Energy dispatch controllers for a photovoltaic system

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**Abstract**

In this paper two energy dispatch controllers for use in a grid-independent photovoltaic (PV) system are presented. The first, an optimal energy dispatch controller, is based on a class of Adaptive Critic Designs (ACDs) called Action Dependent Heuristic Dynamic Programming (ADHDP). This class of ACDs uses two neural networks to evolve an optimal control strategy over time. The first neural network or “Action” network dispenses the actual control signals while the second network or “Critic” network uses these control signals along with the system states to provide feedback to the action network, measuring performance using a utility function. This feedback loop allows the action network to improve behavior over time. The optimal energy dispatcher places emphasis on always meeting the critical load, followed by keeping the charge of the battery as high as possible so as to be able to power the critical load in cases of extended low output from the PV array, and lastly to power the non-critical load in so far as to not interfere with the first two objectives. The second energy dispatch controller is a smart energy dispatch controller and is built using knowledge from an expert, codified into a series of static rules. This smart energy dispatch controller is called the “PV-priority 2” controller. These energy dispatchers are compared with a static scheme called the “PV-priority 1”. The PV-priority 1 controller represents the standard control strategy. Results show that the ADHDP-based optimal energy dispatcher (or controller) outperforms the standard PV-priority 1 energy dispatcher in meeting the stated objectives, but trails the PV-priority 2 energy dispatcher. However, the major advantage of the ADHDP controller is that no expert is required for designing the controller, whereas for a rule-based controller such as the PV-priority 2 controller, an expert is always required.

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1. Introduction

As the costs of fossil fuels continue to rise, it is becoming economically important to investigate other sources of energy. Additionally, increased customer demands and loads are beginning to outstrip the grid’s capacity to serve these loads. As such, distributed generation of alternative energy sources is becoming a very heated research and development area.

Currently, there are several alternative energy sources available: wind, solar, hydro-electric and geo-thermal, to name a few. Hydro-electric and geo-thermal plants often require large footprint prints that are at odds with developed areas and environmental considerations. Wind energy is currently enjoying very energetic growth, at around 24% per year since the year 2000 in the US (US Department of Energy’s Office of Energy Efficiency And Renewable Energy, 2007). But, wind power has its downsides as well since not all locations receive enough sustained winds to be productive, and even then production is sometimes sporadic. Of all of the mentioned sources, solar power seems to be the most promising in that all locations on Earth receive predictable sunlight to some degree, and the solar arrays used to convert sunlight into electricity (photovoltaic or PV arrays) scale very well from very small sizes for calculators to very large sizes used in centralized power plants.

Another benefit of solar energy is that the PV arrays contain no moving parts and can last several decades before needing to be replaced. During this time, the only maintenance that may need to be done to PV arrays is dust or snow clearing and checking for alignment problems. And while the PV arrays are within their rated lifetimes, they generally perform reliably while the Sun is shining.

Even with these advantages, there is one major drawback of PV systems that limits their adoption rate and that is the cost of these systems. The cost of energy derived from these systems makes them not currently competitive with other sources. However, due to technological, manufacturing and resource improvements, these costs have steadily fallen in previous years (Messenger and Ventre, 2004) and are expected to continue to do so. As the price falls, this source will be more competitive. Even so, the payback time (the amount of time required for the initial investment in a PV system to equal the costs accrued from purchasing power through the grid) can be lengthy, and in some cases as long as 30 years or more.
In order to make PV systems cheaper (and shorten the payback period), optimal control can be used to more effectively utilize energy generated by the PV array, resulting in smaller required batteries and arrays while still maintaining the critical load. This reduction in system component size leads to a direct reduction in cost for the entire system.

The traditional energy dispatcher for a PV system is called the “PV-priority” (called “PV-priority 1” in this paper) control scheme (Henze and Dodier, 2003) and will first attempt to power all loads using energy from the PV array; if there is not enough energy available from the PV array then energy from the battery is used to make up the shortfall (if available), and if there is more energy available from the PV array then the batteries are charged with the difference (if possible).

In this paper, two additional controllers are developed: the “PV-priority 2” and an optimal controller based on a class of adaptive critic designs (ACDs) called action-dependent heuristic dynamic programming, or ADHDP (Werbos, 1992; Venayagamoorthy et al., 2002; Prokhorov and Wunsch, 1997). The “PV-priority 2” control scheme is similar to the PV-priority 1 scheme in that its performance is rule based, but is different in that it attempts to always power the critical load first, then charge the battery to 70%, and finally use whatever energy is available from the PV array and anything over 70% state of charge in the battery to power the non-critical load.

The ADHDP-based optimal energy dispatcher on the other hand is not rule based, and develops its control action strategy by adapting its performance in response to a measured metric value. Adaptive critic designs use a combination of dynamic programming and reinforcement learning, and the ADHDP method is the simplest of the ACD family (it uses only 2 neural networks). One of the neural networks (called the “action” network or “actor”) is responsible for providing the control signals while the second (called the “critic” network) critiques these control signals over time. The objectives of this energy dispatcher are the following:

i). Completely power the critical load at all times.
ii). Maintain the battery state of charge as high as possible so as to be able to meet the critical load during times of reduced (or non-existent) energy from the PV array.
iii). Power the non-critical load such that the controller is still able to meet the first two objectives.

Another advantage of the ADHDP-based controller is that since it is not rule based, its behavior can be modified over time to cope with changing meteorological conditions. One such important condition is the behavior of the Sun and its associated output. Even though the output in general remains relatively constant, there are small deviations and at least some work has been performed into predicting sunspot activity (Xie et al., 2006; Day and Nandi, 2008).
device. Likewise, new energy storage systems (Jiang and Dougal, 2006; Lemofouet and Rufer, 2006) may eclipse the performance of the standard lead-acid-type battery technology primarily used today. Because the focus of this study is primarily to evaluate the performance of the presented control strategies, the assumption of 100% efficiency of the photovoltaic system is made. If other efficiencies are desired, they can be set by modifying the appropriate values within the models, as depicted in Fig. 1.

Also, the PV array is simulated to be tilted south at an angle equal to the latitude of each test city and the efficiency of the PV array model is taken as 11% to account for various non-optimal conditions (such as array misalignment, dust on the arrays, etc.). This value is representative of the current commercially available range of efficiencies for PV arrays. Generally, PV panels vary in efficiency from 6% to up to 30%; although the high efficiency panels are generally reserved for spacecraft usage because of their high radiation tolerances and higher power-to-weight ratio. A rough equivalent to the PV arrays being simulated in this paper would be an array of eight Kyocera KC200GT panels. These panels are over 16% efficient and will output 200 W during optimal conditions (Kyocera, 2007). The minimum charge for the battery of 30% is required to supply energy to the loads (this is consistent with standard deep cycle lead-acid batteries).

Due to insufficient PV energy during winter months and no PV energy at night, a control system is required to decide the amount of energy to be dispatched to the different loads, including the charging of the battery. The complete system in schematic diagram form is shown below in Fig. 1 (energy flow depicted by arrows).

3. PV-priority controllers

3.1. PV-priority 1 controller

The standard controller called the “PV-priority 1” controller is a very simple controller which always tries to meet the loads (the critical and then the non-critical) before charging the battery. At any one time, if there is not enough energy from the PV array to supply the loads then the balance is drawn from the battery. If instead there is an excess, then whatever is left over after supplying the loads is dispatched to the battery. In this way, the controller will attempt to power all loads and charge the battery as best it can, without any considerations given to the time-varying states of the system. The flowchart for the decisions that this controller makes in any given hour is given in Fig. 2.

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**Fig. 2.** Flowchart for PV-priority 1 Controller.
This controller works well when there is sufficient PV energy. However, when there is not sufficient PV energy, then the battery will not be fully recharged and the loads will be dropped. The weather and user loads are stochastic in nature; therefore there is no one definitive model at all times. Thus, it makes sense to look at intelligent model-free learning methods of controlling such a system.

3.2. PV-priority 2 controller

The second PV-priority controller that is used in this paper is the PV-priority 2 controller. As mentioned previously, this controller first meets the critical load then attempts to charge the battery to 70% state of charge. Once these two objectives have been met, the controller then attempts to power the non-critical load using any excess PV energy or energy from the battery without depleting it below 70% state of charge, as detailed in Fig. 3.

4. ADHDP optimal controller

As previously mentioned, because user loads and solar insolation are stochastic in nature, it makes sense to look at intelligent model-free methods of control. One such intelligent system can involve the use of adaptive critic designs. ACDs utilize neural networks and are capable of optimization over time in conditions of noise and uncertainty. A family of ACDs was proposed by Werbos (1992) as a new optimization technique combining the concepts of approximate dynamic programming and reinforcement learning. With ACDs, for a given series of control actions that must be taken sequentially (and not knowing
The adaptive critic method determines an optimal control for a system by adapting two neural networks: an Action network and a Critic network. The Action network is responsible for driving the system to the desired states, while the Critic network is responsible for providing the Action network with performance feedback with respect to reaching the desired states over time. With this feedback, the Action network is able to adapt its parameters continuously to maximize its objective. The Critic network learns to optimize the Action network by approximating the Hamilton–Jacobi–Bellman equation associated with optimal control theory.

This Actor–Critic adaptation process starts with a non-optimal or suboptimal policy by the action network; the Critic network then guides the Action network toward an 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. Additionally, it needs no external training, unlike other neural-controllers (Venayagamoorthy et al., 2002).

As mentioned, the objective of the optimal PV control is threefold – to maximize or fully dispatch the required energy to the critical loads at all times, dispatch energy to charge the battery whenever necessary so as to dispatch energy to the critical loads in the absence of energy from the collector and the last objective is to dispatch energy to the non-critical loads not comprising on the first two objectives. The optimal controller is not used for instances where there is sufficient solar energy to power all loads as well as completely charge the battery. When this occurs, all loads are satisfied and the battery is completely charged.

This optimal controller uses two networks (the Action and Critic networks) as previously mentioned. The inputs to the Action network correspond to the states of the system while the outputs correspond to the amount of energy to be dispatched to the critical loads, battery and non-critical loads. The inputs to the Critic consist of the inputs to the Action network at time \( t \), \( t-1 \) and \( t-2 \), as well as the outputs of the Action network at time \( t \), \( t-1 \) and \( t-2 \). The Critic then uses the information from the current states and actions in the current time step (as well as from the recent past) to derive the Action network over time to evolve an optimal control policy. Fig. 4 shows the connection between the Action network, Critic network and the PV system.

### 4.1. Critic neural network

The Critic network is a multilayer feedforward network trained using the standard backpropagation (BP) training algorithm. The input, hidden and output layers consists of 22 linear neurons, 20 sigmoidal neurons and one linear neuron, respectively. As previously mentioned, the inputs to the Critic network are the outputs and inputs of the action network, at times \( t, t-1 \) and \( t-2 \). A diagram of the Critic network is shown in Fig. 5.

The output of the critic network is the estimated cost-to-go function \( J(t) \) of Bellman’s equation of dynamic programming, which is given by (1).

\[
J(t) = \sum_{i=0}^{\gamma} U(t+i)
\]

where \( \gamma \) 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 function. This utility function guides the Critic in critiquing the Actor’s performance. In this study, \( U(t) \) in (2) is chosen to be a function of critical load (CL), state of battery charge (BC) and non-critical load (NCL). \( A_1, A_2 \) and \( A_3 \) are constant coefficients and taken to be 30/23, 15/23 and 13/23, respectively, in order to give emphasis to meeting the critical load over keeping the battery charged and then meeting the...
non-critical loads.

\[ U(t) = A_1 \text{abs}(1 - (E_{NL} / (L_{NL,max} + M_{non-zero}L_{CL,max}))) + A_2 \text{abs}(1 - (E_B / (E_{B,max} - E_B + M_{non-zero}E_{B.max}))) + A_3 \text{abs}(1 - (E_{CL} / (L_{CL,max} + M_{non-zero}L_{CL,max}))) \]  

(2)

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 – 30/23 to the CL term, 15/23 to the BC term and 13/23 to the NCL term. This \( U(t) \) meets the threefold objective for the optimal PV controller design.

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

\[ \sum_{t=0}^{\infty} E^2(t) \]  

(3)

where

\[ E(t) = U(t) + J(t) - J(t-1) \]  

(4)

The weight change and update equations for the Critic network using the BP algorithm is given by (5) and (6), respectively.

\[ \Delta W_c(t) = \eta_c E(t) \frac{\partial J(t)}{\partial W_c} \]  

(5)

\[ W_c(t+1) = W_c(t) + \Delta W_c(t) \]  

(6)

where \( \eta_c \) and \( W_c \) are the learning rate and the weights of the Critic neural network, respectively.

One important note about the Critic network design is that when determining how many previous time steps to use, it is necessary to look at how the Critic network training is proceeding. If the critic network is not training properly, then it may be necessary to increase the number of time steps used as input to the critic network. The critic network requires multiple time steps because it is implemented using a feedforward network and using multiple delayed time steps gives the network more information to calculate (4). However, with more time steps, the Critic network will also require more neurons in order to handle the complexity. For this study, using the current and previous two time steps as previously outlined was found to allow the Critic to train properly using the specified number of neurons. The size of the hidden layer in the Critic network is determined by trial and error, while the size of the input and output layers are determined by the number of inputs and outputs, respectively. In the case of the Critic network, the only output is the approximated \( J(t) \) value so the output size is 1.

4.2. Action neural network

The Action network is a multilayer feedforward network trained using the BP algorithm. The input, hidden and output layers of the Action network consists of five linear neurons, 30 sigmoidal neurons and three linear neurons, respectively, as is shown in Fig. 6. The Action network inputs consist of the following:

- Solar energy from the PV array (as a fraction of total possible energy from the PV array).
- Critical load (as a fraction of total load).
- Non-critical load (as a fraction of total load).
- Current battery state of charge (as a fraction of total charge).
- Bias term.

The Action network outputs consist of the following:

- Energy dispatched to the critical load (as a percentage).
- Energy dispatched to the non-critical load (as a percentage).
- Energy dispatched to the battery; this can be positive or negative, depending on whether the battery is being charged or being used as a source.

Additionally, the Action network’s outputs are checked to ensure the sum of energy dispatched is no more than is available at the inputs. This is accomplished by performing the following series of steps immediately after calculating the outputs from the action network:

(i) Verify that the energy dispatched to each of the loads does not exceed the load demand, and is not negative. Also ensure that the energy to the battery is not higher than the energy collected by the PV arrays.
(ii) Verify that the battery is not being overcharged, or over depleted.
(iii) The outputs (including the energy dispatched to the battery if it is being charged) are scaled by the ratio of energy inputs to outputs.
(iv) After scaling (step iii), another round of checks is made on the Action network outputs in order to be certain that they are not greater than the load or less than zero.

The change in the Action network weights \( \Delta W_A \) are calculated by backpropagating the current \( J(t) \) value back 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 as

\[ E_A(t) = \partial J(t) / \partial A(t) \]  

(7)

The change in the Action network’s weights \( \Delta W_A \) obtained using the BP algorithm and update weight equations are given by
Eqs. (8) and (9), respectively.

\[ \Delta W_A(t) = \eta_A E_A(t) \frac{\partial A(t)}{\partial W_A} \]  
(8)

\[ W_A(t+1) = W_A(t) + \Delta W_A(t) \]  
(9)

Here \( \eta_A \) and \( W_A \) are the learning rate and the weights of the Action neural network, respectively.

As with the Critic network, the size of the hidden layer in the Action network is determined by trial and error, while the size of the input and output layers are determined by the number of inputs and outputs, respectively.

4.3. Actor/Critic training

The flowchart in Fig. 7 outlines the pre-training steps for the Action network, while Fig. 8 details the iterative training technique used to develop the optimal controller over time. 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 training the Action network is used. This means that when the sum of the utility function is decreasing, the performance of the Action network is improving. The simulation is run for a fixed number of iterations, but if the sum of the utility function increases during training then the new Action network weights are discarded and replaced with the previous best weights. When this happens, a very small perturbation (a random number between \(-0.01\) and \(0.01\)) is added to the Action network weights such that the network avoids getting stuck in a local minimum.

After the best Action network weights are found, these weights are then used to optimally dispatch energy to the critical loads, the non-critical loads and the battery.

5. Results

A one year simulation of the PV system is carried out for the following areas under varying conditions with multiple controllers: Phoenix, AZ, Miami, FL, Boulder, CO, Springfield, MO, Caribou, ME and Fairbanks, AK. These simulations use data from the TMY2 database (National Renewable Energy Laboratory, 1995). Phoenix receives more solar radiation than Miami, Miami more than Boulder, Boulder more than Springfield, etc. The actual relationship between cities and total annual solar insolation is shown in Table 1. A map showing the solar insolation received on a flat plate facing south and tilted at the latitude angle for the United States with test cities marked is shown in Fig. 9 (National Renewable Energy Laboratory, 2004).

For three of the six cities (Phoenix, Springfield and Caribou), an action network is separately trained and then these networks are simulated against the data for each city. Selected results of these simulations (along with results from using the PV-priority

<table>
<thead>
<tr>
<th>Test city</th>
<th>Annual insolation (kW/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phoenix, AZ</td>
<td>3318.4</td>
</tr>
<tr>
<td>Miami, FL</td>
<td>2809.9</td>
</tr>
<tr>
<td>Boulder, CO</td>
<td>2647.0</td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>2515.4</td>
</tr>
<tr>
<td>Caribou, ME</td>
<td>2064.0</td>
</tr>
<tr>
<td>Fairbanks, AK</td>
<td>1463.1</td>
</tr>
</tbody>
</table>

Fig. 9. Map of solar insolation received on a flat plate collector facing south and tilted at the latitude angle for the United States with test cities marked. This map was developed by the National Renewable Energy Laboratory for the US Department of Energy.
controllers) are shown in Tables 2–4. All of the results from these tables are obtained using the normal load values (as shown in Fig. 10).

However, in order to show how the controllers perform under varying load conditions, two additional test cases are investigated where the system loads are varied by 10%. Table 5 shows selected results.

Table 2
Table of all controller performances for the Phoenix, AZ area (100% load).

<table>
<thead>
<tr>
<th>Test city: Phoenix, AZ</th>
<th>Controller trained at</th>
<th>Critical load satisfied:</th>
<th>Non-critical load satisfied:</th>
<th>Average battery charge:</th>
<th>PV energy collected: (kWh)</th>
<th>PV energy wasted: (kWh)</th>
<th>Relative performance:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caribou, ME</td>
<td>100% [1086kWh]</td>
<td>93.28% [940.4 kWh]</td>
<td>91.13% [31.5 kWh]</td>
<td>3318.36</td>
<td>1301.72</td>
<td>0.576155</td>
<td></td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>100% [1086kWh]</td>
<td>89.06% [897.9 kWh]</td>
<td>90.75% [31.4 kWh]</td>
<td>3318.36</td>
<td>1346.37</td>
<td>0.557491</td>
<td></td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>98.62% [1071 kWh]</td>
<td>98.26% [990.6 kWh]</td>
<td>84.37% [29.2 kWh]</td>
<td>3318.36</td>
<td>1279.53</td>
<td>0.595341</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 1</td>
<td>98.68% [1072 kWh]</td>
<td>98.19% [989.9 kWh]</td>
<td>84.37% [29.2 kWh]</td>
<td>3318.36</td>
<td>1279.53</td>
<td>0.595594</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 2</td>
<td>100% [1086kWh]</td>
<td>93.56% [943.2 kWh]</td>
<td>91.99% [31.8 kWh]</td>
<td>3318.36</td>
<td>1279.53</td>
<td>0.613554</td>
<td></td>
</tr>
</tbody>
</table>

Table 3
Table of all controller performances for the Springfield, MO area (100% load).

<table>
<thead>
<tr>
<th>Test City: Springfield, MO</th>
<th>Controller trained at</th>
<th>Critical load satisfied:</th>
<th>Non-critical load satisfied:</th>
<th>Average battery charge:</th>
<th>PV energy collected: (kWh)</th>
<th>PV energy wasted: (kWh)</th>
<th>Relative performance:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caribou, ME</td>
<td>100% [1086kWh]</td>
<td>76.89% [775.1 kWh]</td>
<td>84.37% [29.2 kWh]</td>
<td>2515.37</td>
<td>669.336</td>
<td>0.657436</td>
<td></td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>100% [1086kWh]</td>
<td>73.56% [741.6 kWh]</td>
<td>82.62% [28.6 kWh]</td>
<td>2515.37</td>
<td>705.391</td>
<td>0.636819</td>
<td></td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>91.29% [991.6 kWh]</td>
<td>89.42% [901.5 kWh]</td>
<td>72.66% [25.1 kWh]</td>
<td>2515.37</td>
<td>646.449</td>
<td>0.634973</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 1</td>
<td>91.64% [995.4 kWh]</td>
<td>89.05% [897.7 kWh]</td>
<td>72.66% [25.1 kWh]</td>
<td>2515.37</td>
<td>646.449</td>
<td>0.636213</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 2</td>
<td>100% [1086kWh]</td>
<td>77.01% [776.3 kWh]</td>
<td>86.91% [30 kWh]</td>
<td>2515.37</td>
<td>646.441</td>
<td>0.702766</td>
<td></td>
</tr>
</tbody>
</table>

Table 4
Table of all controller performances for the Caribou, ME area (100% load).

<table>
<thead>
<tr>
<th>Test City: Caribou, ME</th>
<th>Controller trained at</th>
<th>Critical load satisfied:</th>
<th>Non-critical load satisfied:</th>
<th>Average battery charge:</th>
<th>PV energy collected: (kWh)</th>
<th>PV energy wasted: (kWh)</th>
<th>Relative performance:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caribou, ME</td>
<td>96.54% [1049 kWh]</td>
<td>61.87% [623.7 kWh]</td>
<td>74.35% [25.7 kWh]</td>
<td>2063.99 kWh</td>
<td>415.604 kWh</td>
<td>0.656067</td>
<td></td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>96.25% [1045 kWh]</td>
<td>59.22% [597 kWh]</td>
<td>72.96% [25.2 kWh]</td>
<td>2063.99 kWh</td>
<td>445.645 kWh</td>
<td>0.636655</td>
<td></td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>83.44% [906.3 kWh]</td>
<td>78.05% [786.9 kWh]</td>
<td>63.87% [22.1 kWh]</td>
<td>2063.99 kWh</td>
<td>394.981 kWh</td>
<td>0.61361</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 1</td>
<td>84.22% [914.8 kWh]</td>
<td>77.21% [778.4 kWh]</td>
<td>63.87% [22.1 kWh]</td>
<td>2063.99 kWh</td>
<td>394.981 kWh</td>
<td>0.616802</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 2</td>
<td>96.9% [1053 kWh]</td>
<td>62.02% [625.2 kWh]</td>
<td>76.82% [26.5 kWh]</td>
<td>2063.99 kWh</td>
<td>394.98 kWh</td>
<td>0.695698</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 10. This figure shows the total load of the daily repeating load profile (solid line), with the constant critical load component shown (dashed line).
results of the simulations when the loads are lowered by 10% and Table 6 shows selected results when the loads are increased by 10%. Previous and less extensive studies have been explored by the authors (Welch and Venayagamoorthy, 2006a, 2006b, 2007) but did not extensively examine controller performance across wider insolation changes nor did they examine differences in loading. Also, all of the results tables give values for total PV energy collected and total PV energy wasted (energy which could not be stored because the battery is full and all loads can be met by using only energy from the PV array; usually occurs in the summer). Finally, each table contains a column labeled “Relative Performance”, which shows an insolation-independent weighted sum of the results from each test – the higher the score, the better the result. The equation used to calculate this metric is based on the utility function (2), and is shown below as (10).

\[
\text{Relative Performance} = \frac{1}{365} \sum_{m=1}^{365} \frac{k_{\text{max}}}{24} \left( A_1 \left( L_{\text{CL}} / L_{\text{CL, max}} \right) + A_2 \left( E_{\text{PV}} / E_{\text{max}} \right) + A_3 \left( L_{\text{NCL}} / L_{\text{NCL, max}} \right) \right)
\]

In the base case of 100% load, Figs. 11 and 12 show the ability of the PV-priority 1 controller and optimal controller (trained with data from the Caribou area) to satisfy the critical load and also the total load, using data from Springfield, MO. The results for this city are shown because it is a fairly typical city, receiving a somewhat average amount of insolation. In each of these figures, the solid black line indicates demanded load while the dashed black lines indicate satisfied load. These figures show the

<table>
<thead>
<tr>
<th>Test City: Caribou, ME</th>
<th>Controller trained at:</th>
<th>Critical load satisfied:</th>
<th>Non-critical load satisfied:</th>
<th>Average battery charge:</th>
<th>PV energy collected: (kWh)</th>
<th>PV energy wasted: (kWh)</th>
<th>Relative performance:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caribou, ME</td>
<td>97.99% [957.9 kWh]</td>
<td>66.82% [606.2 kWh]</td>
<td>77.97% [26.9 kWh]</td>
<td>2063.99</td>
<td>523.762</td>
<td>0.648725</td>
<td></td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>97.75% [955.6 kWh]</td>
<td>63.99% [580.6 kWh]</td>
<td>76.74% [26.5 kWh]</td>
<td>2063.99</td>
<td>551.88</td>
<td>0.629326</td>
<td></td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>85.94% [840.1 kWh]</td>
<td>81.97% [743.8 kWh]</td>
<td>67.24% [23.2 kWh]</td>
<td>2063.99</td>
<td>504.273</td>
<td>0.690159</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 1</td>
<td>86.51% [845.8 kWh]</td>
<td>81.35% [738.1 kWh]</td>
<td>67.23% [23.2 kWh]</td>
<td>2063.99</td>
<td>504.273</td>
<td>0.611469</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 2</td>
<td>98.4% [961.9 kWh]</td>
<td>68.79% [606.6 kWh]</td>
<td>80.65% [27.9 kWh]</td>
<td>2063.99</td>
<td>504.266</td>
<td>0.689386</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test city: Caribou, ME</th>
<th>Controller trained at:</th>
<th>Critical load satisfied:</th>
<th>Non-critical load satisfied:</th>
<th>Average battery charge:</th>
<th>PV energy collected: (kWh)</th>
<th>PV energy wasted: (kWh)</th>
<th>Relative performance:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caribou, ME</td>
<td>94.65% [1131 kWh]</td>
<td>57.68% [639.7 kWh]</td>
<td>71.04% [24.6 kWh]</td>
<td>2063.99</td>
<td>317.485</td>
<td>0.65867</td>
<td></td>
</tr>
<tr>
<td>Springfield, MO</td>
<td>94.32% [1127 kWh]</td>
<td>55.4% [614.3 kWh]</td>
<td>69.87% [24.1 kWh]</td>
<td>2063.99</td>
<td>346.82 kWh</td>
<td>0.640465</td>
<td></td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>81.22% [970.4 kWh]</td>
<td>74.72% [828.6 kWh]</td>
<td>61.12% [21.1 kWh]</td>
<td>2063.99</td>
<td>289.216 kWh</td>
<td>0.618444</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 1</td>
<td>82.12% [961.3 kWh]</td>
<td>73.76% [817.9 kWh]</td>
<td>61.12% [21.1 kWh]</td>
<td>2063.99</td>
<td>289.216</td>
<td>0.622085</td>
<td></td>
</tr>
<tr>
<td>N/A: PV-Priority 2</td>
<td>95.21% [1138 kWh]</td>
<td>57.95% [642.6 kWh]</td>
<td>72.51% [25.1 kWh]</td>
<td>2063.99</td>
<td>289.21</td>
<td>0.696549</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 11. Performance of the PV-priority 1 controller and optimal controller (trained using data from Caribou, ME) in meeting the critical load in the city of Springfield, MO.
demanded load and satisfied load on a daily basis, so the
demanded load curve is a constant value since the load profile
varies on a 24 h cycle. As can be seen by these figures, the optimal
controller is able to completely outperform the PV-priority 1
controller in powering the critical load but does so at the expense
of powering the non-critical load.

In Fig. 13, the daily energy balance is shown for the same area.
This surplus (or deficit) is calculated by subtracting the demanded
energy of the loads from the energy received from the PV arrays.
This is a good measure of absolute possible performance of a
controller. If there is always a surplus, then the controller has an
easier job of supplying energy to the loads, but if there is always a
deficit, then the controller would have a more difficult time
supplying energy to the loads without dropping them.

Interestingly, the optimal PV controller trained using the Caribou,
ME data set seems to always equal or perform better than any other
ccontroller except for the PV-priority 2 controller. Also, it seems that
the performance of the PV-priority 1 controller is generally slightly
better than the optimal PV controller trained using data from the
Phoenix, AZ area, especially as the environment becomes more
demanding and less solar insolation is available.

Fig. 14 shows the battery state of charge for Springfield,
MO for the period of late fall and early winter using both
the PV-priority 1 controller as well as the optimal PV controller
trained using Caribou data. As can be seen from this figure,
the optimal controller keeps the battery state of charge higher
than the conventional PV-priority 1 controller. Additionally, it
meets much more of the critical load but a little less of the non-
critical load. It is also interesting to state of note that this
controller changed behavior as the battery charge increased.
When it was lower it would power less of the non-critical
load and focus on the critical load, and when it was more fully

![Fig. 12. Performance of the PV-priority 1 controller and optimal controller (trained using data from Caribou, ME) in meeting the total load in the city of Springfield, MO.](image1)

![Fig. 13. The daily energy balance for Springfield, MO.](image2)
charged it would attempt to power both loads. This is in sharp contrast to the PV-priority controller 1 which always tried to power both loads, leading to a much lower average battery state of charge for the battery (and less met critical load demand). This behavior results from the coefficients used in the utility function (2).

Another interesting result was that the optimal controller trained using the Phoenix, AZ data set performed similarly to the PV-priority 1 controller (and in some cases slightly worse) and never as well as the other optimal controllers. This is most likely because the region received so much more sunlight than the other regions that it had less ‘opportunity’ to learn a more optimal technique, since there were more periods of excess sunlight where all loads could be satisfied. This most likely led to a different operating characteristic that did not lend itself well to other locations that received less sunlight. Further verifying this point is the Caribou-trained controller, which was trained at a location that received the least amount of sunlight of all 3 locations that were used for controller training, but seemed to perform better than any of the optimal controllers. The complete relative performances of each controller at each city for each load level are shown in Figs. 15–17.

These figures reinforce the fact that the optimal controller trained using data from the Caribou, ME area is generally superior to the performance of all other optimal controllers, except in the cases of very high solar insolation (Phoenix and Miami), at which locations the PV-priority 1 controller and the optimal controller trained using data from the Phoenix, AZ area slightly outperformed. The PV-priority 2 controller seems to generally outperform all controllers though.

**Fig. 14. Battery state of charge using the PV-priority 1 controller (black line) and the optimal PV controller trained with Caribou data (red line) for late fall and early winter in the Springfield, MO area.** (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Fig. 15. Relative performance of each controller tested at each city at 100% load.**
Furthermore, it can be seen that as the load increases, the margins by which the Caribou-trained optimal controller and PV-priority 2 controller outperforms the others increases. This is because more of the loads are able to be met with a constant value of insolation, resulting in a higher overall relative performance. Because the relative performances all of the ADHDP optimal controllers except the one trained at Phoenix, AZ are nearly always above the relative performance of the PV-priority 1 controller (especially as the load increases), it is shown that the optimal ADHDP controllers are superior to the standard PV-priority 1 controller, especially when trained using insolation data from cities that receive very little solar radiation and as the operating conditions become increasingly severe, as in the case of lower available insolation and higher loads. However, the other PV-priority controller developed in this paper, PV-priority 2 controller, is able to outperform all other controllers presented. It is only able to do this with knowledge from an expert on system behavior that is codified into the PV-priority 2 controller. For this reason, the ADHDP (which is generally able to outperform the PV-priority 1 controller), is a success since it does not require knowledge from an expert to craft its decision-making ability and instead relies solely upon a performance metric to evolve its control strategies.

6. Conclusion

In this paper, an optimal energy control scheme based on adaptive critic designs for a grid-independent photovoltaic solar energy system has been developed and compared with the conventional PV-priority control scheme used today (PV-priority 1), as well as with another controller (PV-priority 2) developed for this paper. 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 demand. The battery state 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. Results have been presented for six different cities with different solar radiation profiles using five controllers: 2 PV-priority controllers and 3 optimal ADHDP-based controllers trained at 3 locations. In most cases, the optimal PV controller has exhibited better control than the PV-priority 1 controller but not better than the PV-priority 2 controller. The comparison between the two controller schemes shows that for the most part, the optimal PV controller satisfies the critical load and some of the non-critical loads demand better than the PV-priority 1 control scheme, while keeping a higher battery state of charge. The hardware of implementation of such an ACD controller is feasible and cheap compared to savings as a result of proper energy management. This scheme is adaptive and therefore can fine tune to different locations and weather profiles within a short period of time. Thus, it is a promising and a potentially inexpensive technique for practical deployment on growing solar energy system installations.

Future work involves real-time investigations to try to further optimize the energy controller to follow more closely the load profiles and provide even better performance. In addition to improving performance, integration with other energy sources and hybrid forms of storage, such as hydrogen fuel cells with compressed air and supercapacitors with maximum efficiency point tracking (MEPT). IEEE Transactions on Industrial Electronics 3 (4), 1036–1047.


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References


