Design of Optimal Power Point Tracking Controller Using Forecasted Photovoltaic Power and Demand

AliAkbar Shafi, Hussein Sharadga, Shima Hajimirza

***Abstract*—With the advent of grid-connected Photovoltaic systems for energy generation, new technologies must be created that maintain a continuous and stable balance between supply and demand of generated electricity. Consequently, accurate prediction of solar energy generation and consumption is required. Solar energy generation and electric power demand are both stochastic and non-stationary in nature and often incongruous. The imbalance between demand and supply can be costly and leads to long-term ineffectiveness of power generation and distribution. The aim of this work is to propose methods for maintaining demand-supply balance in PV power generation and distribution systems. To achieve this, we build and combine three different tools: 1) a predictive model for forecasting solar energy generation, 2) a predictive model for demand prediction, and 3) a real-time control algorithm that uses the outputs of prediction models and adjusts the output voltage of PV system to maintain demand- supply balance. Our prediction models are based on time-series forecasting tools and Artificial Neural Networks. The control algorithm is called Optimal Power Point Tracking (OPPT) and is based on the Perturb and Observe algorithm. We evaluate the performance of the combined prediction-controller system using real-world data.**

***Index Terms*—Neural Network, Forecasting, Optimal power, Fuzzy Logic, Modeling, Optimization.**

I. Introduction

SOLAR photovoltaic (PV) energy has become an essential part of our energy consumption and would soon be an indispensable component of sustainable energy systems. As better sensors continue to evolve; module prices continue to fall and PV panels become more efficient, solar energy keeps replacing other conventional energy resources. Economies around the world are investing ambitiously on Grid-Connected PV systems. [1], [2].

Unlike traditional energy generation systems, PV energy is unpredictable and depends upon solar irradiation and other meteorological factors such as temperature, humidity, precipitation, wind speed and cloud coverage. The implementation of large-scale grid-connected solar PV plants has introduced major issues to power networks such as lack of system stability, reliability and electric power balance [3]. To maintain a stable energy supply through PV grids, it is imperative to forecast solar energy generation. Accurate predictive models eliminate the impact of solar PV output uncertainty, improve the system stability and reduce the maintenance cost of additional devices [4].

In addition to meteorological factors, non-linearity of voltage-current (V-I) characteristics of PV systems have a considerable impact on power delivery. The V-I characteristics of a PV module are a function of irradiation and temperature. For maximum utilization efficiency, Solar Cell Arrays (SCA) are accompanied by Maximum Power-Point Tracking (MPPT) controllers. A comprehensive list of 40 different MPPT techniques and their classification has been gathered by Karami et. al and can be found in [5]. Much work is available in the literature describing various MPPT algorithms and designs to improve the efficiency of PV system, including Perturb and Observe (P&O), variable step size P&O, distributed MPPT, Incremental conductance (INC), Fuzzy Logic Controller (FLC), Particle Swarm Optimization (PSO) based P&O method and Neural Networks (NN). All these methods vary in oscillation around the actual maximum power point, convergence speed, complexity, stability, cost and requirement of electronic equipment [6], [7], [8].

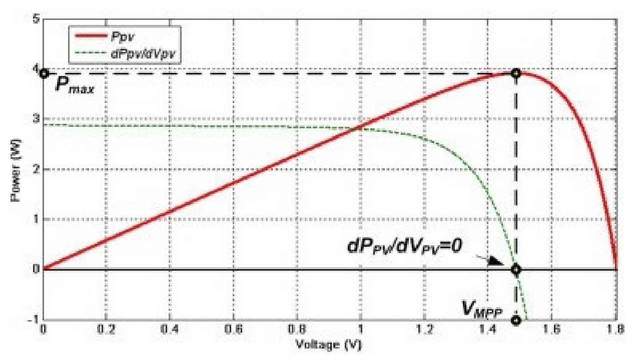

Fig. 1: Simulation results for the network.

Demand of electricity is also stochastic (though more predictable than the PV-based generation rate). The uncontrollable nature of solar energy generation and stochastic demand can lead to solar energy supply-demand imbalance. The generation rate must continuously meet the demand, but the surplus can be costly. For instance, in March 2017 the state of California produced excessive solar power on some days than required and had to pay the neighboring states to take the excess electricity to avoid overloading of power lines [9]. In similar recurrent instances, Germany has had to pay consumers multiple times in the past for disposing the excessive power supplied by the wind and solar farms [10]. Energy storage could be used to smooth PV MPPT power fluctuations for grid injection [11], but it is a very costly option. To better manage

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the demand-supply balance, power control algorithms have been proposed and used [12], [13], [14], but the applicability of these methods are limited to deterministic or non-stationary conditions.

The aim of this work is to propose methods for maintaining demand-supply balance in PV generated power distribution system. To achieve this, we build and combine three different tools: 1) a predictive model for forecasting solar energy generation, 2) a model for demand prediction, and 3) a real-time control algorithm that uses the outputs of the prediction models and adjusts the output voltage of power generating PV systems to maintain demand-supply balance. Our prediction models are based on time-series forecasting tools and Artificial Neural Networks. We propose a strategy to extract the optimal amount of solar energy from PV panels rather than the maximum instant power. The algorithm is called optimal power point tracking (OPPT) and is based on the concept of Perturb & Observe algorithm. It requires the operating voltage of the solar module to be adjusted as per the short-term demand forecast, thus eliminating the excess power generation and creating a balance between supply and demand. We evaluate the performance of the combined prediction- controller system using real-world data.

A. Solar Irradiance and Demand Forecast

1) Solar Energy Forecast: Various techniques have been used to accurately forecast available solar energy so that scheduling generation and distribution of related electricity can be optimized. Sobri et. al [15] provide an extensive review of advancements in the field of solar photovoltaic power forecasting. In summary, solar photovoltaic power forecasting methods can be grouped into three categories: (i) time-series statistical models, (ii) ensemble methods, and (iii) physical methods. Generally speaking, solar intensity can be used as an acceptable proxy for solar energy generation [16], and that in turn is linked to various meteorological parameters. The relation between various meteorological parameters and solar irradiation is shown in the scatter plots of Fig. 2.

The nonlinear relationship between input factors and output solar irradiance can be well-captured by Artificial Neural Network (ANN). While forming predictive models, we need to consider day of the year and hour of the day along with environmental parameters to address the non-stationary nature of irradiation.

The hourly data for meteorological parameters of solar irradiation, temperature, precipitation, wind and humidity for modeling the solar energy is taken from a photovoltaic plant established at Gatton, Australia. The hourly data for all the parameters are considered within the period May 2016 to January 31, 2017.

2) Demand Forecast: Similar to solar irradiance, there is time of day and month of year seasonality to the demand. However, there is an extra day of week periodicity component to the demand that is intrinsically absent in irradiance data. Due to unavailability of load profile form the Gatton, we have used the hourly load profile from Coastal Texas because of the similar weather conditions. The hourly data for all the parameters are considered within the period May 2016 to January 31, 2017.

3) Prediction methods: To capture the nonlinear input-output relation and auto-regressive time-variability of the data, we have chosen to use nonlinear autoregressive models with exogenous input network (NARX) as the main predictive model for both supply and demand. NARX is a dynamical neural architecture commonly used for input-output modeling of nonlinear dynamical systems. At its core is the ability to use neural networks to discover input/output relationship, while benefiting from the lagged auto-regressive input responses. For time series prediction the NARX network is designed as a feed-forward time delay neural network (TDNN) [17]. The NARX model is defined by (1):

$$y_t = f(y_{t-1}, y_{t-2}, ..., y_{t-n_y}, u_{t-1}, u_{t-2}, ..., u_{t-n_u}) \quad (1)$$

where n_y is the number of time delays in the feedback, n_u is the number of time delays in the input and $f(.)$ is the mapping function of a standard multilayer perceptron network. The NARX network is trained using two modes: parallel and series-parallel. In the parallel mode, the output is fed back to the input of feed-forward neural network as part of the standard NARX architecture, using a tapped delay line. In the series-parallel mode, the true output is used instead of feeding back the estimated output. With series-parallel mode the resulting network has a purely feed-forward architecture, and static back-propagation can be used for training. The series-parallel mode NARX network is created for training at first and can be used for single step forward prediction. For multi-step forward prediction, the series-parallel mode NARX network is converted to the parallel mode. The results of prediction using NARX are compared with simpler predictive models such as ARIMA and SARIMA. The training iterations for TDNN models were restricted to 150 for both solar irradiance and demand models. The input and feedback delays were kept at 24, equivalent to a day. We chose Bayesian Regularization as the training function for the NARX network that resulted in lowest RMSE values for solar irradiance and demand.

4) Results and Evaluation: The performance measures of NARX, ARIMA and SARIMA predictive models for solar irradiation and demand are shown in Table I and Table II respectively. The performances are gauged via R^2 and mean squared error (MSE) statistical notions. Phillips-Perron test was applied on the first difference of solar radiation and demand data that indicated that the first differences of those data set are stationary. Therefore the degree of integration of ARIMA and SARIMA is set to 1. The seasonality action for solar radiation and demand occurs every 24 hours. Thus the seasonality order of SARIMA for both solar radiation and demand forecasting is chosen to be 24. Different combinations of moving average and autoregressive orders were tested to optimize the forecasters performances. The optimal models with the corresponding forecasting errors are given in Table I and II. It is evident that NARX outperforms the other two models, thus providing a better correlation between the input parameters and predicted solar irradiation and demand.

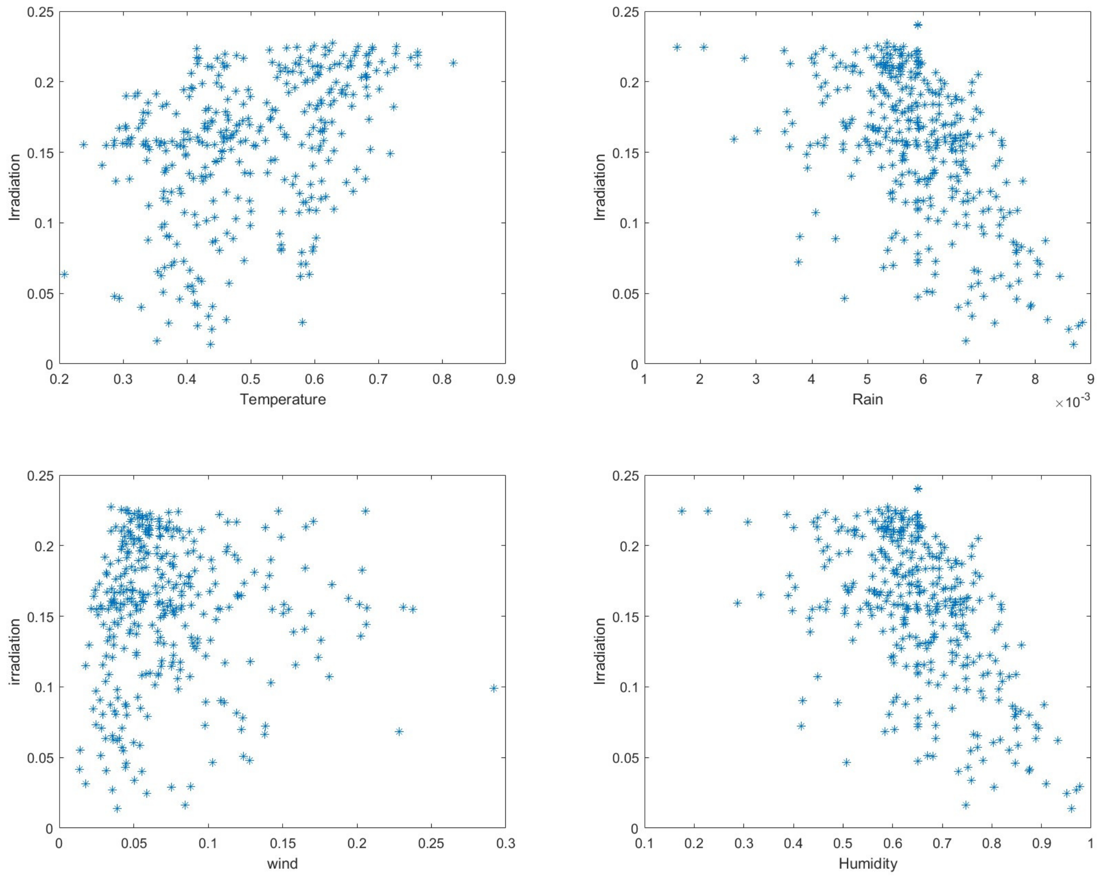


Fig. 2: Scatter plots of solar irradiance versus meteorological parameters

TABLE I: Performance metrics for solar irradiance predictive models

Algorithm	R^2	***MSE***
NARX	0.976	63.14
SARIMA $(4, 1, 3) * (1, 0, 0)_{24}$	0.904	64.23
ARIMA (5,1,3)	0.887	68

TABLE II: Performance metrics for demand predictive models

Algorithm	R^2	***MSE***
NARX	0.98	136.28
SARIMA $(4, 1, 5) * (2, 0, 1)_{24}$	0.95	188.8
ARIMA (5,1,4)	0.923	208.2

B. PV System Controller Design

MPPT algorithms maximize power output by steadily increasing or decreasing the duty ratio of the power converter according to the PV module output power versus the voltage characteristics. The perturbing and observing (P&O) method [18] and the incremental conductance method [19] are the most common methods for designing MPPT algorithms. These methods use fixed step size for the increment of the duty ratio. As per the P&O MPPT algorithm if the operating voltage of the PV array is changed in a given direction and if the power drawn from the PV array increases, it indicates that the operating point has moved toward the MPP and, hence, the operating voltage should be changed further in the same direction. If the power drawn from the PV array decreases, the operating point has moved away from the MPP and the direction of the operating voltage change must be reversed.

When PV systems are designed to match the peak loads, the power generated and the peak demand are incongruous. If the module always operates at MPP, it would produce more energy than demand during a significant period of the day. In the absence of adequate storage capacity, the excess power dumped in grids would result in situations like overloading of lines, islanding effects, negative pricing or unstable grid-operations. To prevent such situations, we can take advantage of the non-linear relation of Voltage-Current characteristics of PV array system by operating at an optimal power point rather than the maximum power point. We assume that power and demand predictions and voltage controlled is done every hour. At hour t the predictions for generated solar power and demand are $P_{pv}(t)$ and $P_{load}(t)$ respectively, and the optimal controller set the output power $P_{out}(t)$ as follows:

1. If the available PV power is less than the demanded load power (i.e. $P_{pv}(t) < P_{load}(t)$), the system should work at the MPP, i.e. $P_{out}(t) = P_{MPP}(t)$.

2. If the available PV power is more than the demanded load

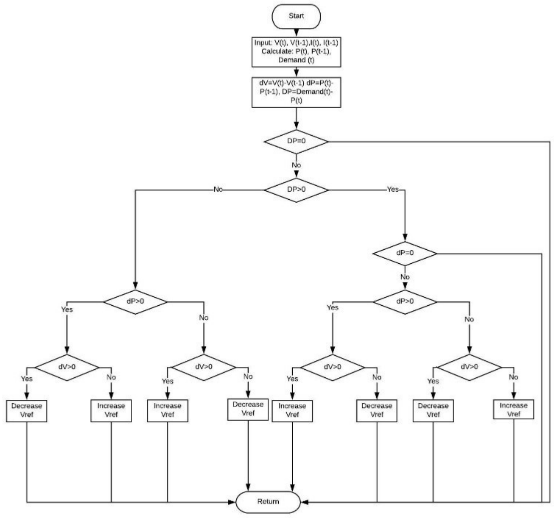


Fig. 3: Flowchart of the proposed OPPT P&O algorithm

power (i.e. $P_{pv}(t) > P_{load}(t)$), then $P_{out}(t) = P_{load}(t)$.

1) Proposed Controller: We are proposing an OPPT controller that minimizes the difference between (predicted) PV power generation and demand, rather than maximizing the power output of the SCA. This is achieved by gradually increasing or decreasing the duty ratio of the power converter according to the PV module output power versus the voltage curve. The controller operates on similar principles as the P&O algorithm and utilizes predicted values of available solar power and demand. Namely, it inspects the instantaneous predictions of supply and demand. If the demand exceeds the maximum available power, the controller operates similar to the MPPT P&O method, thus delivering maximum power. However, if the demand prediction is less than the maximum power available, the controller tunes the PV array voltage such that the output PV power closely matches to predicted demand. The adjustments are achieved through small perturbations in the output voltage as in Perturb & Observe. The output of P&O OPPT controller is fixed size duty cycle change. A schematic flowchart of the proposed OPPT P&O algorithm is shown in Fig 5. The voltage of solar cell array corresponding to optimal power point is denoted by V_{ref}.

2) Fuzzy Logic for Adaptive Step Sizing: To adjust step sizes, variable step sizing algorithms based on adaptive and artificial intelligence techniques such as fuzzy logic and adaptive neuro-fuzzy system have been studied [20], [21], [22], [23]. Fuzzy controllers are able to use empirical methods to design variable step size increments of duty ratio command for the power converter. The advantage of these methods is that they do not require access to a thorough mathematical model of the underlying power plant. Adaptive step size adjustments of these sorts have been used in MPPT algorithms as in [20], [21], [22], [23], [24]. As mentioned by Shiau et. al [24], fuzzy logic MPPT controllers can be designed using various combinations of input parameters. The output variable of the fuzzy MPPT algorithm would usually be duty ratio command of the power switch for the power converter. We

TABLE III: Fuzzy rules for the OPPT controller

ΔP		**dP**				
	dV	*NB*	*NS*	*ZE*	*PS*	*PB*
Positive	*NB*	NB	NS	ZE	PS	PB
	NS	NS	NS	ZE	PS	PS
	ZE	ZE	ZE	ZE	ZE	ZE
	PS	PS	PS	ZE	NS	NS
	PB	PB	PS	ZE	NS	NB
Zero		ZE	ZE	ZE	ZE	ZE
Negative	*NB*	PB	PS	ZE	NS	NB
	NS	PS	PS	ZE	NS	NS
	ZE	ZE	ZE	ZE	ZE	ZE
	PS	NS	NS	ZE	PS	PS
	PB	NB	NS	ZE	PS	PB

adopt a variation of this technique for adaptive step sizing of the proposed OPPT controller. The corresponding fuzzy logic OPPT controller uses the change in output power (dP), change in Voltage (dV) and difference between (predicted) demand and instantaneous power generated (ΔP) as inputs. The output is change in duty cycle (dU) for controlling Pulse Width Modulation (PWM) generator. More formally, the three FLC input variables (dP), (dV) and (ΔP), and output variable dU are defined as

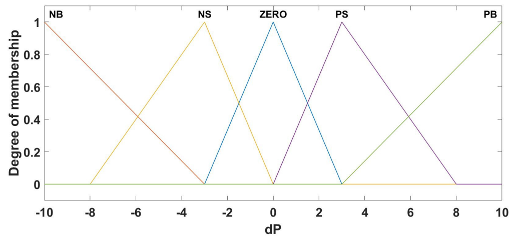
$$\begin{aligned} dP = P(k) - P(k-1),\ dV = V(k) - V(k-1) \\ \Delta P = P_{load}(k) - P(k),\ dU = U(k) - U(k-1) \end{aligned} \tag{2}$$

where $P(k)$, $V(k)$, $P_{load}(k)$ and $U(k)$ are output power, voltage, predicted demand and duty cycle at instant k respectively. Table III describes the fuzzy rules designed according to the fuzzy input variables. A fuzzy set comprising of five terms: positive big (*PB*), positive small (*PS*), zero (*ZE*), negative small (*NS*), and negative big (*NB*), is used to describe (dP), (dV) and (dU). For describing (ΔP), three-term fuzzy set: Negative, Zero and Positive have been used. Output from the fuzzy controller would change the output voltage and current of the PV module. Once the output changes, it would affect the values of the next round of fuzzy input variables. The controller would then re-adjust the output commands accordingly.

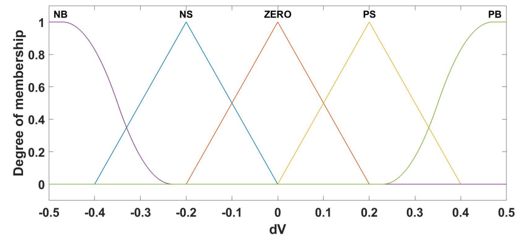
Membership functions for controller inputs and output are defined as shown in Fig.4 (a-d). Asymmetric triangular and sigmoidal membership functions have been considered which are denser at the center and thus, provide more sensitivity against variations in the PV terminal voltage. In defuzzification we obtain the crisp value of the change of duty cycle. The well-known center of gravity method for defuzzification [25] has been used to find the change in magnitude of the duty cycle. The crisp value of control output is computed from:

$$dU = \left(\sum_{1}^{n} W(i) dU(i) \right) \left(\sum_{i}^{n} W(i) \right)^{-1} \tag{3}$$

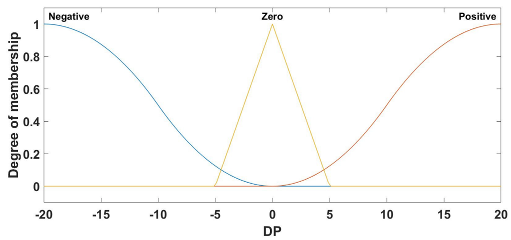
where n is the maximum number of effective rules, $W(i)$ is the weighting factor, and $dU(i)$ is the value corresponding to the membership function of dU.



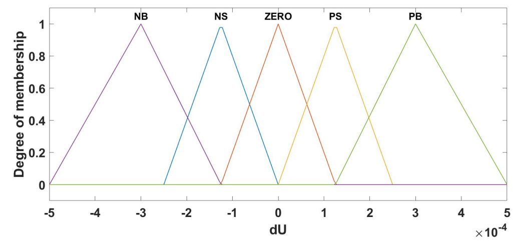
(a) Membership functions for dP



(b) Membership functions for dV



(c) Membership functions for ΔP



(d) Membership functions for dU

Fig. 4: Membership functions

TABLE IV: Specification of the Simulink PV array and module

1	2
Parallel Strings	5
Series-connected Strings	10
Module data	22
Module	First Solar FS-395
Maximum power	95 W
Open circuit voltage	60.5 V
Voltage at the maximum power point	47.5 V
Current at the maximum power point	2 A
Cells per module	77
Short circuit current	2.17

C. Modeling of System in Simulink

Fig. 5 shows the Block diagram of the PV system under consideration.

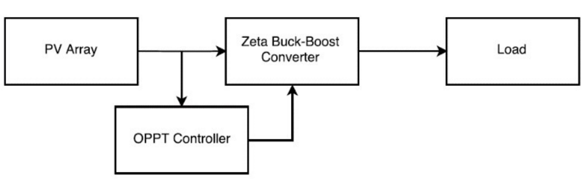


Fig. 5: Block diagram of the studied OPPT controller system

1) Modeling of PV array: The PV array block is modeled using PV modules in series and parallel. PV array block accepts irradiation in W/m^2 and temperature in centigrade degrees and provides array current and voltage. The specifications and parameters for the PV array and solar cell used for simulation are shown in Table IV.

2) Modeling of P&O OPPT controller: The P&O OPPT algorithm as shown in Fig. 3 is designed using Simulink and is depicted in Fig. 6. The MATLAB function Block is used to code the algorithm which takes the change in voltage, change in power and difference of instantaneous PV array power and demand as inputs. The output is the duty cycle which drives the PWM generator for controlling the power converter.

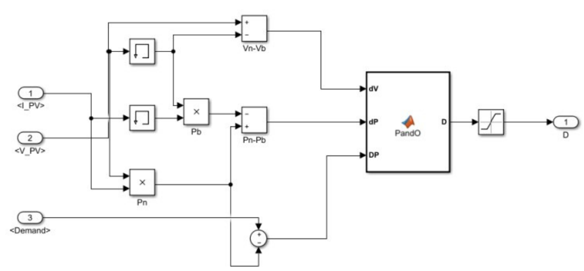


Fig. 6: OPPT P&O Controller Subsystem
Input:Voltage, Current & Demand; Output: Duty Cycle

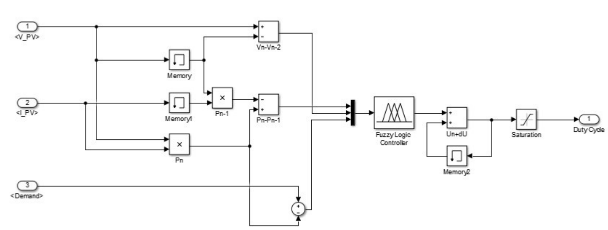


Fig. 7: OPPT Fuzzy Logic Controller Subsystem
Input:Voltage, Current & Demand; Output: Duty Cycle

3) Modeling of fuzzy logic OPPT controller: The Fuzzy Logic OPPT controller is designed using Simulink and is depicted in Fig. 7. The fuzzy logic control block and fuzzy

TABLE V: Zeta Buck Boost Converter Parameters

Parameter	Parameter Value
L_1	470 μH
L_2	470 μH
C_1	1000 μF
C_{in}	1000 μF
C_2	200 μF
PWM switching frequency	For P&O: 200 kHz, For Fuzzy Logic: 15 kHz

inference system are used to implement the OPPT controller which takes the change in voltage, change in power and difference of demand and instantaneous PV array power as inputs. The output is a change in duty cycle which adds up to the current duty cycle for driving the PWM generator to control the power converter.

4) Modeling of Zeta buck-boost converter: The Zeta type buck-boost converter [26] is used to control the power flow from the PV panel to the load. Optimal power could be achieved by adjusting the duty ratio command of the converter. Converter parameters are selected to operate the power converter in continuous conducting mode (Table V)[22]. Q is MOSFET switch controlled by the PWM signal generator.

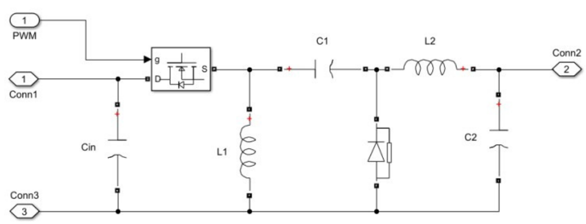


Fig. 8: Zeta Type Buck-Boost Converter Subsystem

The above-modeled subsystems in Simulink are now connected to obtain the Simulink model of the entire system. OPPT controller subsystems (Fig.s 8 and 9) are used along with DC-DC PWM generator and Zeta buck-boost converter subsystem to change the terminal voltage across PV array. With P&O controller and fuzzy logic controller we have used a resistive load of 50W, nominal voltage 20V and a resistive load of 10KW, nominal voltage 350 V respectively. For P&O controller we have chosen the operating frequency to be 200 kHz to operate in a continuous mode. With a fuzzy logic controller, the model has been simulated in a discrete mode with sampling time of 5e-06 secs and 15 kHz frequency for PWM generator. Fig.s 11 and 12 show the Simulink model of overall system under consideration.

5) Results: In order to validate the model performance, the following simulations were performed with different combinations of solar irradiation and demand profiles with both controllers: P&O controller with fixed step sizing change of duty cycle and fuzzy logic controllers with adaptive step sizing change of duty cycle.

Case 1: Irradiation was held constant at 1000 W/m^2 between 0-2 secs. At 2 sec, it was decreased to 900 W/m^2. After every 2 sec, irradiation was decreased by 100 W/m^2. Demand is kept constant at 5000 W.

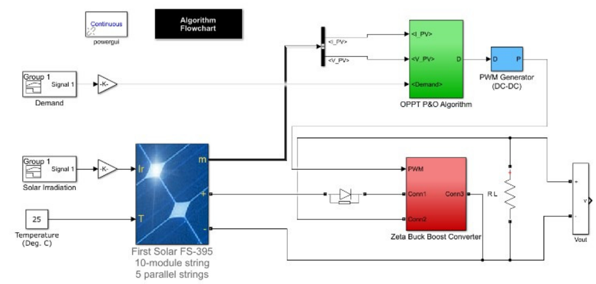


Fig. 9: Simulink model with P&O OPPT controller

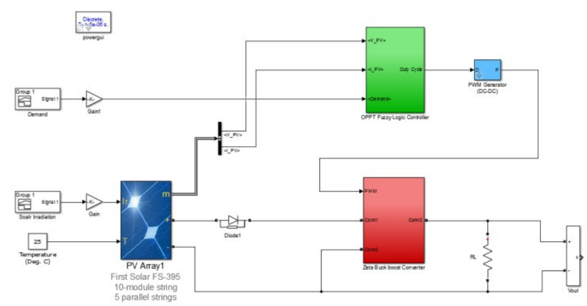


Fig. 10: Simulink model with Fuzzy Logic OPPT controller

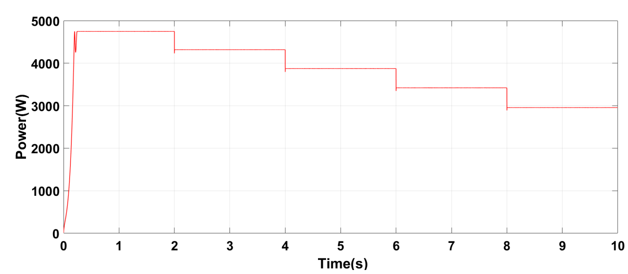


Fig. 11: Case1, P&O Controller

Case 2: Irradiation was constant at 1000 W/m^2 between 0-2 secs. At 2 sec, it was decreased to 900 W/m^2. After every 2 sec, irradiation was increased by 100 W/m^2. Demand is kept constant at 1500 W.

Case 3: Irradiation is kept constant at 1000 W/m^2. Demand was held constant at 1000 W between 0-2 secs. At 2 sec, it was increased to 2000 W. After every 2 sec, demand was increased by 1000 W.

Case 4: Irradiation was held constant at 1000 W/m^2 between 0-2 secs. At 2 sec, it was decreased to 900 W/m^2. After every 2 sec, irradiation was decreased by 100 W/m^2. Demand was held constant at 1000 W between 0-2 secs. At 2 sec, it was increased to 2000 W. After every 2 sec, Demand was increased by 1000 W.

Case 1 shows scenarios where the demand is always greater than the available PV power and thus the solar cell array always operates in the MPPT mode delivering maximum power. With current designs of OPPT controllers, P&O OPPT controller [Fig. 13] tracks the MPP more efficiently than the fuzzy logic controller [Fig. 14]. However, the transition of MPP when solar irradiation changes is smoother with the

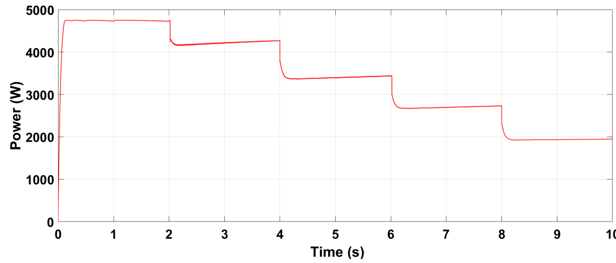


Fig. 12: Case 1, Fuzzy Logic Controller

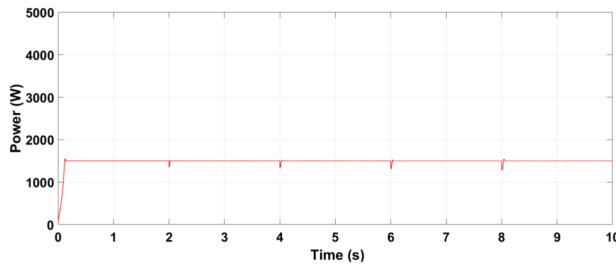


Fig. 13: Case2, P&O Controller

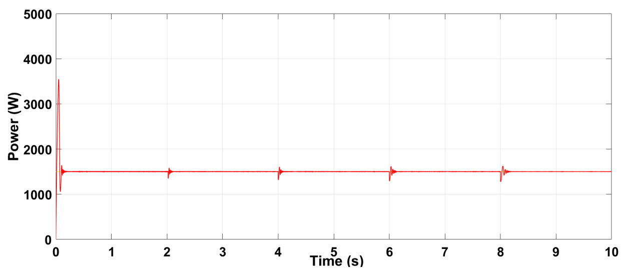


Fig. 14: Case 2, Fuzzy Logic Controller

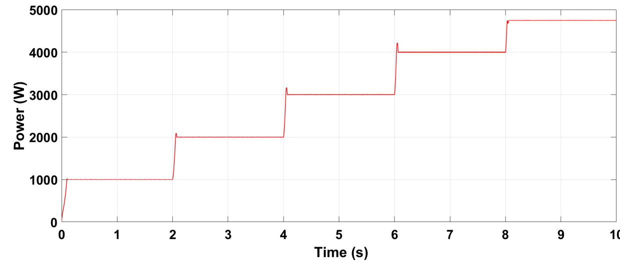


Fig. 15: Case3, P&O Controller

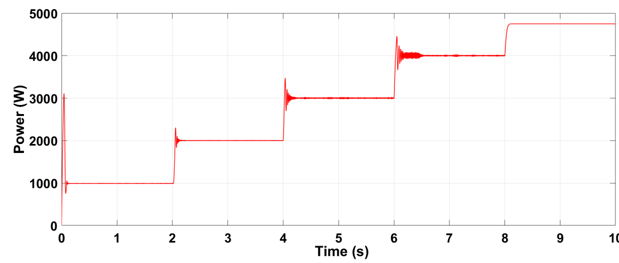


Fig. 16: Case 3, Fuzzy Logic Controller

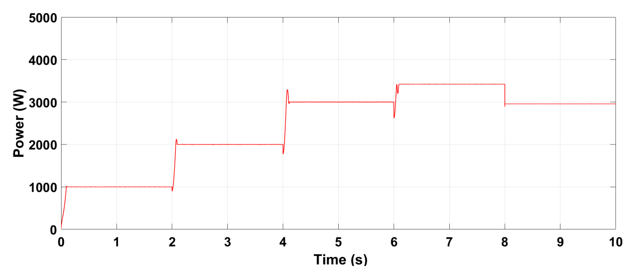


Fig. 17: Case1, P&O Controller

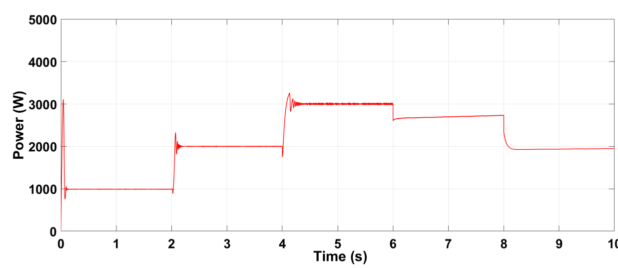


Fig. 18: Case 4, Fuzzy Logic Controller

fuzzy logic OPPT controller. Case 2 [Fig. 15] and [Fig. 16] represent the scenarios where the demand remains constant but is always lesser than the available photovoltaic power. The P&O controller takes 0.02 secs for every demand transition. However, the settling time for FLC keeps increasing with each transition. Case 3 represents cases where the maximum available Photovoltaic energy is higher than the demand from 0-8 sec and demand exceeds the available PV energy from 8-10 sec. Both the P&O and fuzzy logic OPPT controllers restrict the output power to meet the demand. The settling time for P&O controller remains same (0.07s) with changing demand [Fig. 17]. However, for Fuzzy logic OPPT controller [Fig. 18] the settling time keeps on increasing with increasing demand (the decreasing difference between available PV energy and Demand). Case 4 [Fig. 19] and [Fig. 20] represent cases where available solar energy keeps on decreasing with time while the demand steadily increases. From 0-6 secs, the available energy is more than the demand, hence the output power is restricted to demand. From 6-10 secs the demand exceeds the maximum power available from instantaneous solar irradiation hence the OPPT controllers operate the PV systems at MPP.

II. Conclusion

In this paper, a simple framework was proposed to balance the demand-supply equation for PV systems designed for peak-load. The framework comprises of predictive models for solar energy and load and real-time controllers. The predictive models were designed using the nonlinear autoregressive neural network with exogenous input (NARX) including time and weather parameters. Predictive models were compared and it was shown than NARX ANN has better accuracy than ARIMA and SARIMA models. OPPT controllers were designed using a modified Perturb and Observed algorithm and Fuzzy Logic to control the power flow between SCA and the load. Simulation results showed that the controller results in realistic source-load balance. With the designed P&O OPPT controller, tracking is more reliable than the fuzzy logic controller.

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REFERENCES

[1] S. Kouro, J. I. Leon, D. Vinnikov, and L. G. Franquelo, "Grid-connected photovoltaic systems: An overview of recent research and emerging pv converter technology," *IEEE Industrial Electronics Magazine*, vol. 9, no. 1, pp. 47–61, 2015.

[2] B. Tarroja, B. Shaffer, and S. Samuelsen, "The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies," *Energy*, vol. 87, pp. 504–519, 2015.

[3] S. Koohi-Kamal, N. Rahim, H. Mokhlis, and V. Tyagi, "Photovoltaic electricity generator dynamic modeling methods for smart grid applications: A review," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 131–172, 2016.

[4] M. De Giorgi, P. Congedo, and M. Malvoni, "Photovoltaic power forecasting using statistical methods: impact of weather data," *IET Science, Measurement & Technology*, vol. 8, no. 3, pp. 90–97, 2014.

[5] N. Karami, N. Moubayed, and R. Outbib, "General review and classification of different mppt techniques," *Renewable and Sustainable Energy Reviews*, vol. 68, pp. 1–18, 2017.

[6] E. Iyasere, E. Tatlicioglu, and D. Dawson, "Backstepping pwm control for maximum power tracking in photovoltaic array systems," in *Proceedings of the 2010 American Control Conference*. IEEE, 2010, pp. 3561–3565.

[7] S. R. Chowdhury and H. Saha, "Maximum power point tracking of partially shaded solar photovoltaic arrays," *Solar energy materials and solar cells*, vol. 94, no. 9, pp. 1441–1447, 2010.

[8] G. De Cesare, D. Caputo, and A. Nascetti, "Maximum power point tracker for portable photovoltaic systems with resistive-like load," *Solar Energy*, vol. 80, no. 8, pp. 982–988, 2006.

[9] IER, "Californias solar energy overload," 2017, last accessed 12 May 2018. [Online]. Available: https://instituteforenergyresearch.org/analysis/californias-solar-energy-overload/

[10] B. Geier, "Why germany is paying people to use electricity," 2016, last accessed 12 May 2018. [Online]. Available: http://fortune.com/2016/05/11/germany-excess-power/

[11] Y. Cheng, "Impact of large scale integration of photovoltaic energy source and optimization in smart grid with minimal energy storage," in *Industrial Electronics (ISIE), 2010 IEEE International Symposium on*. IEEE, 2010, pp. 3329–3334.

[12] W. Yi-Bo, L. Hua, W. Chun-Sheng, and X. Hong-Hua, "Large-scale grid-connected photovoltaic power station's capacity limit analysis under chance-constraints," in *Sustainable Power Generation and Supply, 2009. SUPERGEN'09. International Conference on*. IEEE, 2009, pp. 1–6.

[13] L. Ma, K. Sun, R. Teodorescu, J. M. Guerrero, and X. Jin, "An integrated multifunction dc/dc converter for pv generation systems," in *Industrial Electronics (ISIE), 2010 IEEE International Symposium on*. IEEE, 2010, pp. 2205–2210.

[14] S. Chiang, H.-J. Shieh, and M.-C. Chen, "Modeling and control of pv charger system with sepic converter," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 11, pp. 4344–4353, 2009.

[15] S. Sobri, S. Koohi-Kamali, and N. A. Rahim, "Solar photovoltaic generation forecasting methods: A review," *Energy Conversion and Management*, vol. 156, pp. 459–497, 2018.

[16] N. Sharma, J. Gummeson, D. Irwin, and P. Shenoy, "Cloudy computing: Leveraging weather forecasts in energy harvesting sensor systems," in *Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on*. IEEE, 2010, pp. 1–9.

[17] T.-N. Lin, C. L. Giles, B. G. Horne, and S.-Y. Kung, "A delay damage model selection algorithm for narx neural networks," *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2719–2730, 1997.

[18] N. Femia, G. Petrone, G. Spagnuolo, and M. Vitelli, "Optimization of perturb and observe maximum power point tracking method," *IEEE transactions on power electronics*, vol. 20, no. 4, pp. 963–973, 2005.

[19] K. Hussein, I. Muta, T. Hoshino, and M. Osakada, "Maximum photovoltaic power tracking: an algorithm for rapidly changing atmospheric conditions," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 142, no. 1, pp. 59–64, 1995.

[20] M. A. Cheikh, C. Larbes, G. T. Kebir, and A. Zerguerras, "Maximum power point tracking using a fuzzy logic control scheme," *Revue des energies Renouvelables*, vol. 10, no. 3, pp. 387–395, 2007.

[21] B. N. Alajmi, K. H. Ahmed, S. J. Finney, and B. W. Williams, "Fuzzy-logic-control approach of a modified hill-climbing method for maximum power point in microgrid standalone photovoltaic system," *IEEE Transactions on Power Electronics*, vol. 26, no. 4, pp. 1022–1030, 2011.

[22] C. S. Chin, P. Neelakantan, H. P. Yoong, and K. T. K. Teo, "Optimisation of fuzzy based maximum power point tracking in pv system for rapidly changing solar irradiance," *Transaction on Solar Energy and Planning*, vol. 2, pp. 130–137, 2011.

[23] H. Mahamudul, M. Saad, and M. Ibrahim Henk, "Photovoltaic system modeling with fuzzy logic based maximum power point tracking algorithm," *International Journal of Photoenergy*, vol. 2013, 2013.

[24] J.-K. Shiau, Y.-C. Wei, and B.-C. Chen, "A study on the fuzzy-logic-based solar power mppt algorithms using different fuzzy input variables," *Algorithms*, vol. 8, no. 2, pp. 100–127, 2015.

[25] S. Roychowdhury and W. Pedrycz, "A survey of defuzzification strategies," *International Journal of intelligent systems*, vol. 16, no. 6, pp. 679–695, 2001.

[26] J. Falin, "Designing dc/dc converters based on zeta topology," *Analog Applications*, 2010.

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