).

The price of photovoltaic (PV) panels has fallen dramatically over the past 30 years [1] as improvements in technology are made. Another contributing factor to the overall decline of the cost of PV systems is an increase in production volume. And, when factoring in the rising costs of

fossil fuel generated electricity and heating, PV systems have become very competitive in certain markets such as California, New Jersey, Illinois, and Hawaii.

Even though the prices of PV systems have fallen, they are still quite expensive: the payback time for a typical system can be 30 years (or more), depending on the size of the installation, type of equipment used and the solar radiation available. Fortunately, the life of the PV arrays themselves is around 30 years. And since they have no moving parts, maintenance requirements are very low. It is possible to reduce the overall costs of the PV system with an efficient control scheme determining when and how much of the electrical loads are to be supplied. This will allow for more efficient use of the PV system components, and thus enable the designer to design a system with smaller (and less costly) PV arrays and batteries while still allowing the PV system to provide adequate coverage to the base (or critical) load.

Traditionally, the control scheme that is used for PV systems is usually called a “PV Priority” control scheme [3]. In this control scheme, the controller attempts to power the entire load (both critical and non-critical loads) and if there is any excess electrical energy it will try to charge the battery. If there is not enough energy to power the loads, then it will draw energy from the battery to do so.

In order to improve upon the PV priority scheme, an optimal controller can be designed such that the critical load is only powered when there is insufficient amount of energy from the PV arrays, for instance. In this way, an optimal controller can conserve battery energy during times of reduced solar radiation so that it there will be energy available to power the critical load whenever required. An example of a critical load would be the refrigeration of vaccines and medication in remote locations without access to a reliable electrical grid.

While there have been other attempts to create an optimal controller, they have either used Q-learning [3] or fuzzy logic [4]. In this paper, an optimal controller based on the Adaptive Critic Designs (ACDs) [5] approach is designed to optimally allocate distribute energy primarily to the critical load and then to the non-critical loads. The Action Dependent Heuristic Dynamic Programming (ADHDP) approach is adopted for the optimal controller design [6, 7].

The rest of the paper is organized as follows. Section II describes the PV system considered in this study. Sections III and IV describe the traditional PV priority control and the

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Richard L. Welch and Ganesh K. Venayagamoorthy are with the Real-Time Power and Intelligent Systems Laboratory in the Department of Electrical and Computer Engineering, University of Missouri-Rolla, MO 65409 USA (e-mails: rwelch@umr.edu and gkumar@ieee.org).

ACD based optimal control schemes respectively. Section V presents some simulation results. Finally, the conclusion and future work is given in Section VI.

II. PHOTOVOLTAIC SYSTEM MODEL

The photovoltaic system model is made up of the following components: PV array, maximum power point tracker, controller, battery charge controller, batteries, critical load (refrigerator, standby lighting, etc), non-critical load (TV, extra lights, etc). In the case of the maximum power point tracker, battery charge controller, and batteries, it is assumed that they are 100% efficient (and so the maximum power point tracker and charge controller are omitted in the simulation model).

Photovoltaic arrays generally range in efficiency from 6% to 30%, with costs varying tremendously. Usually, the 30% efficiency arrays are used for space applications because of their power generation density (and radiation tolerances), while arrays with 6% to 15% efficiency are used for typical terrestrial applications. In this paper, the simulated efficiency of the PV array is set to 11% (to account for dust on the array, wiring losses, alignment issues, etc). A block diagram of this PV system setup is shown in Fig. 1.

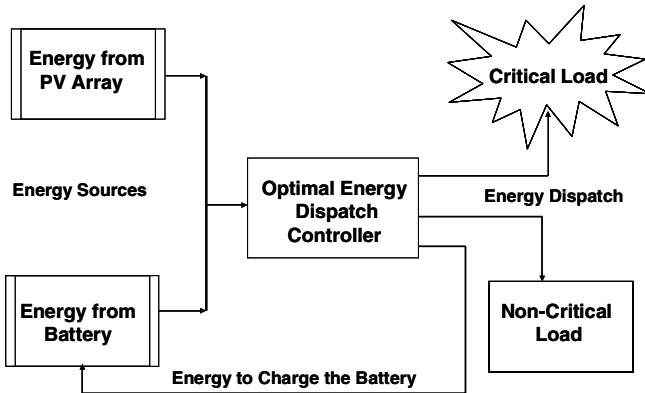


Fig. 1. Block diagram of the PV system model.

III. PV PRIORITY CONTROLLER

In the conventional controller (called the “PV Priority” scheme), no analysis of current state is performed while making decisions. Instead, energy (provided from the solar arrays) is first supplied to meet the critical load demand, any excess energy left is then supplied to meet the non-critical loads; and finally, any available energy after supplying the loads is used for charging the storage batteries. Conversely, if there is not enough electrical energy to first power the critical load and then the non-critical load, the balance of energy is taken from the batteries. If the batteries have already been depleted, then all load(s) will not be met since there will insufficient energy to power them.

This scheme works well in climates where there is an abundance of solar insolation and utility rates are relatively

high, but in an environment where there is lack of abundance of solar insolation (or anywhere cost is a major constraint) then a more optimal method of controlling the PV system is desirable.

IV. OPTIMAL CONTROLLER

Adaptive critic designs (ACDs) are neural network designs capable of optimization over time under conditions of noise and uncertainty. A family of ACDs was proposed by Werbos [5] as a new optimization technique combining the concepts of reinforcement learning and approximate dynamic programming. For a given series of control actions that must be taken sequentially, and not knowing the effect of these actions until the end of the sequence, it is possible to design an optimal controller using the traditional supervised learning neural network.

The adaptive critic method determines optimal control laws for a system by successively adapting two neural networks, namely, an *action network* (which dispenses the control signals) and a *critic network* (which learns the desired performance index for some function associated with the performance index). These two neural networks approximate the Hamilton-Jacobi-Bellman equation associated with optimal control theory. The adaptation process starts with a non-optimal, arbitrarily chosen control by the action network; the critic network then guides the action network toward the optimal solution at each successive adaptation. During the adaptations, neither of the networks needs any “information” of an optimal trajectory, only the desired cost needs to be known. Furthermore, this method determines optimal control policy for the entire range of initial conditions and needs no external training, unlike other neuro-controllers [6].

The design ladder of ACDs includes three basic implementations: Heuristic Dynamic Programming (HDP), Dual Heuristic Programming (DHP) and Globalized Dual Heuristic Programming (GDHP), in the order of increasing power and complexity. The interrelationships between members of the ACD family have been generalized and explained in [7]. In this paper, an Action dependent HDP (ADHDP) approach is adopted for the design of a PV optimal controller. Action dependent adaptive critic designs do not need system models to develop the optimal control policy (action network output).

The PV optimal controller is developed to optimally dispatch energy to power certain loads and/or charge the batteries (so that the batteries can be used to power the loads later on). This technique utilizes two neural networks: one (called the action network) takes a set of inputs (energy availability, critical and non-critical load demands) and provides optimal energy distribution as its output and the second of the two neural networks (called the critic) critiques the action network performance over time in order to maximize the total energy supplied over time, especially to the critical load maintaining the battery charge within a certain threshold. This action-critic networks’ interaction eventually leads to an optimal control strategy for the system.

Figure 2 illustrates the ADHDP architecture for the development of the PV optimal controller. The critic and action neural networks and their trainings are described in following subsections.

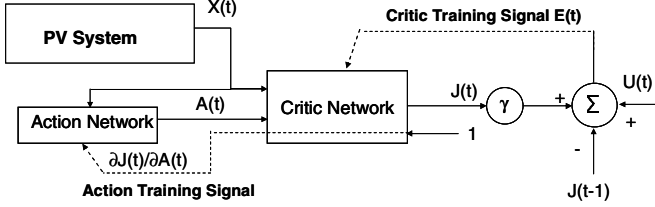


Fig. 2. Structure of the ADHDP based PV optimal controller design.

A. Critic Neural Network

The critic network is a multilayer feedforward network trained with the standard backpropagation (BP) training algorithm. The numbers of neurons in the input, hidden and output layers are chosen to be nineteen (linear), forty (sigmoidal) and one (linear) respectively. The inputs to the critic network are the outputs and inputs of the action network, A , at time t , $t-1$ and $t-2$. These are shown below in Fig. 3.

The output of the critic network is the estimated *cost-to-go* function J of Bellman's equation of dynamic programming, which is given by (1).

$$J(t) = \sum_{i=0}^{\infty} \gamma^i U(t+i) \quad (1)$$

Where γ is the discount factor for finite horizon problems with the range of $[0, 1]$ and is chosen to be 0.8 in this study. $U(t)$ is known as the utility function or the local cost. This utility function guides the critic in critiquing the actor's performance, in order to create an optimal control policy. In this study, $U(t)$ is chosen to be function of critical load (CL), battery charge status (BC) and non-critical load (NCL) and is given in (2).

$$U(t) = (15/23) * \text{abs}(1 - (ECL / (CL + M * MCL))) + (5/23) * \text{abs}(1 - (EB / ((MBC - CBC) + M * MBC))) + (3/23) * \text{abs}(1 - (ENCL / (NCL + M * MNCL))) \quad (2)$$

Where:

ECL = Energy Dispatched to the Critical Load

CL = Critical Load

MCL = Maximum Critical Load

EB = Energy Dispatched to the Battery

MBC = Maximum Battery Charge

CBC = Current Battery Charge

$ENCL$ = Energy Dispatched to the Non Critical Load

NCL = Non Critical Load

$MBCL$ = Maximum Non Critical Load

M = Multiplier (used to ensure divisor is non-zero; for this experiment, a value of 0.1 was used).

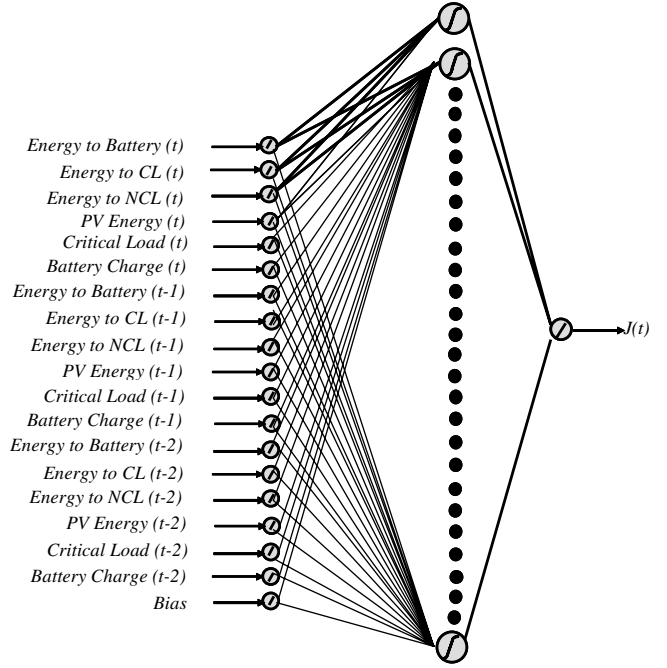


Fig. 3. Critic neural network.

In the $U(t)$ function given in (2), a higher priority is given to meeting the critical load at all times over the batteries being charged or the non-critical load being supplied by assigning different weightings - 15/23 to the CL term, 5/23 to the BC term and 3/23 to the NCL term.

In the training of the critic network, the objective is to minimize (3) given below.

$$\sum_{t=0}^{\infty} E^2(t) \quad (3)$$

where

$$E(t) = U(t) + \gamma J(t) - J(t-1) \quad (4)$$

The weight change and update equations for the critic network using the standard backpropagation is given by (5) and (6) respectively.

$$\Delta W_c(t) = \eta_c \cdot E(t) \cdot \frac{\partial J(t)}{\partial W_c} \quad (5)$$

$$W_c(t+1) = W_c(t) + \Delta W_c(t) \quad (6)$$

Where η_c and W_c are the learning rate and the weights of the critic neural network respectively.

B. Action Neural Network

The action network is a multilayer feedforward network trained with the BP algorithm. The number of neurons in input, hidden and output layers is four (linear), forty (sigmoidal) and three (linear) respectively. The inputs to the action network is the available PV energy, the critical load as a percentage of the total load, state of charge of the batteries

and a constant bias value of 1, and its outputs are energy supplied to the battery, to the critical load and to the non-critical load. The action neural network is shown in Fig. 4.

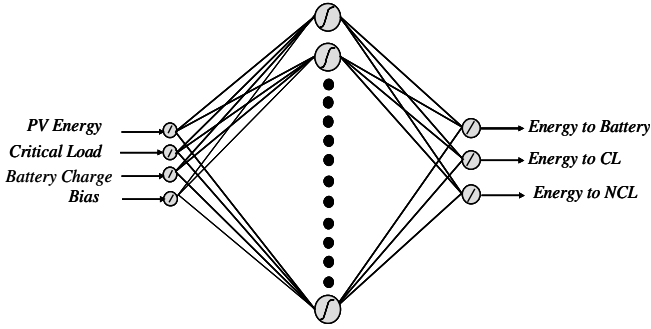


Fig. 4. Action neural network.

The change in the action network weights ΔW_A are calculated by backpropagating a '1' through the trained critic network as shown in Fig. 2 to obtain $\partial J/\partial A$. The error in the action network output is given by (7).

$$E_A(t) = \partial J(t) / \partial A(t) \quad (7)$$

The change in the action network's weights ΔW_A obtained using the standard backpropagation algorithm and update weight equations are given by (8) and (9) respectively.

$$\Delta W_A(t) = \eta_A \cdot E_A(t) \cdot \frac{\partial A(t)}{\partial W_A} \quad (8)$$

$$W_A(t+1) = W_A(t) + \Delta W_A(t) \quad (9)$$

Here η_A and W_A are the learning rate and the weights of the action neural network respectively.

C. Actor/Critic Training

The flowchart in Fig. 5 outlines the training steps for both the critic and action networks. During the iterative training phase, several metrics can be used to determine if the actor's performance is increasing. For this study, the simple sum of the utility function for each cycle of the training action network is used. This means that when the sum of the utility function is decreasing, the performance of the action network is improving. As soon as the sum of the utility function increases, the training is terminated and weight that resulted in the minimum sum is stored.

After the best action network weights were found, these weights were then used for to optimally dispatch energy to the critical load, the non-critical loads and the battery.

V. RESULTS

One year simulation of the PV system for Springfield, MO area is carried out using the data from the TMY2 database [2]. The solar profile (or global horizontal radiation) for a typical year for this region is illustrated in Fig. 6. Figure 7

shows the PV array output over a period of 4 days in early January (5th through 9th).

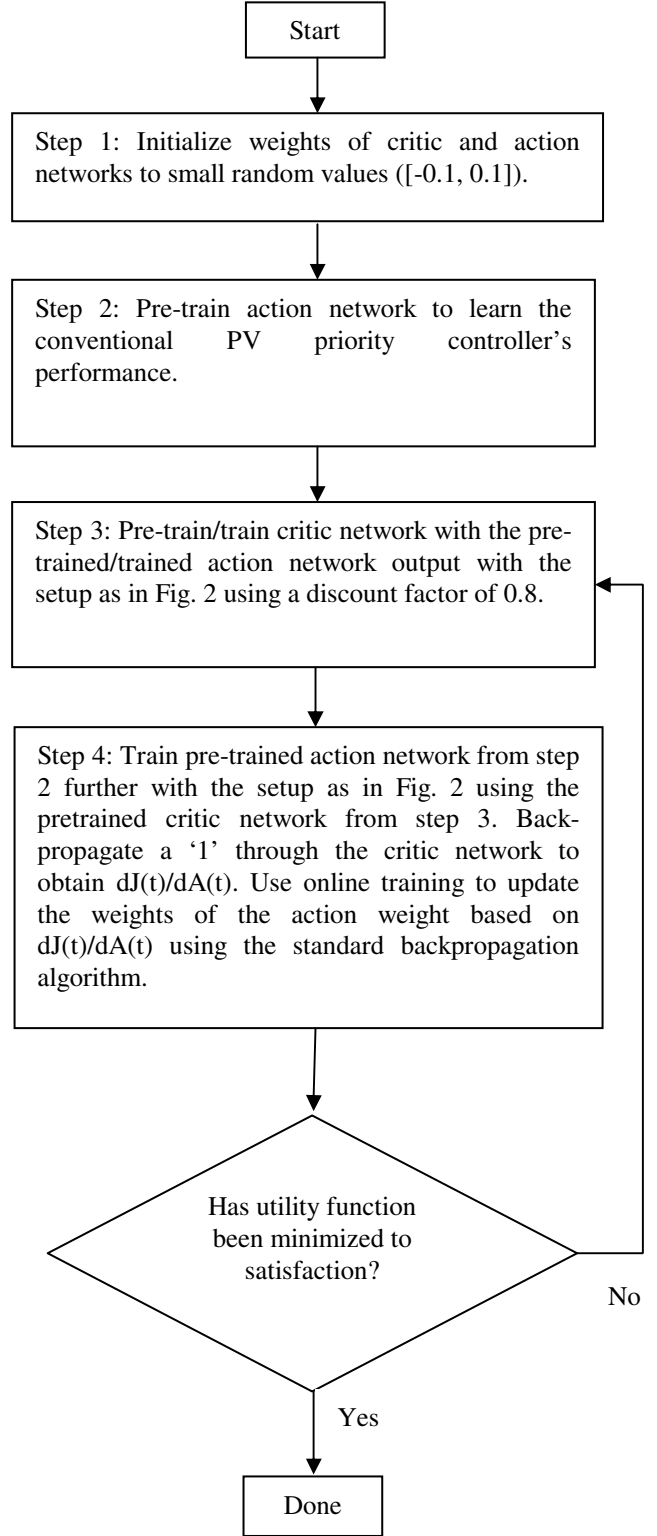


Fig. 5. Critic/Action network training steps.

The PV energy captured by the solar array is optimally dispatched to power a time varying load (as shown in Fig. 8 as the sum of both the critical and non-critical loads). When there is insufficient energy from the PV array to supply the

loads, energy from the battery is dispatched. The states of the battery charge when the PV system is controlled by the ACD optimal controller and the PV priority controller for the entire 12 month period is shown in Fig. 9.

As it can be observed from Fig. 9, with the PV priority controller, the state of charge of the battery falls from the initial full charge (100%) to 30% and remained at this level until the spring and partly into early summer months. During the summer, the battery charge rises close to 100% and then falls again as the available solar energy decreased during the winter months. During the same period, the battery charge with the optimal controller is maintained close to 100% though there is still a dip during the winter months. Overall, the state of the battery charge is better with the ACD neurocontroller compared to that with the PV priority controller.

If there was adequate solar energy available during the previous day, then generally both schemes were able to meet the base load (and at least some of the non-critical load) the next day. However, once again the optimal controller worked much better. It was able to nearly always power the critical load and non-critical loads. This is evident from Fig. 10.

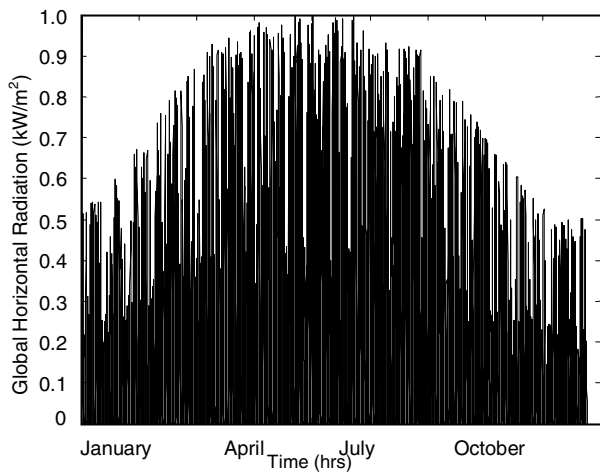


Fig. 6. Global horizontal radiation for Springfield, MO.

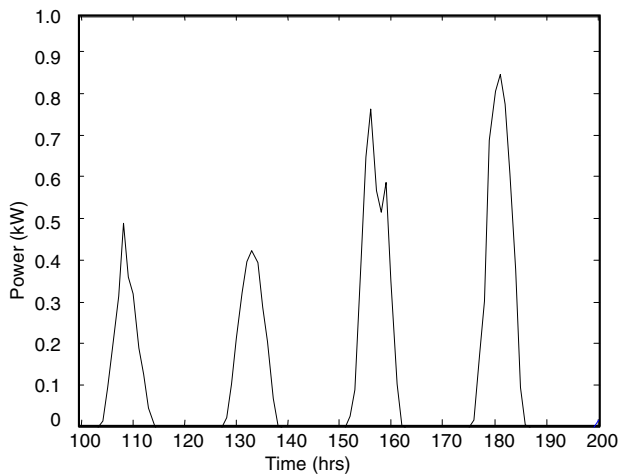


Fig. 7. Power output of the PV array.

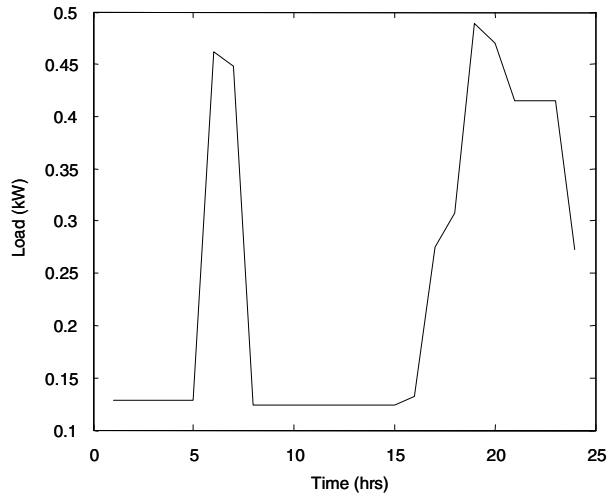


Fig. 8. Daily time varying load profile.

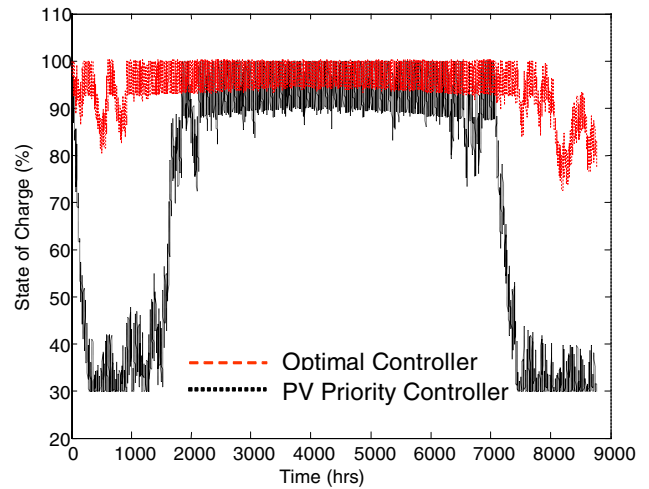


Fig. 9. State of charge of the battery for two controller types over a period of 12 months.

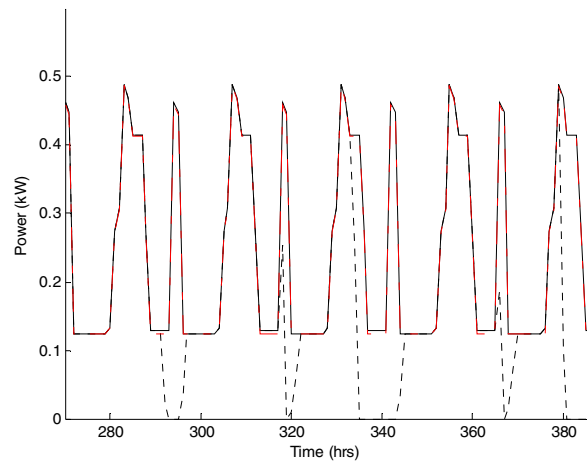


Fig. 10. Load versus dispatched power for period between January 12th and January 16th. Solid black line represents the load, dashed red line represents the load supplied by the ADHP neurocontroller and the dotted black line represents the load supplied by the PV priority controller.

VI. CONCLUSION

A new optimal control scheme based on adaptive critic designs for the photovoltaic system is developed and compared with the conventional priority control scheme used today. The ACD method optimizes the control policy over time to ensure that the critical load demand is met primarily all the time and then the non-critical load demands. The state of the battery charge is also maintained as high as possible to ensure energy supply to the critical loads during nights and the winter months. This in turn provides the benefit of extended battery life. The comparison between the two control schemes show that the neurocontroller satisfies the critical load and most of the non-critical loads demand better than the priority control scheme.

Future work will involve investigations to try to further optimize the controller to more closely follow the load profiles and provide even better performance, as well as trying out the proposed controller design on various TMY2 database solar radiation profiles.

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VIII. BIOGRAPHIES

Richard L. Welch received B. S. degrees in computer science and computer engineering from the University of Missouri-Rolla and is currently pursuing a M. S. Degree in computer engineering, also from the University of Missouri-Rolla. His research focuses on optimal control systems.

Ganesh Kumar Venayagamoorthy (M' 97, SM'02) received his PhD degree in Electrical Engineering from the University of Natal, Durban, South Africa, in February 2002. He is currently an Assistant Professor of Electrical and Computer and the Director of the Real-Time Power and Intelligent Systems Laboratory at University of Missouri, Rolla. His research interests are in computational intelligence, power systems control and stability, evolvable hardware and signal processing. He has published over 140 papers in refereed journals and international conferences. Dr. Venayagamoorthy is the recipient of the following awards - 2005 IEEE Industry Application Society (IAS) Outstanding Young Member award, the South African Institute of Electrical Engineers Young Achiever's award, 2004 NSF CAREER award, the 2004 IEEE St. Louis Section Outstanding Young Engineer award, the 2003 International Neural Network Society (INNS) Young Investigator award, 2001 IEEE Computational Intelligence Society (CIS) W. J. Karplus summer research grant and five prize papers with the IEEE IAS and IEEE CIS. He is a Senior Member of the IEEE and the South African Institute of Electrical Engineers, a Member of INNS and the American Society for Engineering Education. He is an Associate Editor of the IEEE Transactions on Neural Networks. He is currently the IEEE St. Louis IAS Chapter Chair, the Chair and the founder of IEEE St. Louis CIS Chapter, the Chair of the Task Force on Intelligent Control Systems and the Secretary of the Intelligent Systems subcommittee of IEEE Power Engineering Society. Dr. Venayagamoorthy was the Technical Program Co-Chairs of the 2003 International Joint Conference on Neural Networks, Portland, OR, USA and the 2004 International Conference on Intelligent Sensing and Information Processing, Chennai, India. He has served as member of the program committee, organized and chaired sessions, and presented tutorials at several international conferences and workshops.