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Energy Disaggregation with Reserve Power Estimation and Non-Intrusive Load Monitoring in Standalone Solar Photovoltaic Based Microgrid

Gautam A. Raiker[1], Subba Reddy B[1], L. Umanand[1]

1 Interdisciplinary Center for Energy Research, Indian Institute of Science, Bangalore, 560012

ABSTRACT

A major problem in Solar Photovoltaic (PV) based systems is the need for storage, which increases the system's cost and complexity. In many applications like water pumping, desalination, and heating/cooling, it is only necessary to use solar energy as available due to the inherent storage capacity of these applications. In such applications, the effectiveness can be improved with proper energy management, which involves estimating the intermittent source, monitoring the loads, and reducing losses. This paper provides a solar reserve power estimate (RPE) metric for Standalone Solar Photovoltaic systems without storage which is an estimate of the availability of solar output measured with only the sensor voltage and current operating at any point. Load monitoring is implemented by non-intrusive techniques with Energy Disaggregation. Once supply and demand in a standalone system are estimated, it is possible to make intelligent decisions for maximum utilization of the Solar PV resource. A boost converter interface with PV provides the DC link voltage for the inverter. The system operation is validated experimentally for a 1kW standalone PV system.

Keywords: Solar Photovoltaic (PV), Direct Coupled System, Reserve Power Estimation, Energy Disaggregation, Demand Side Energy Management, DC Boost Converter

NONMENCLATURE

Abbreviations	
PV	Photovoltaic
RPE	Reserve Power Estimate
NILM	Non Intrusive Load Monitoring

1. INTRODUCTION

Photovoltaic Systems are required where access to the electrical grid is limited. In some situations, it is more practical to go for such systems over a grid-connected system [1]. The problem with standalone remote systems is the cost of Energy Storage. In direct-coupled systems, electrical storage or battery energy storage systems are absent. It is useful for applications that have inherent storage in the form of potential energy, for pumping systems, thermal inertia for Heating/Cooling applications, or in case of Desalination for storing potable drinking water [2,3]. A problem with such systems is that the available energy is to be estimated. In this work, a metric given as Reserve Power Estimate is defined to estimate available energy from Direct Coupled Solar Photo-voltaic Systems. Once the reserve power estimate is determined, it is easy to match the supply and demand. The supply and demand management can also be done intelligently based on other parameters of the application system like temperature, in case of air conditioning or water level for pumping. At the demand side, non-intrusive load monitoring-based Energy Disaggregation gives a breakdown of the load usage which is based on the factorial hidden markov model. The novelty of this paper is the use of Reserve Power Estimate and Energy Disaggregation to manage energy in Direct Coupled PV Systems more effectively. The effectiveness is measured and validated by how close the estimate is to actual reserve power. The Energy Disaggregation Algorithm has been validated with metrics such as Mean Error in Power and F1 Score in previous work of the author based on selectively enabled Hidden Markov Models. Non-Intrusive Load Monitoring is done with the Factorial Hidden Markov Model, which is a standard technique for Energy Disaggregation. With

IoT based control, even further automation of the standalone system can be provided.

2. PV RESERVE POWER ESTIMATION

The problem statement of Reserve Power estimation is to determine the light generated current, given any operating point of the solar PV module. With the light generated current, the maximum power from the solar cell can then be determined from which the reserve power is found. A few authors have worked on irradiance estimation from the operating point of Solar Photo-voltaic Modules. These methods use the diode model of the Solar PV cell to estimate light generated current and correspondingly the irradiance [4]. These have been extended for maximum, and reserve power forecasting methods and using filters and estimators like Kalman filters [5]. In other work, irradiance and temperature sensors have been used to find maximum power and in turn reserve power in real time [6]. Sensor error is a problem in these methods. A sensorless estimation method was introduced in [7], which perturbs the system occasionally. The advantage of our proposed method is that it's an estimation technique from only the present voltage and current point at which the Solar PV system is operating and doesn't perturb the system and neither uses additional sensors. The IV curve of the PV panels under experimental test for irradiance of 700W/m2 was plotted as in Fig. 1 with the input sensor board of the PV Boost Interface by varying the duty cycle to extract parameters to be fed to the model.

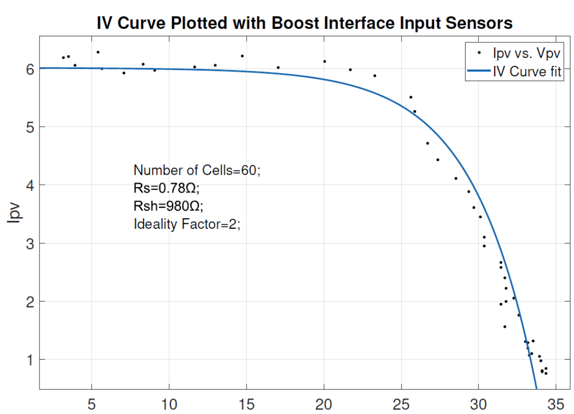

Figure 1: Tracing of IV curve to extract parameters

The PV interfaced boost converter is connected to a load and the duty cycle is varied from low to high. This variation leads to tracing of the IV curve. The data from voltage and current sensors is collected and then plotted. The consequent IV curve is used to determine the parameters of the solar module. From this the model is fit and RPE metric is estimated in real time. For estimating reserve power first light generated current is determined which is given by the following equation.

$$I_L = I + I_{rec} + I_{leakage}$$

Where I is the PV current, I_{rec} is the recombination current and $I_{leakage}$ is the leakage current. This equation becomes

$$I_L = I + \left(I_{sc} - \frac{V_{oc}}{R_{sh}}\right) e^{\left(\frac{V - V_{oc} + IR_s}{nNkT/q}\right)} + \frac{V + IR_s}{R_{sh}}$$

Where I_{sc} is short circuit current, and V_{oc} is open circuit voltage at NTC, R_s and R_{sh} is series and shunt resistance. After the light generated current (I_L) is estimated the Available Power which is directly proportional to I_L is given by multiplying with an effective voltage V_{eff} (V_{mp} and I_{mp} are voltage and current at maximum power at STC).

$$V_{eff} = \frac{V_{mp}@STC \times I_{mp}@STC}{I_{sc}}$$

$$P_{available} = V_{eff} \times I_L$$

The Reserve Power (RPE), where P is actual output of PV panels is given by

$$RPE = P_{available} - P$$

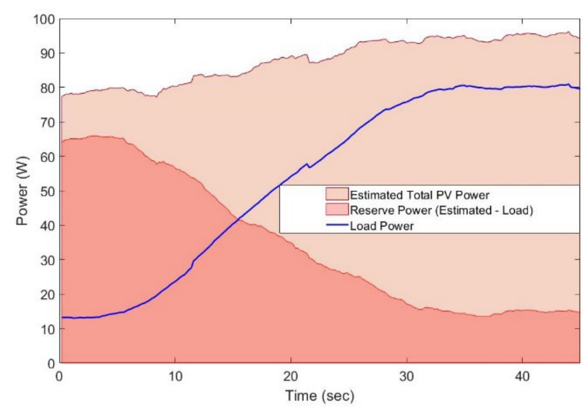

Figure 2: Reserve Power Estimation.

The real time estimation of Reserve Power is shown in Fig. 2 where, as load increases the reserve power decreases while the total available load power remains fairly constant.

	V_{pv} (V)	I_{pv} (A)	H_{at} (kW/m2)	P_{est} (W)	P_{act} (W)	RPE (W)	P_{mp} (W)	Error %
1a.	30	9.21	1.00	313.1	275.4	37.70 (A)	310.1	0.96
2a.	34	9.02		313.1	307.1	4.000 (B)		1.00
3a.	38	7.27		313.4	276.3	40.74 (C)		1.06
4a.	42	1.82		311.4	76.4	234.9 (D)		0.45
1b.	30	4.66	0.50	162.2	139.8	22.4	155.6	4.24
2b.	35	4.43		163.1	155.1	8.05		4.8
3b.	40	2.20		163.6	88.00	75.6		4.9
1c.	30	0.93	0.10	41.10	27.90	13.2	29.75	38
2b.	33	0.89		42.02	29.40	12.62		41
2c.	36	0.73		43.00	26.30	16.7		44

3. VALIDATION

In this section the simulated and experimental validation of the RPE estimate model is discussed. For simulation of the model the estimate of maximum available power is done for different values of irradiances (0.1, 0.5 and 1kW/m^2 as shown in Table 1. It shows the simulated RPE metric for different points on the IV curve. The error in RPE versus actual values increases as the irradiance decreases. The error % is below 5% for most cases but shoots up when irradiance is below 0.1kW/m^2, which is because at low irradiances thermally generated currents also contribute to the final PV current and cause the above error. Further work is needed to compensate the thermally generated offset error.

4. PV BOOST INTERFACE

A PV Boost Interface is designed for 270W mono-crystalline module (SW270-mono). The task of this interface is to provide a constant DC link voltage (48V in this experiment) for the inverter and sense and control the PV power. A half bridge is designed with IGBTs (FGA25N120) with the top switch in OFF state. The switch is driven at 10kHz with a ISO5451 based gated driver. The input and output both have voltage and current sensors. Isolated Voltage sensor (AMC1200) and Current Sensor (ACS712) is used and the analog interface for the sensors is designed. The C2000 controller is used for processing the control loops. Load is varied with the help of a Load Bank at the steps of 10W and at 48V.

The software code for the sensing and control is written in C and complied into the hardware. Interrupt service routines for the ADC and control loops run at 50kHz sampling rate. Moving average filters are used for the sensor inputs from the ADC. The PI controllers are designed for the outer output voltage and inner current loops. Serial Communication Interface is used for sending data to a PC. The hardware setup is shown in Fig.3.

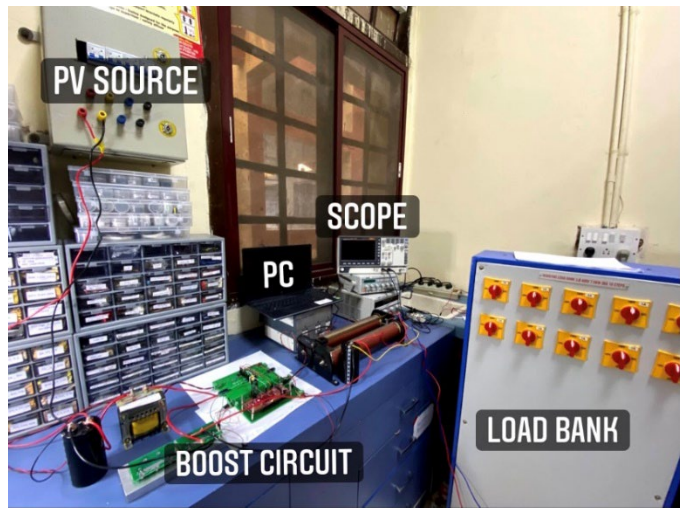

Figure 3: Hardware Setup

5. ENERGY DISAGGREGATION

The PV output load power was collected from the sensor module and sent to the PC at five samples/sec from the Serial Communication interface. The PV operating voltage and current data are used to estimate the PV total and reserve power. As seen in Fig.4, the power is estimated to around 180W. The load is increased in steps of 10W, as seen in the same figure. Non-Intrusive Load Monitoring with factorial hidden Markov model (FHMM) was used for demonstrating energy disaggregation. The FHMM based framework was described in the previous work of the authors and has been cited in [8-10]. The NILM-TK libraries were used for disaggregation. The loads L1-L7 were switched sequentially from the load bank shown in Fig.4. The breakdown of energy of the loads is shows that reserve energy is 53%.

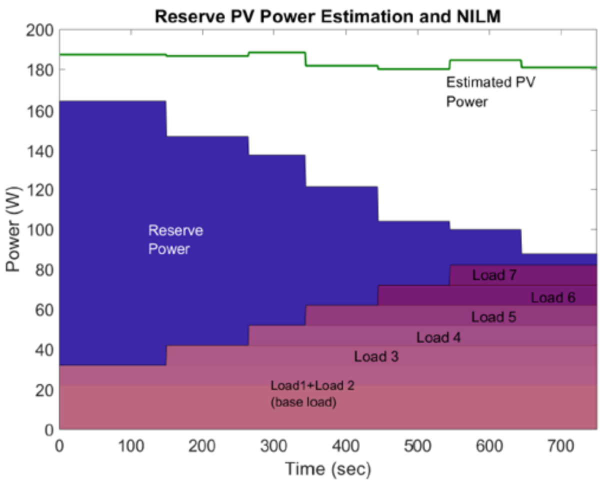

Figure 4: NILM and Reserve Power Estimation

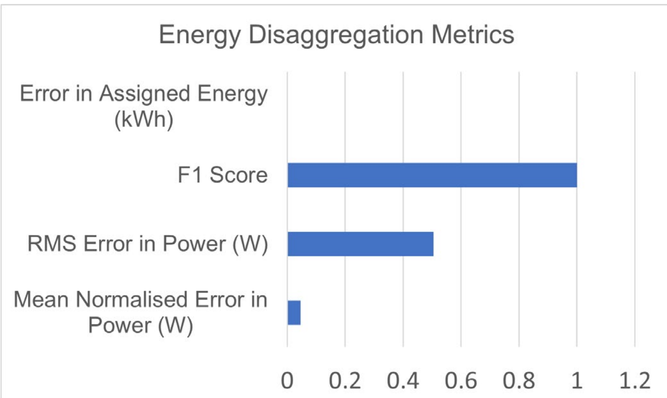

Figure 5: NILM and Reserve Power Estimation

Different metrics were calculated to determine the efficacy of the NILM method used and are shown in Fig. 5. The F1 score was 1, indicating that the predicted and true disaggregated power was matching and there were no false positive or false negative predictions. Next, the mean error in power and RMS error in power can be seen with RMS error being higher in value. The error in assigned energy was zero indicating that even though there was slight error in disaggregated power the disaggregation of energy was correctly predicted. With energy disaggregation the individual components of the total demand can be deduced. With Internet of Things based control, the loads can be switched according to priority based on intelligent machine learning algorithms as in. Since the reserve power is known, informed decisions on scheduling of the loads can be made.

6. CONCLUSIONS

In Solar PV systems, there is a need for PV Total Power and Reserve Power Estimation, which can give the user an indication of power available from PV in case of power curtailment or in standalone systems. A method was developed to determine the estimated maximum power from the PV panels from just the voltage and current operating point, which is easily observable from the input sensors. The bond graph model for PV modules was developed and validated experimentally, which was used to determine the estimation methodology. Experimental setup for the Boost Converter inter- face was built to get the constant 48V DC-link voltage and control the PV power input, which makes the DC section of the experiment. Finally, the load connected to the system is disaggregated by factorial hidden Markov model based non-intrusive load monitoring. The PV power estimation (supply) and load disaggregation (demand) can help to manage the power in standalone systems and improve the utilization of Solar Power. With IoT control, it is possible to even for automatic demand management. Intelligent systems may be built around these techniques depending on the application by taking other inputs and optimizing the objective function. Finally, to conclude, the major contributions of this work are: a power estimation methodology for direct coupled and curtailed PV; and, energy disaggregation of the demand for better insights, to improve solar power utilization in standalone systems.

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