Agent-Based Simulation of Distribution Systems with High Penetration of Photovoltaic Generation

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Abstract—This paper discusses the development of an agent-based test bed permitting the integrated study of retail and wholesale power markets operating over realistically rendered transmission and distribution systems. A key issue to be addressed using this test bed is the dynamic effect of increased penetration of consumer-owned distributed energy resources, such as PV generation, particularly when coupled with increased price-sensitivity of demand as realized through demand response, demand dispatch, and/or price-sensitive demand bidding.

Index Terms—Distributed power generation, multiagent systems, photovoltaic generation, power distribution, power system economics, smart grids.

I. Introduction

THIS paper reports ongoing project work on the development of an agent-based test bed for the computational study of electric distribution systems with high penetration of photovoltaic (PV) panels within the context of a larger power system. The main objective is to simulate realistic representative power distribution feeders with high fidelity (in terms of electrical topology, household loads and smart appliances, and environmental parameters) in order to eventually perform detailed analyses of the integration of the bulk transmission system (and its market operations) with price-sensitive loads and dispersed generation at the distribution level. There is an increased need for such a simulation tool arising from the evolution of today's electrical system to tomorrow's more advanced and "smarter" grid. In particular, this project focuses on the modeling of a future grid that will include a significant amount of distributed renewable energy generation, mainly from photovoltaic panels.

The test bed is agent-based in the sense that all system components are modeled as interacting agents whose actions (if any) are determined by their individual objectives subject to financial and/or physical constraints. For example, these objectives might involve the minimization of a household's energy costs or the maximization of solar power harvested from a PV panel. In this context, system-level objectives (e.g.,

the minimization of power loss on the cables) may be achieved via market operations, that is, not necessarily by a central controlling authority.

The test bed is based on the seaming together of two previously developed agent-based test beds, namely:

- AMES [1], an open-source software platform developed by a team of researchers at Iowa State University for the study of strategic trading in restructured wholesale power markets with congestion managed by locational marginal prices (LMPs).
- GridLAB-D [2], an open-source software platform developed by DOE at PNNL for the study of power distribution systems for end-use customers with power loads arising from a variety of modeled appliances and equipment.

The resulting integrated retail and wholesale power system test bed will enable us to investigate a series of critical issues for smart grid operation in a more compelling and rigorous manner than is possible with more limited modeling efforts. Examples of such issues include:

1) The effects of more "price-sensitive demand" on both the economic efficiency and reliability (in terms of supply adequacy) of power system operations. By price-sensitive demand we are referring to three options: (i) demand response; (ii) demand dispatch; and (iii) price-sensitive demand bidding.[1]

2) The ability of price-sensitive demand (in the above two senses) to substitute effectively for reserve generation (in particular in relation to the integration of intermittent renewable energy resources such as PV) to permit lower costs in terms of both operation/investment costs and environmental damage.

3) The reduced-order modeling of aggregations of distribution feeders with price-responsive loads. Such models are required by system operators, who are not interested in the details of the medium- and low-voltage systems. For instance, such a model would have the form of a

[1]As explained at greater length in [3], "demand response" typically refers to the top-down ability of market operators to curtail load at peak demand hours or in emergency situations. "Demand dispatch" refers to the ability to turn loads on or off on a continuous basis, thus enabling "generation following" as a possible alternative to "load following." "Price-sensitive demand bidding" refers to the ability of buyers in restructured wholesale power markets to submit demand bids (offers to buy) in the form of price-quantity blocks expressing the buyers maximum willingness to pay for each successive block of purchased energy.
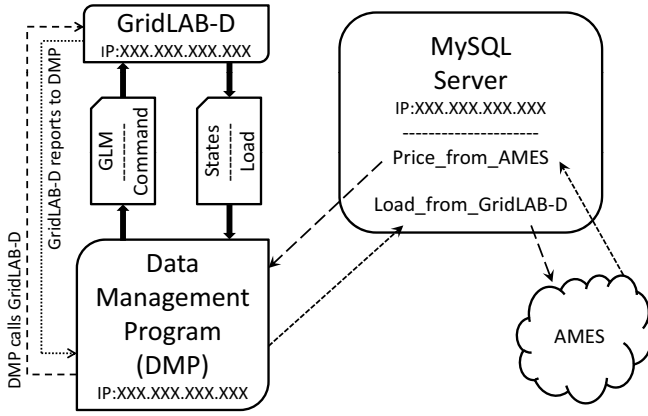
Fig. 1. Structure of the test bed.

"mapping"

$$P = \Phi(\text{price}, \text{weather}, \text{time of day}, \text{contract price},$$
$$\text{consumer's demand elasticity}, \dots) \quad (1)$$

that would compute the price-sensitive aggregate load as a function of certain parameters and a household's contract for electric power (e.g., the contract could be for a regulated price, or it could be for the day-ahead energy price determined on the previous day for the particular hour at hand).

4) Ways to reduce the computational effort required to simulate representative distribution feeders with smart loads.

5) Identification of voltage limit violations arising from the operation of PV-based distributed generation, and control strategies to ensure that the voltage constraints are always satisfied.

6) The provision of ancillary services by the inverters of the PV panels (and financial incentives to do so). Such an application is the supply of reactive power by the inverters to minimize the power loss on the distribution cables. Optimally, the inverter's actions (each inverter is modeled as an agent) need to be coordinated in some fashion. This may be achieved by a central controller, or in a distributed fashion (using an appropriate distributed optimization algorithm).

Section II explains the basic architecture of the proposed test bed. The operation of the test bed is described in Section III. An initial test case is presented in Section IV.

II. TEST BED ARCHITECTURE

As shown in Fig. 1, the first version of the test bed consists of four main components, namely, one or more instances of GridLAB-D (possibly running on separate computers), a Data Management Program (DMP), a MySQL database server, and AMES. These programs communicate via a local area network, and can be placed on systems running different operating systems, thus increasing overall flexibility.

The DMP has four tasks: (i) to prepare input files that define the simulation parameters for GridLAB-D, such as the network topology, the definition of the agents, and the time scheduling of various model parameters; (ii) to collect simulation results from GridLAB-D, such as the model's dynamic states at the end of a simulation, or power consumption data; (iii) to receive the feeder's price information from the database; and (iv) to transmit load data to the database. A detailed description of input/output files for GridLAB-D can be found in [4]. The functionality of the DMP basically represents the communication between various components at the distribution level (e.g., advanced meters) and entities that exist at a higher level (e.g., transmission/distribution utilities, load serving entities, aggregators of demand response, or aggregators of plug-in electric vehicles).

The database contains two tables that store information about the LMP from AMES and the load obtained from GridLAB-D. Note that GridLAB-D is based on C/C++ and AMES is based on Java. To ensure that communication remains independent of operating system and programming language, a MySQL database server has been selected, because it provides Open Database Connectivity (ODBC) drivers and libraries for both C/C++ and Java. In addition, the recorded data is useful for post-processing and analysis.

III. TEST BED OPERATION

In this section, the test bed's operation is described in more detail. Two of the functions that are performed in AMES (among many others) are the calculation of day-ahead LMPs and the calculation of real-time market prices. GridLAB-D is used to simulate a distribution feeder (modeled in significant detail). The load that is calculated will depend on the electricity price supplied by AMES, but also on the weather and other parameters (see (1)). A high-level overview of the execution flow diagram is depicted in Fig. 2, and described below:

1) AMES and DMP are started by the user at the beginning of the simulation, followed by an initialization process for the first day, $D = 1$.

2) AMES transmits the day-ahead (DA) LMP variation for day D to the database server.

3) Meanwhile, DMP keeps querying the database for this price. Once the query is successful, DMP will initiate a series of simulations for day D. Each day is divided into I^* intervals, so that a real-time price can be calculated. For example, the real-time price could be calculated every 5 minutes, as done in ERCOT today.

4) DMP prepares the necessary input files for GridLAB-D, and then calls an instance of GridLAB-D to simulate the distribution feeder for the ith interval in day D. Once the simulation is finished, the aggregate feeder load is saved in the database.

5) AMES queries the database for the load of interval i. Once this becomes available, the calculation of the real-time price is triggered.

6) Steps 4)–5) are repeated until day D ends.

7) If the maximum number of days to simulate, D^*, has not been reached, then AMES calculates the DA price for day $D + 1$, and the algorithm repeats from step 2).
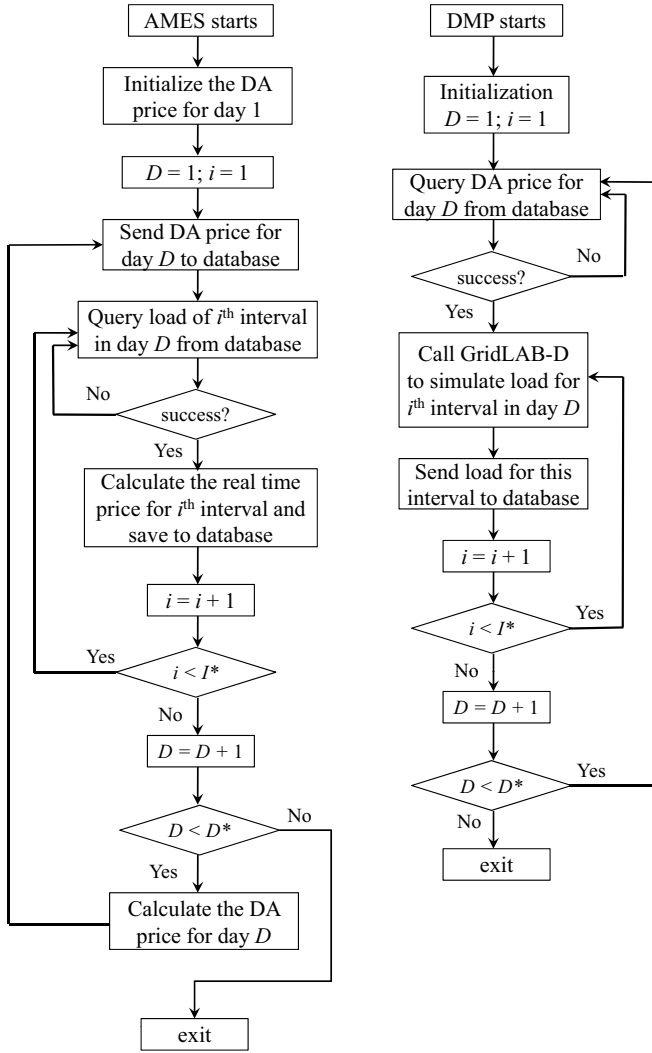
Fig. 2 flowchart (left — AMES):

AMES starts → Initialize the DA price for day 1 → $D = 1$; $i = 1$ → Send DA price for day D to database → Query load of ith interval in day D from database → success? (No → loop back to Query; Yes →) Calculate the real time price for ith interval and save to database → $i = i + 1$ → $i < I^*$ (Yes → loop back to Query load; No →) $D = D + 1$ → $D < D^*$ (No → exit; Yes →) Calculate the DA price for day D → exit

Fig. 2 flowchart (right — DMP):

DMP starts → Initialization $D = 1$; $i = 1$ → Query DA price for day D from database → success? (No → loop back to Query; Yes →) Call GridLAB-D to simulate load for ith interval in day D → Send load for this interval to database → $i = i + 1$ → $i < I^*$ (Yes → loop back to Call GridLAB-D; No →) $D = D + 1$ → $D < D^*$ (Yes → loop back to Query DA price; No →) exit

Fig. 2. Execution flow of seamed AMES and GridLAB-D software.

IV. INITIAL TEST CASE

Given the fixed retail rate structure still prevalent at the retail distribution level in most U.S. energy regions, retail energy consumers have little incentive or opportunity to respond to wholesale power prices. In consequence, the occurrence of price-sensitive demand bidding by load-serving entities in wholesale power markets remains relatively rare, usually less than 1% of total cleared demand.

Nevertheless, policy makers and researchers are increasingly calling for more demand response, demand dispatch, and price-sensitive demand bidding in wholesale power markets to achieve better market performance [3], [5], [6]. For example, the computational experiments reported in [7] demonstrate that the exercise of market power by generation companies (GenCos), which can include both economic and physical capacity withholding, is increasingly curtailed as demand bids are varied from 100% fixed to 100% price sensitive.

In addition, it is expected that the integration of renewable energy resources will dramatically increase over the next few years in response to the adoption of renewable portfolio standards (RPS) in many U.S. states or similar programs worldwide. Demand response, demand dispatch, and price-sensitive demand bidding could all play key roles in facilitating this integration at both retail and wholesale levels. The intermittency and volatility of renewable energy sources requires quick counterbalancing by other energy sources to maintain system integrity. For example, if an unexpected drop in wind power results in a price spike, this should discourage demand that is sensitive to price and hence help to maintain the needed balance between generation and load. Alternatively, this situation could trigger automated curtailment or interruption of certain loads under a previously arranged demand dispatch agreement, or a controlled shedding of load under a demand response program managed by an Independent System Operator (ISO).

The test bed presented here can be used to test the effects of increased penetration of price-sensitive demand, both with and without consumer-owned distributed energy resources. As a first step, to facilitate model verification, a relatively simple test case is being designed. Specifically, as shown in Fig. 3, we are currently working to extend a generic load bus k in AMES to include a downstream retail market. This downstream market consists of a collection of households, all of which have appliances, and some of which have consumer-owned distributed energy resources in the form of PV panels and/or Plug-in Electric Vehicles (PEV). The aggregated power demands from this downstream retail market are connected to wholesale power market operations at bus k through a distribution feeder line. As previously discussed, the real-time load and power flow on this feeder line are simulated in GridLAB-D.

The initial test case stresses the inclusion of household-owned roof-top PV panels, and a PV module has been developed specifically for this implementation; see the Appendix for details on the mathematical modeling of this PV module. Distributed generation by residential-scale wind turbines is not considered in this initial test case, but could be added in a future version of this software. Plug-in electric vehicles with vehicle-to-grid capability will be incorporated in future versions as well.

The residential load from this downstream retail market is aggregated and commercially serviced by a single AMES LSE. This LSE can offer residential households a variety of contractual arrangements ranging from flat-rate pricing at a fixed regulated rate to dynamic pricing in which wholesale power prices are passed through to households via advanced metering or other technology.

As depicted in Fig. 4, wholesale power prices are determined via the AMES two-settlement system in which a day-ahead energy market and a real-time balancing market are operated in tandem by an ISO. At the beginning of each operating day D, the ISO receives demand bids from LSEs and supply offers from GenCos for each hour H of the day-ahead energy market for day $D+1$. At the end of each operating day D the ISO settles all 24 hours of the day-ahead market for day $D + 1$ using the LMPs determined via hourly bid/offer-based DC optimal power flow solutions for the day-ahead market for day $D + 1$.

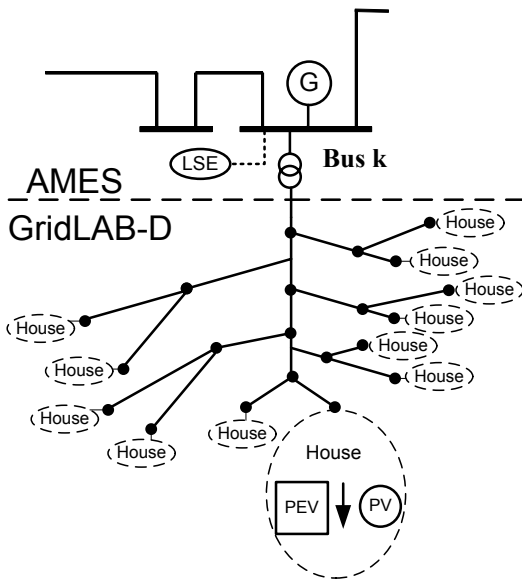In particular, for each hour H of day $D + 1$ the LSE at

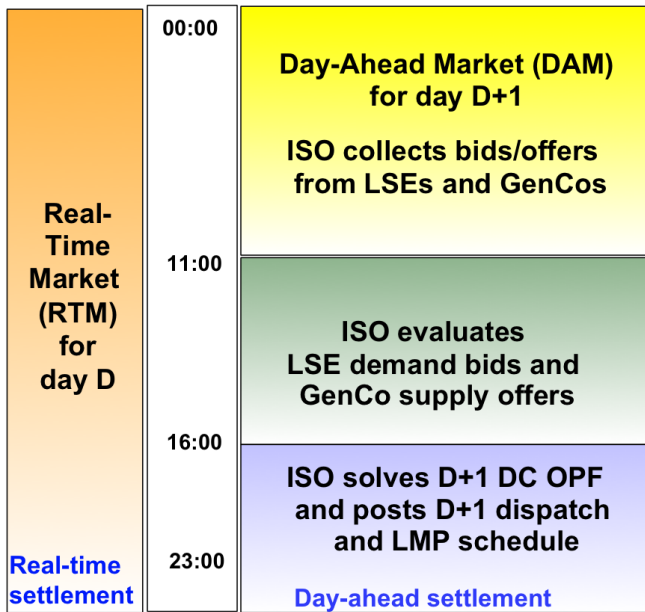Fig. 3. Schematic depiction of initial test case for the integrated retail and wholesale power system test bed.

Fig. 4. AMES two-settlement system managed by an ISO on a typical operating day D. [Note: Depicted timing is from the Midwest ISO.]

to wholesale market participants. Given retail dynamic-price contracts involving pass-through of wholesale LMPs, retail consumers would also receive these price signals. However, no such price signals are transmitted to retail consumers in energy regions in which retail consumers pay regulated fixed rates, which is the typical situation in the U.S. today. It is conjectured in [8] that retail restructuring permitting some degree of retail dynamic-price contracting would increase the welfare of retail consumers, both those with dynamic-price contracts and those on fixed-rate contracts. We will use our test bed to investigate this conjecture using systematic computational experiments.

A second key issue we will examine is the effect of retail contract choice on risk sharing between an LSE and its retail customers. Under a fixed-rate contract, all of the price risk is borne by the LSE since the LSE buys energy at fluctuating prices but resells this energy to its retail customers at a fixed rate. In an attempt to compensate for this risk, a premium charge could be included in the fixed rate. Alternatively, by passing through wholesale prices to its retail customers, the LSE could shift all price risk to these customers. As detailed in [9], there is a wide range of possible retail contracts lying between these two extremes. We will carry out computational experiments with our test bed to investigate the risk-sharing implications of a sampling of these retail contract forms.

A third key issue we will examine is the extent to which the increased penetration of price-sensitive demand affects the reliability (adequacy) of system operations. A concern expressed by some GenCos and market operators is that a high penetration of dynamic-price contracting at the retail level could increase the volatility and uncertainty of load profiles, thus reducing the ability to forecast load for system balancing ("load following"). For example, if wholesale LMPs are passed through to retail consumers, the result could be different degrees of "peak shaving" by consumers anxious to avoid high prices. The question is whether the resulting flattened load profiles would be easier to forecast or whether LSEs and market operators would find themselves in a "chasing the peak" situation in which the ability to predict peak hours with accuracy is substantially reduced. This important concern will be thoroughly explored by means of carefully designed computational experiments conducted using the proposed test bed.

V. CONCLUSION

As discussed in previous sections, three distinct tasks are being addressed in this project.

1) Development of a retail distribution module that exploits the capabilities of GridLAB-D for simulating retail load arising from a wide variety of appliances and equipment as well as retail generation arising from consumer-owned distributed energy resources such as PV panels.
2) Development of extended LSE agents in AMES able to aggregate, service, and settle net load arising at the retail distribution level.
3) Development of a communication system (a data management program together with a MySQL database server) permitting back and forth communication be-

bus k must pay the day-ahead LMP at bus k for all energy it was cleared to buy during that hour as a result of its day-ahead market demand bidding on day D. Any deviation between this cleared demand and the actual load withdrawn at bus k by the LSE's retail customers during hour H of day $D+1$ are settled at the real-time LMPs for bus k during hour H of day $D+1$ determined via DC optimal power flow problems based on actual load conditions.

One key issue to be examined using our initial test case is the effect of retail contract choice on market efficiency and the welfare of market participants. In principle, prices should convey to market participants when and where to both inject and withdraw power. Wholesale LMPs transmit these price signals

tween AMES wholesale operations and GridLAB-D distribution-level operations.

To our knowledge, the resulting agent-based test bed will be the first noncommercial open-source platform permitting the integrated study of retail and wholesale power markets operating over realistically rendered transmission and distribution systems.

APPENDIX
MODELING OF PV MODULE

This section provides information on the mathematical modeling of PV-based distributed generation for inclusion in the agent-based test bed. Each house will have the option of a roof-top PV installation. In accordance with the agent-based modeling principle, each installation is represented as a separate object in GridLAB-D. The inverter is assumed to be operating in a quasi steady-state, under maximum power point tracking control. It also has the capability to supply or absorb reactive power from the grid, for improving the local distribution system voltage profile and reducing the distribution system losses. The design of algorithms for determining the appropriate reactive power compensation by the PV inverters is the subject of ongoing work.

Previous work by other researchers has focused extensively on high-fidelity modeling of PV panels' voltage-current characteristics [10]–[12]. Herein, the model that is needed for the test bed is one that can quickly provide the power output as a function of environmental factors, such as the solar irradiation and the panel temperature. At the same time, the accuracy should be maintained at an acceptable level. A new method of constructing a maximum power point tracking surface is discussed, after introducing the basic model of a PV panel.

A. PV Panel Modeling

Figure 5 shows the equivalent circuit of a single PV cell, whose I-V characteristic is given by

$$I = I_{PV} - I_d - \frac{V + IR_s}{R_p}, \qquad (2)$$

where R_p and R_s are the parallel and series resistances, perspectively, I_{PV} is the light-generated current (directly proportional to the sun irradiation) defined by (3), and I_d is the diode current defined by the Shockley diode equation (4).

$$I_{PV} = (I_{PV,n} + K_I \Delta_T)\frac{G}{G_n} \qquad (3)$$

$$I_d = I_s \left[\exp\left(\frac{V + IR_s}{nV_T}\right) - 1 \right] \qquad (4)$$

$$V_T = \frac{kT}{q} \qquad (5)$$

In (3), $I_{PV,n}$ is the light-generated current under standard test conditions, in which $T_n = 25°C$ and $G_n = 1000$ W/m^2; $\Delta_T = T - T_n$ is the difference between the actual temperature and nominal temperature of the PV cell in Kelvin; G and G_n are actual and nominal irradiation on the device surface respectively in W/m^2; K_I is the temperature coefficient of
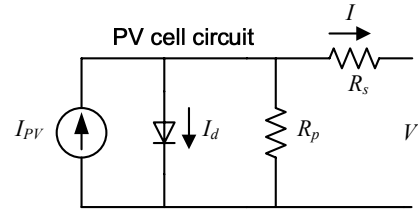
Fig. 5.   Single-diode model of a PV cell.
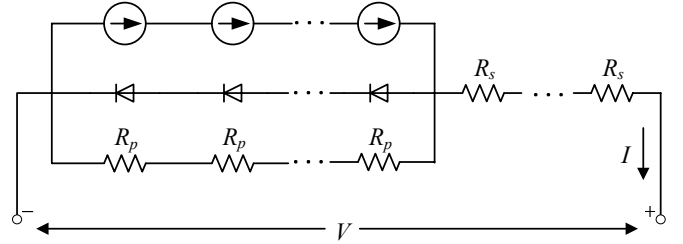
Fig. 6.   PV array model consisting of series-connected PV cells.

current in A/K. For most cases, the value of $I_{PV,n}$ is not provided in the PV panel's datasheet. However, this value is usually approximated using the nominal short circuit current ($I_{sc,n}$) [10]–[12]. In (4), I_s is the reverse bias saturation current, $(V + IR_s)$ is the voltage across the diode, V_T is the thermal voltage defined in (5), n is the emission coefficient, also known as the ideality factor. The emission coefficient n varies from ca. 1 to 2 depending on the fabrication process and semiconductor material, and in many cases is assumed to be approximately equal to 1 [10]. In (5), k is the Boltzmann constant, T is the absolute temperature of the PV cell, and q is the electric charge of an electron. The above equations completely describe the I-V characteristic of a single PV cell.

A PV array is considered to be constructed by connecting a number N_s of PV cells in series, as shown in Fig. 6. After manipulations, the following expression can be derived for the I-V characteristic of a PV array:

$$I = (I_{PV,n} + K_I\Delta_T)\frac{G}{G_n} -$$
$$- I_s \left[\exp\left(\frac{V + N_sIR_s}{N_snV_T}\right) - 1 \right] - \frac{V + N_sIR_s}{N_sR_p}. \quad (6)$$

Typically, a PV panel's datasheet will provide the following basic information:

1) the nominal open-circuit voltage
2) the nominal short-circuit current
3) the voltage and current at the maximum power point
4) the open-circuit voltage/temperature coefficient
5) the open-circuit current/temperature coefficient
6) the maximum output power

These parameters do not correspond directly to the ones used in (6). However, [10] provides a methodology to approximate these from the datasheet information.

B. Maximum Power Point Tracking Surface

The maximum power point can be determined numerically from (6) for any given solar irradiation and panel temperature.
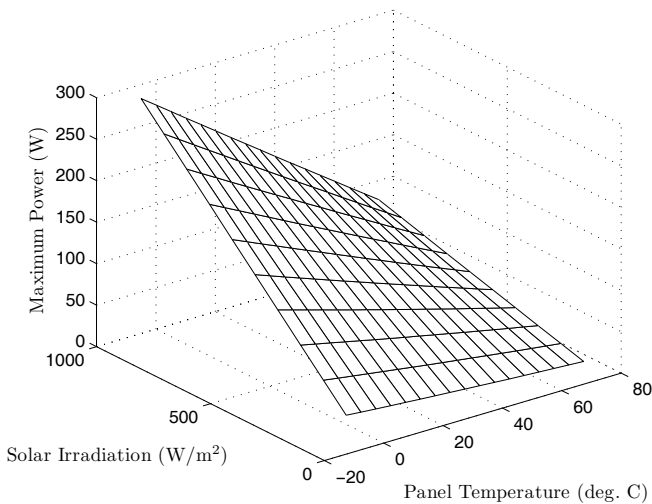
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