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# Multi-Objective Optimization and Design of Photovoltaic-Wind Hybrid System for Community Smart DC Microgrid

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***Abstract*—Renewable energy sources continues to gain popularity. However, two major limitations exist that prevent widespread adoption: availability of the electricity generated and the cost of the equipment. Distributed generation, (DG) grid-tied photovoltaic-wind hybrid systems with centralized battery back-up, can help mitigate the variability of the renewable energy resource. The downside, however, is the cost of the equipment needed to create such a system. Thus, optimization of generation and storage in light of capital cost and variability mitigation is imperative to the financial feasibility of DC microgrid systems. PV and wind generation are both time dependent and variable but are highly correlated, which make them ideal for a dual-sourced hybrid system. This paper presents an optimization technique base on a Multi-Objective Genetic Algorithm (MOGA) which uses high temporal resolution insolation data taken at 10 seconds data rate instead of more commonly used hourly data rate. The proposed methodology employs a techno-economic approach to determine the system design optimized by considering multiple criteria including size, cost, and availability. The result is the baseline system cost necessary to meet the load requirements and which can also be used to monetize ancillary services that the smart DC microgrid can provide to the utility at the point of common coupling (PCC) such as voltage regulation. The hybrid smart DC microgrid community system optimized using high-temporal resolution data is compared to a system optimized using lower-rate temporal data to examine the effect of the temporal sampling of the renewable energy resource.**

***Index Terms*—Genetic algorithm, microgrid, optimization, photovoltaic, PV-storage system, smart grid, wind turbine.**

## I. Nomenclature

| | |
|---|---|
| $I_i$ | Initial cost. |
| $OM_i$ | Operation & Maintenance cost. |
| $N$ | Life cycle of the system. |
| $C_{Grid}$ | Cost of power imported from grid. |
| $A_{PV}$ | PV surface area. |
| $A_{Wind},$ | Wind footprint area. |
| $P_{CapBatt}$ | Battery capacity. |
| $\Psi$ | Ratio of power imported from grid to load. |
| $OM_{yearly}$ | Yearly O&M per unit. |
| $\beta$ | Inflation rate. |
| $P_{grid,t}$ | Power purchased from utility at time $t$. |
| $T$ | Operational duration under consideration. |
| $A$ | Index of availability. |
| $DNM$ | Demand not met (kWh/year). |
| $D$ | Yearly demand. |
| $P_D(t)$ | Demand at time $t$. |
| $P_{\underset{MIN}{Batt}}(t)$ | Minimum allowable storage level at time $t$. |
| $P_{\underset{SOC}{Batt}}(t)$ | State of charge of battery bank at time $t$. |
| $\lambda_{Grid}$ | Price of grid power. |
| $\gamma$ | Interest rate. |
| $\upsilon$ | Escalation rate. |
| $\eta_{PV}$ | Photovoltaic system efficiency. |
| $\eta_{Wind}$ | Wind turbine system efficiency. |

Manuscript received August 12, 2013; revised November 23, 2013; accepted March 23, 2014. Funding for the 27.6 kW photovoltaic system studied in this paper at Texas A&M University, College Station, Texas was provided by a grant from the US Department of Energy (DOE) and the Texas State Energy Conservation Office (SECO). Paper no. TSG-00652-2013.

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Digital Object Identifier 10.1109/TSG.2014.2315043

## II. Introduction

DC distribution systems are ideal for integrating distribute renewable energy sources and energy storage into point-of-use energy systems [1]–[3]. Renewable energy adoption has increased with 60% annual growth in the installed capacity of photovoltaic (PV) systems from 2004 to 2009, and 80% in 2011 [4]. However, two major fundamental limitation exists that prevent truly widespread adoption: availability of electricity generated and cost of equipment. At the same time, DC systems have been gaining popularity because of the high efficiency, high reliability and easy interconnection of renewable sources compared to AC systems [1], [5]. A DC microgrid system with distributed PV and wind generation and employing centralized battery storage, illustrated in Fig. 1, is an

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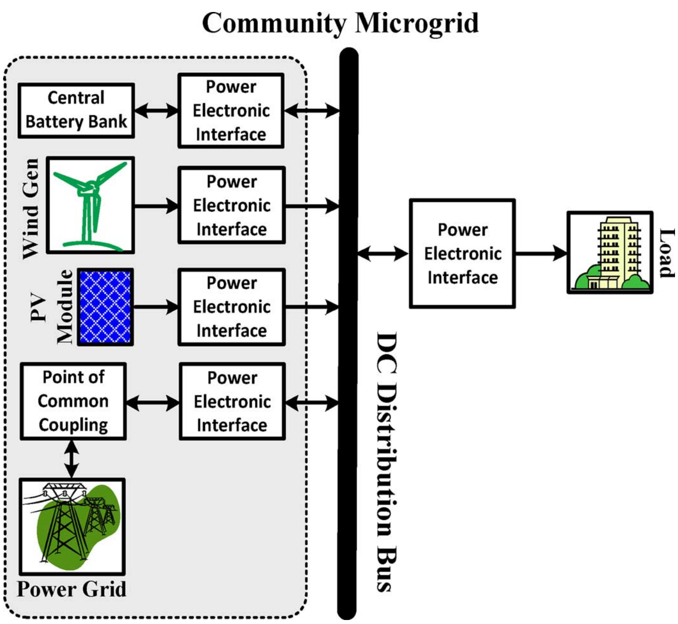


Fig. 1. One line system diagram.

attractive technology solution for communities to "go-green" while simultaneously ensures reliable electricity.

To mitigate fluctuations in the generation portion of the hybrid system, a battery bank is used for energy storage. This will absorb the surplus power and supply deficit power under different operating conditions. The proposed methodology has been previously used for assessing standalone distributed photovoltaic systems and has been experimentally verified through long-term field testing [6].

DC distributed generation (DG), grid-tied PV-wind systems with centralized battery back-up, illustrated in Fig. 1, have been proposed for community-scale microgrids such as the Pecan Street project in Austin Texas [7] and other communities [8]. An example of the power electronic interface between the utility-power grid and the community distribution bus is the solid state transformer [9], [10] being developed by the FREEDM Center at NC State, Fig. 1. The control and management of the islanded PV-wind and storage systems have been proposed in [11]–[14].

Due to the stochastic behavior of wind and solar energy, one of the most vital factors in optimal sizing of the hybrid systems is the temporal resolution of collected data to provide sufficient resolution [15], particularly on cloudy days, Fig. 2. Optimization techniques such as Multi-Objective Genetic Algorithm (MOGA) [16]–[18] are able to take advantage of high temporal resolution data for renewable resources instead of relying only on mathematical probabilistic models. The main contribution of this paper is to employ an energy availability technical assessment in conjunction with economic assessment to optimize the sizing of the PV panel, wind turbine, battery storage, and the power imported from grid in order to determine the system that would guarantee a reliable energy supply with the lowest investment.

The objective of this paper is to simultaneously maximize the power availability and minimize the cost which will optimize

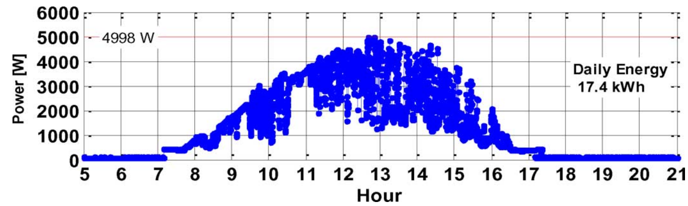


Fig. 2. Example of high temporal resolution PV data on a cloudy day.

system size with highest availability. The problem is firstly visualized based on MOGA technique and Pareto Front for purpose of engineering trade off when analyzing high temporal resolution data. Then a utility function will be determined in order to do a decision making for the multi-objective problem. Uncertainty analysis is added because of the stochastic behavior of the insolation and wind speed data.

The "average month" technique [19], [20] is not used in this paper because the system designed in this way may not be able to satisfy the load during some periods of real-work operation. On the other hand, the calculation of each subsystem (wind, photovoltaic, storage, and ratio of power imported from grid) separately for the worst month in each resource makes the total system oversized. The optimized hybrid system, based on accurate and enhanced 10 seconds insolation data rate of photovoltaic system, is compared to conventional PV-Wind optimized systems based on hourly insolation data. Using MOGA as the optimization technique when analyzing high temporal resolution insolation data shows that the system availability is maximized for lowest possible cost comparing to conventional hybrid system sizing [21]–[23].

Due to the different operating life of various components, reliability analysis is critical [24], [25]. In this paper, though no reliability analysis details will be discussed, the results of the extra cost overhead to the owner due to maintenance and repairs will be included. In addition, the mathematical modeling of the system considers the economic aspects such as inflation, interest, and escalation rates which makes the model more realistic.

## III. Case Study for Apartment Complexes

The case study is a grid-tied community living environment in College Station, Texas. The case study uses high temporal resolution data collected from a 27.6 kW PV system installed on Texas A&M University campus [26]. The system, configured as five independent residential-scale arrays, has the PV generation (ac output) data sampled every 10 seconds, Fig. 2. Details of the hybrid system and selected site are:

- The apartment complex consists of 70 units with 28 two story buildings, the load schedule is shown in Table I
- The monthly average load requirement for the apartment complex is approximately equal to 82,920 kWh
- There is 5.27 kWh/m2 of available incident solar energy
- The site has class-1 wind [27], and Wind Finder [28] is used to gather wind resource data

The hourly demand of the case study is illustrated in Fig. 3. The load profile of each apartment is estimated over an entire year as it is illustrated in Fig. 4. A center of mass approach is

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TABLE I
SUMMARY OF APARTMENT COMPLEX ENERGY USAGE

| Summary of Apartment Units | | |
|---|---|---|
| *Type of Units* | *No. of Units* | *Average Energy Usage (KWh)* |
| Efficiency | 2 | 830 |
| 1bed 1bath | 20 | 940 |
| 2bed 1bath | 10 | 1150 |
| 2bed 1.5bath | 32 | 1330 |
| 2bed 2bath | 6 | 1410 |

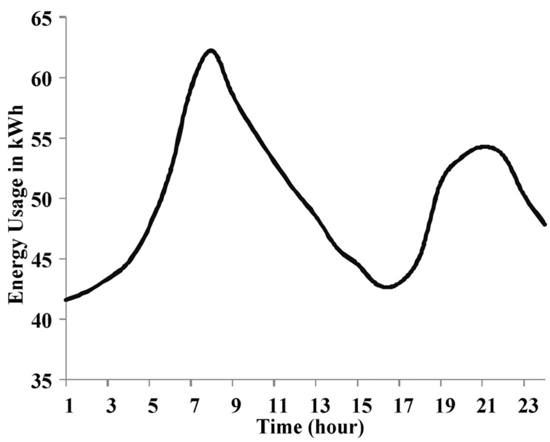


Fig. 3. Daily load profile.

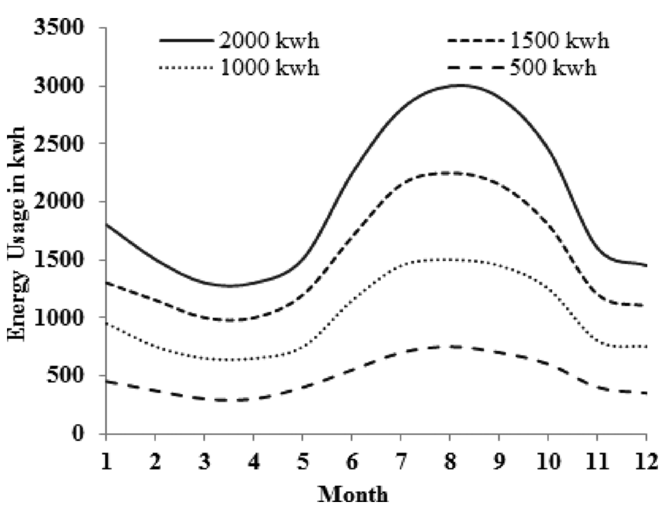


Fig. 4. Estimated monthly residential load profiles.

utilized to estimate the load profiles for apartment units which lie between energy profiles. For example the unit with 1150 kWh which is between 1000 kWh and 1500 kWh, we get $1000\mathrm{P} + 1500(1-\mathrm{P}) = 1150$, where $\mathrm{P} = 70\%$. Therefore, 1150 kWh has 70% resemblance to 1000 kWh load pattern and 30% to 1500 load pattern. By using this methodology and base on the information provided in Table I, the monthly average load requirement for the apartment complex is determined to be approximately 82,920 kWh.

## IV. PROBLEM STATEMENT

In this section, the objectives of the system will be mathematically formulated for optimization. These objectives are to simultaneously maximize the power availability and minimize the cost which minimizes the system size with highest possible availability. The output power of PV and wind generators has the highest priority to feed the DC bus, and if the power generated is inadequate, the battery bank can be discharged to a certain amount to feed the bus. If there is still insufficient power, a certain amount of power can be purchased from grid to feed the load. Thus, the power imported from grid has the lowest priority.

### A. Cost

Major component of the system cost consists of the price of PV panels, wind turbines, and battery bank. The total system cost (\$/year) includes initial cost and operational & maintenance cost (O&M), this can be formulated as

$$Cost = C_{Grid} + \frac{\sum_{i=PV,Wind,Batt} (I_i + OM_i)}{N} \tag{1}$$

where $I_i$ and $OM_i$ indicate the initial cost and Operation & Maintenance (O&M) cost of each individual components respectively. $N$ and $C_{Grid}$ are the life cycle of the system and cost of power imported from grid respectively. So the first objective can be formulated as

$$\overset{Minimize}{Cost}\ (A_{PV}, A_{Wind}, P_{CapBatt}, \Psi) \tag{2}$$

where $A_{PV}, A_{Wind}, P_{CapBatt}$ and $\Psi$ are the design parameters in this project.

For the photovoltaic sub-system, the initial and O&M cost can be formulated as

$$I_{PV} = \lambda_{PV} \times A_{PV} \tag{3}$$

$$OM_{PV} = OM_{yearly} \times A_{PV} \times \sum_{i=1}^{N} \left(\frac{1+\upsilon}{1+\gamma}\right)^i. \tag{4}$$

For the wind turbine sub-system, the initial and O&M cost can be similarly formulated as

$$I_{wind} = \lambda_{wind} \times A_{wind} \tag{5}$$

$$OM_{wind} = OM_{yearly} \times A_{wind} \times \sum_{i=1}^{N} \left(\frac{1+\upsilon}{1+\gamma}\right)^i. \tag{6}$$

For the battery bank, the initial cost and O&M cost can be formulated as

$$I_{Batt} = \lambda_{Batt} \times P_{Cap\_Batt} \tag{7}$$

$$OM_{Batt} = OM_{yearly-Batt} \times P_{yearl-Batt} \times \sum_{i=1}^{T_b} \left(\frac{1+\upsilon}{1+\beta}\right)^{(i-1)N_{Batt}}. \tag{8}$$

For the battery bank, since the operational life cycle is less than PVs and wind turbines, it is expected that they must be replaced several times during the system life span. This replacement cost is taken into consideration as O&M costs in (8).

The cost of importing power from the grid can be formulated as

$$C_g = \sum_{i=1}^{T} P_{grid,t} \times \lambda_{Grid}. \tag{9}$$

### B. Availability

Availability, the fraction of the time when energy is available, is a key figure of merit for the proposed system. It is important to make a clear distinction between availability and reliability. Reliability is the ability of the system to operate without failure; availability is the ability of the system to supply power to the load. As an example, a highly reliable photovoltaic energy system, where the components are not prone to failure, can have low availability if there is insufficient energy storage to support the load's power requirements during the night or during an overcast day.

A specified level of availability can be achieved with many configuration of a system. The availability can be formulated for duration under consideration $T$ as

$$A = 1 - \frac{DNM}{D}. \tag{10}$$

The *DNM* can be formulated as

$$DNM = \sum_{t=1}^{T} \begin{pmatrix} P_{\underset{MIN}{Batt}}(t) - P_{\underset{SOC}{Batt}}(t) - \\ (P_{PV}(t) + P_{Wind}(t) + P_{Grid}(t) - P_D(t)) \times u(t) \end{pmatrix} \tag{11}$$

where $u(t)$ is a step function which is zero if the supply power is greater or equal demand and one if the demand is not met.

The imported power from grid is:

$$P_{Grid} = \Psi \times (P_D(t) - P_{PV}(t) - P_{Wind}(t) - P_{Batt}(t)) \tag{12}$$

where

$$P_{Wind} = P_{WTG} \times A_{Wind} \times \eta_{Wind} \tag{13}$$

$$P_{PV} = Insolation \times A_{PV} \times \eta_{PV}. \tag{14}$$

The second objective can be formulated as:

$$\overset{Maximize}{A} \quad (A_{PV}, A_{Wind}, P_{CapBatt}, \Psi). \tag{15}$$

The hybrid system parameters values are given in Table II.

TABLE II
NUMERICAL VALUE OF HYBRID SYSTEM PARAMETERS

| Parameters | Values |
|---|---|
| Life cycle of the project $N$ | 20 *years* |
| Battery life cycle $N_{Batt}$ | 5 *years* |
| Inflation rate $\beta$ | 8% |
| Interest rate $\gamma$ | 12% |
| Escalation rate $\upsilon$ | 12% |

TABLE III
CONSTRAINTS NUMERICAL DATA

| Parameters | Values |
|---|---|
| $A_{\underset{Min}{PV}}$ | 0 $m^2$ |
| $A_{\underset{Max}{PV}}$ | 4,221 $m^2$ |
| $A_{\underset{Min}{Wind}}$ | 100 $m^2$ |
| $A_{\underset{Max}{Wind}}$ | 4,221 $m^2$ |

## V. OPTIMIZATION

### A. Design Constraints

A physical constraint which must be added to the optimization algorithm is the available area for PV panels and wind generators installation:

$$A_{\underset{Min}{PV}} < A_{PV} < A_{\underset{Max}{PV}} \tag{16}$$

$$A_{\underset{Min}{Wind}} < A_{Wind} < A_{\underset{Max}{Wind}}. \tag{17}$$

Obviously the lower bounds can be zero, but in order to make the system more reliable for the purpose of uncertain analysis, the lower bound for wind turbines is decided to be about 100 $\mathrm{m}^2$. For the selected apartment complex the upper bound was determined to be approximately 12% of the available area, which was approximately 4,221 $\mathrm{m}^2$.

The imported power from the grid should be within a certain range:

$$P_{\underset{Min}{Grid}} < P_{Grid} < P_{\underset{Max}{Grid}}$$

$$0 < \Psi < 1. \tag{18}$$

The fraction of the power $\Psi$ to be imported from grid can vary from zero to one, this can be seen from (12).

Finally, the total generated power should not exceed the demand in order to avoid oversizing the system and adding excessive cost. This constraint is formulated as:

$$P_{PV}(t) + P_{Wind}(t) + P_{Batt}(t) + P_{Grid}(t) \le P_D(t). \tag{19}$$

The numerical values of design constraints are given in Table III for the presented case study.

### B. NSGA-II Optimization for the Hybrid System

Multi Objective Genetic Algorithm (MOGA) which is commonly called Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [18], [29] is used as an optimization algorithm or search method to find a set of equally good solutions for the objectives mentioned in Section III as a form of a Pareto frontier. However other optimization techniques can be used, but this method has been one of the most popular heuristic search methods for multi-objective optimization [18]. The Genetic Algorithm is a well-known non-gradient-based search method which mimics the natural evolution process.

The key distinction between single-objective and multi-objective optimization is that in the case of multi-objective optimization, there may be multiple feasible solutions that satisfy the optimization criterion. Further, it may not be possible to identify one solution as being *better* than another if neither is *dominated* by the other in some sense. In other words, in multi-objective optimization, there could exist a set of equally-good solutions rather that a single solution as we expect in single-objective optimization problems. The results of multi-objective optimization can be also be described as a set of non-dominated solutions, the so called Pareto frontier.

MOGA uses Genetic Algorithm (GA) as its core with two important new concepts in order to achieve good multi-objective optimization. These two concepts are non-dominated sorting and crowding distance as described in [16], [18]. By using these two concepts and GA principle, MOGA algorithm can be formed which is called Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [18]. This algorithm is briefly explained in this section.

In iteration $t$, parent population $P_t$ and offspring population $Q_t$, each with $N$ solutions, are combined to form a bigger population with $2N$ solutions. Non-dominated sorting is then performed to find solutions with similar ranks.

A sorting process is then performed by selecting solutions with the lowest rank and then solutions with the next lowest rank and so on. This process continues until the number of solutions in the parent population exceeds $N$. Then, for the latest sorted subpopulation included in the parent population, only the solutions with a larger crowding distance are selected until parent population has exactly $N$ solutions. Crossover and mutation operators are then performed to find the next offspring population. Fig. 5 illustrates the flowchart of NSGA-II algorithm used in this paper for optimizing the hybrid system.

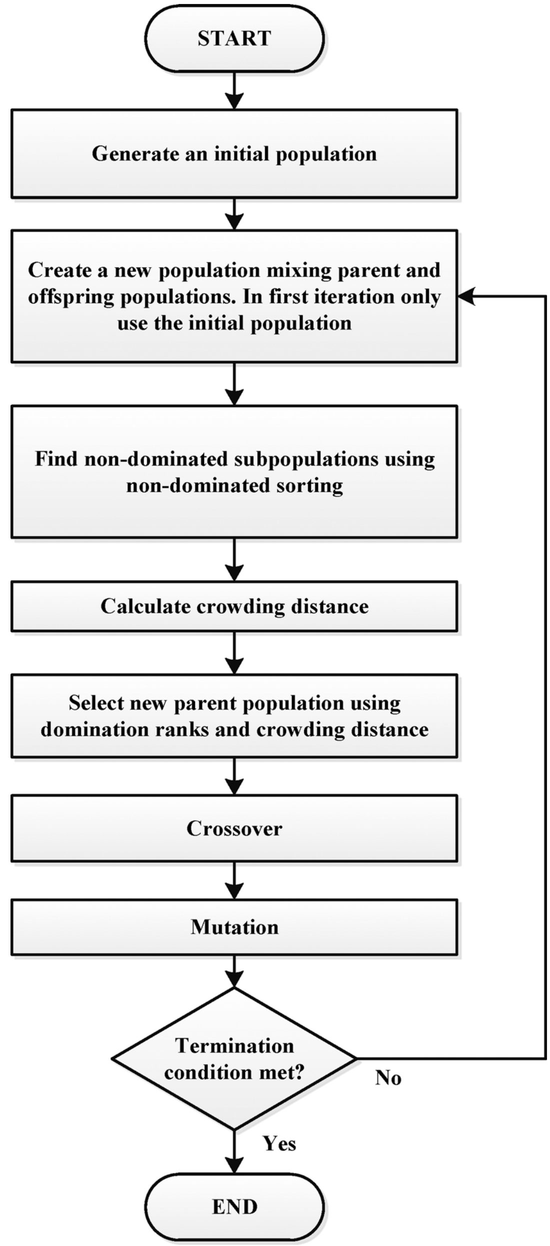


Fig. 5. MOGA (NSGA-II) optimization algorithm for hybrid system.

The comprehensive design procedure of the hybrid system for DC smart microgrid is illustrated in Fig. 6. Without loss of generality, the models of the various components, including the wind generator, solar cells, and power electronics interfaces can be made arbitrarily complex to improve the fidelity of the model. In a PV-wind hybrid energy harvesting system, there are many factors which contribute to the overall conversion efficiency. One of the most important conditions is the geographical location where the system is deployed which determines the latitude and the meteorological conditions. Therefore, the first step in the design procedure is to specify the geographical location. Based on the location, conditions such as available wind and solar resources and weather data are used to determine the ratings for the PV array and wind generator. Usable roof area, desired availability of power (loss of load probability), desired lifetime, and limits on maximum imported grid power are considered as design constraints for the objective functions. Finally, by using the optimization tool illustrated in Fig. 5, a set of equally good solutions, the Pareto Frontier, is found that maximize the availability and minimize the cost of the hybrid system.

Fig. 7 illustrates a set of optimal design solution for the hybrid system. The PV panel cost ($\lambda_{PV}$), wind turbine cost ($\lambda_{Wind}$), battery bank cost ($\lambda_{Batt}$), and price of grid power ($\lambda_{Grid}$) are assumed 450 $\$/\mathrm{m}^2$, 100 $\$/\mathrm{m}^2$, 100 \$/kWh, and 0.10 \$/kWh respectively. Fig. 7 illustrates the trade-off between cost and availability. This is due primarily from the need to supply the

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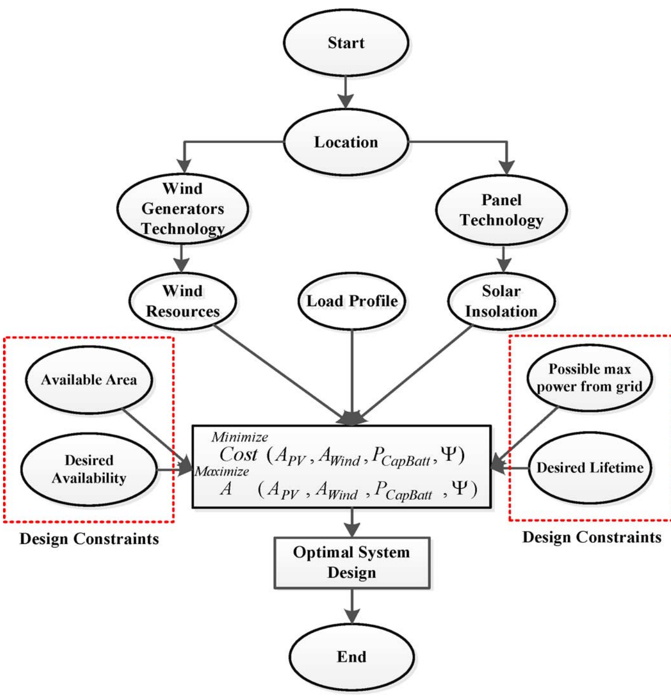


Fig. 6. Comprehensive design and optimization procedure of the hybrid system for smart DC microgrid.

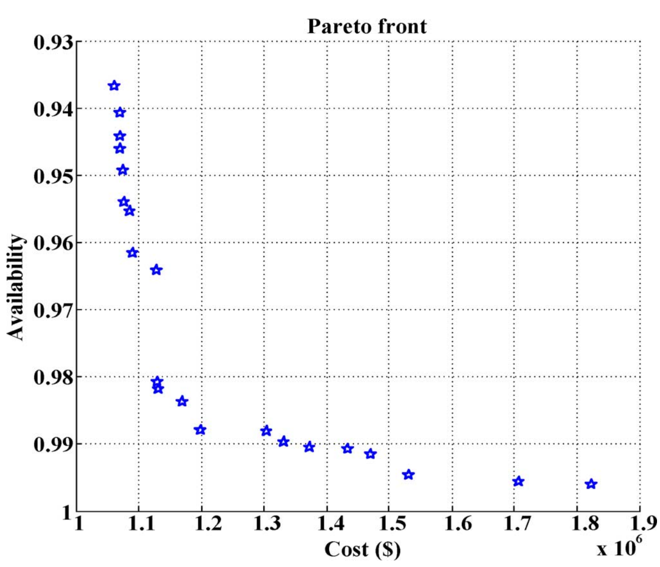


Fig. 7. Pareto frontier reveals the set of optimal solutions found from the evaluation of (1)–(15) for the proposed hybrid system.

peak load during as determined by the system energy availability. Thus, the Pareto Frontier is a tool that enables engineering tradeoff analysis to choose the unique design from the set of feasible designs based on particular preferences.

Due to stochastic behavior of the solar and wind, in this paper the decision making is done for two scenarios: without uncertainty and with uncertainty. A more detail discussion on uncertainty analysis is presented in the next section.

## VI. Decision Making

The set of optimal solution given by the Pareto Frontier is illustrated in Fig. 7 and can be used to visualize the optimal solutions and perform engineering tradeoff studies. In this paper the utility theory [30], [31] is used to decide the optimal solution based on the preferences for the smart DC microgrid. Therefore, a function need to be defined to clearly rank-order the alternatives for decision making, this function is commonly called the *utility* or *value* function [31]. Usually the term "*value function*" denotes the decision under certainty and the term "*utility function*" denotes a decision under uncertainty.

Two decision making scenarios are investigated in this paper: with and without uncertainty in the solar radiation, wind speed, and demand data. Firstly a utility function will be formulated for decision on system design without uncertainty, then the expected value of utility function will be used for decision by taking into consideration the uncertainties.

### A. Decision Without Uncertainty

Objectives and attributes are used as tools for modeling the preferences or the utility function, and then an irrevocable allocation of resources will be done. An attribute, or figure of merit (FOM), is the measure of progress toward an objective. The attributes in this paper are the availability and cost. So a function need to be defined that relates every point in an n-dimensional attribute space to a scalar value or utility as follow

$$\begin{aligned} u &= u(z) \\ z &= [Cost \quad A] \end{aligned} \tag{20}$$

which allow the designer to rank order the alternatives. The next step is to convert all attributes to same scale, frequently called "pricing out". The summary of the decision modeling without uncertainty is illustrated in Fig. 8. By using the procedure illustrated in Fig. 8, the general form of value function for the hybrid system optimization is given by

$$\begin{aligned} u(Cost, A) = \lambda_1 &\frac{Cost - (Min(Cost))}{Max(Cost) - Min(Cost)} \\ &- \lambda_2 \frac{A - (Min(A))}{Max(A) - Min(A)} \end{aligned} \tag{21}$$

where $\lambda_1$ and $\lambda_2$ are the weighing factors that can be defined by the designer. If $\lambda_1 = \lambda_2$, it means the designer are indifferent between the availability and cost of the hybrid system for the DC distribution systems. Consequently, the proposed value function provides the designer the ability to perform the engineering trade study. Finally by minimizing $u(Cost, A)$ using GA optimization toolbox in MATLAB, the irrevocable decision on the design variables can be obtained.

The optimized design variables of the hybrid system for two scenarios are given in Table IV. In the first design scenario, $\lambda_1$ is assumed to be equal to $\lambda_2$ which means an indifference to cost and availability. For the second design scenario, more weight is given to the availability than cost ($\lambda_1 = 0.3$, $\lambda_2 = 0.7$) in the $u(Cost, A)$ function. As expected, inspection of the Pareto

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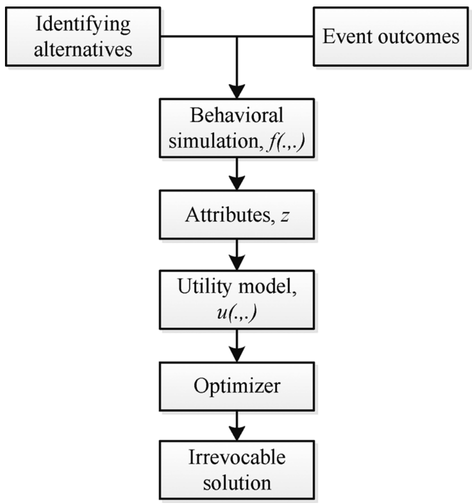


Fig. 8. Decision model without uncertainty.

TABLE IV
OPTIMIZED HYBRID SYSTEM DESIGN VARIABLES FOR TWO SCENARIOS WITHOUT UNCERTAINTY

| Design Scenario | $A_{PV}$ ($m^2$) | $A_{Wind}$ ($m^2$) | $P_{Cap\_Batt}$ (kWh) | Ψ | A | Cost |
|---|---|---|---|---|---|---|
| 1 | 2102.61 | 376.74 | 248.78 | 13% | 98.5% | $1,164,523 |
| 2 | 2911.95 | 662.8 | 395.31 | 17% | 99.3% | $1,526,928 |

Front of the optimal solutions of the system (Fig. 7), reveals that the cost of the system increased significantly.

*B. Decision With Uncertainty*

A normal probability distribution is assumed over the attribute vectors. The solar insolation, wind speed, and demand have the following normal distribution:

$$\varepsilon_{PV}, \varepsilon_{Wind} \sim N(0, 0.2) \tag{22}$$

$$\varepsilon_{Demand} \sim N(0, 40). \tag{23}$$

Now their corresponding parameter in system modeling should be modified as:

$$P_{Wind} = (P_{WTG} + \varepsilon_{Wind}) \times A_{Wind} \times \eta_{Wind} \tag{24}$$

$$P_{PV} = (Insolation + \varepsilon_{PV}) \times A_{PV} \times \eta_{PV} \tag{25}$$

$$P_{Demand} = (Demand + \varepsilon_{Demand}). \tag{26}$$

In order to optimize the utility function (21) under uncertainty, the expected value of the utility function must be determined. In this paper Monte Carlo is used for uncertainty propagation purpose. The proposed methodology is illustrated in Fig. 9. The simulation is performed for 100 iterations; the results are given in Table V for the two design scenarios discussed in the previous section. As shown, the cost of the system is increased significantly when considering uncertainties. Interestingly, the analysis revels similar availability comparing to results given in Table IV, but the cost of the system what is increased substantially.

It is important to note that an optimization design based on collected data does not guarantee worst case system availability. A worst case optimized system design specifying absolute limits on availability such as two days without solar insolation is possible, but will result in a larger and more costly system. Thus, the main contribution of this paper is to introduce a step by step optimization design procedure for desired availability and cost.

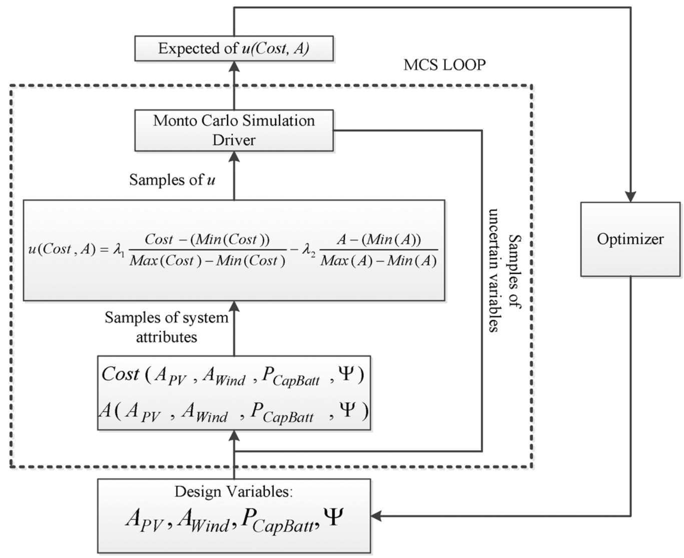


Fig. 9. Procedure of optimizing the utility function with uncertainty on sola insolation, wind speed, and demand data.

TABLE V
OPTIMIZED HYBRID SYSTEM DESIGN VARIABLES FOR TWO SCENARIOS WITH UNCERTAINTY

| Design Scenario | $A_{PV}$ ($m^2$) | $A_{Wind}$ ($m^2$) | $P_{Cap\_Batt}$ (kWh) | Ψ | A | Cost |
|---|---|---|---|---|---|---|
| 1 | 2865.33 | 711.30 | 371.80 | 21% | 97.8% | $1,477,528 |
| 2 | 3465.73 | 871.2 | 399.37 | 27% | 99.1% | $1,788,931 |

## VII. DISCUSSION

This section compares the proposed modeling approach of hybrid system for DC microgrid based on high-temporal resolution data to conventional sizing approach [21], [32] based on hourly National Solar Radiation Database (NSRDB) [33]. The histogram of power flow at the point of common coupling (Fig. 1), based on a second data set, is used for comparison and verifying the optimization technique. Fig. 10 illustrates the histogram of power flow of the conventional sizing using hourly data, and Fig. 11 illustrates histogram of power flow of the proposed multi criteria design approach based on high-temporal resolution data. The histogram of power flows are plotted for the optimization without uncertainty and design scenario 1 of Section VI.

As shown in Fig. 11, a significant unmet demand can't be seen. As mentioned in previous section, an optimization design based on collected data does not guarantee worst case system availability. The unmet demand can be further reduced by adjusting the weight factor of availability and cost in the utility function. When comparing the proposed modeling approach to conventional sizing approach, a significant further increase in the availability of the community DC microgrid as a load on the utility grid can be seen while minimizing the system cost. Operationally this means the system becomes easier to dispatch and

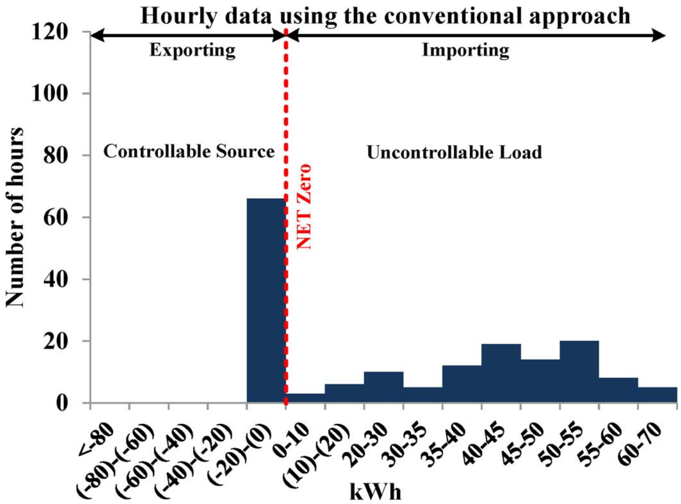


Fig. 10. Histogram of power flow at the point of common coupling for 7 days using the conventional sizing approach based on hourly data.

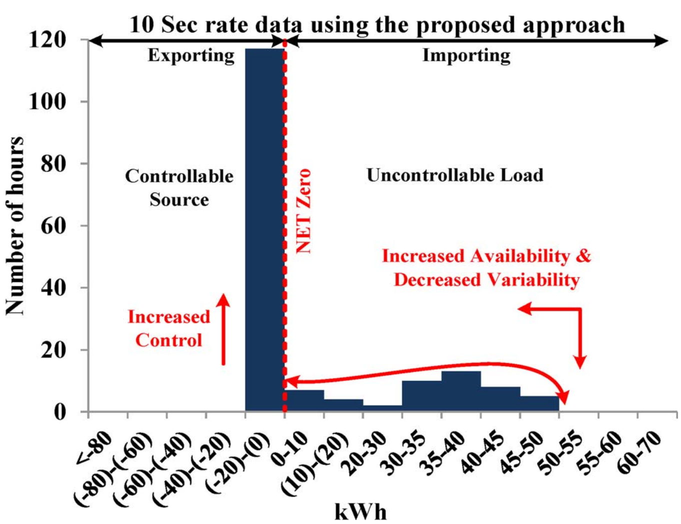


Fig. 11. Histogram of power flow at the PCC for 7 days using the proposed modeling approach based on high-temporal resolution data.

control. Overlaying the capability of a smart grid communication system, the excess energy generated, shown as "exporting" can be selectively injected into the utility grid by adjusting the power point tracking of each power sources.

## VIII. Conclusion

An important contribution of this paper is a sizing model that considers desired availability and cost simultaneously. The proposed methodology avoids oversizing the system for high percentage of availability by using accurate and enhanced high-temporal resolution data. The main objective of this paper is to provide a general model that quantifies the availability and cost of hybrid renewable energy systems for smart DC microgrid.

In this paper high temporal resolution data for PV system is used to optimize the hybrid system based on Multi-Objective Genetic Algorithm (MOGA). MOGA is used to plot the Pareto Front in order to visualize the problem for engineering tradeoff. A utility function based on availability and cost formulated to find the final optimal solution. The optimization is done for two scenarios: with certainty and uncertainty on available resource. The proposed methodology guarantees a reliable energy supply with lowest investment.

Costs for PV-Wind based renewable energy have declined steadily over the last 30 years as the technology has improved, and the trend is expected to continue. Overall, the cost differences between clean and traditional energy are less extreme than critics often imply and the differential continues to decline steadily and the proposed sizing methodology is a push in this direction by integrating the resources and load profiles with economics to provide an optimal solution which has lowest investment cost.

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