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Genetic-Algorithm-Based Optimization Approach for Energy Management

Prof. G. B. Hangaragi* and Prof. Santosh Kolaki**
**Associate professor, VSM Institute of Engineering, Nipani-591237 Belgaum*
***Associate professor, VSM Institute of Engineering, Nipani-591237 Belgaum*

(Corresponding Author: Prof. G. B. Hangaragi)
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ABSTRACT: This paper proposes a new strategy to meet the controllableheating, ventilation, and air conditioning (HVAC) load with a hybrid-renewable generation and energy storage system. Historical hourly wind speed, solar irradiance, and load data are used to stochastically model the wind generation, photovoltaic generation, and load. Using fuzzy C-Means (FCM) clustering, these data are grouped into 10 clusters of days with similar data points to account for seasonal variations. In order to minimize cost and increase efficiency, we use a GA-based optimization approach together with a two-point estimate method. Minimizing the cost function guarantees minimum PV and wind generationinstallation as well as storage capacity selection to supply the HVAC load. Different scenarios are examined to evaluate the efficiency of the system with different percentages of load shifting. The maximum capacity of the storage system and excess energy are calculated as the most important indices for energy efficiency assessment. The cumulative distribution functions of these indices are plotted and compared. A smart-grid strategy is developed for matching renewable energy generation (solar and wind) with the HVAC load.

Key words: Energy efficiency, genetic-algorithm (GA)-based optimization approach, HVAC load, probabilistic modeling, smart grid strategy, two-point estimate method.

a,b	Shape parameters for Beta distribution
Ac	Surface area of the PV array.
c	Cluster number.
C	Total number of clusters
Cp	Cost of power rating of the storage system
Cpv	Installation cost of the storage system
Cs	Installation cost of the storage system
Cw	Installation cost of wind
d	Hourly self-discharge rate of the storage System.
EE	Excess energy.
EEt	Excess energy at hour.
fx_k	PDF for the th input random variable
Gpv	Net PV output power.
Gw	Net output power of the wind generator
Gpv,t	PV power generation at hour.
Gw,t	Wind power generation at hour.
Gw,r	Wind rated power
$G`pv$	PV output power.
$G`w$	Output power of the wind generator
k	Shape parameter for Weibull distribution
Lt	Load demand at hour.
$L`t$	Modified HVAC loads at hour.
$L\,s,t$	Shifted load demand at time
P	Maximum power rating of the storage system.
$Pk,_1,Pk,_2$	Probabilities of concentrations
Pt	Power rating of the storage system at time .
S	Maximum capacity of the storage system.
St	Energy stored in the storage system at time .
t	Time.
v	Wind speed.
v_i	Cut-in wind speed.
v_o	Cut-out wind speed.
v_r	Rated wind speed
$_{Xk,1}X_{k,2}$	Concentrations of .
Xk	th input random variable
αpv	Installed capacity of PV
αw	Installed capacity of wind
δ	Percentage of HVAC load to be shifted to thenext hour.
$\acute{\eta}pv$	Efficiency of the PV power interface
$\acute{\eta}s$	Roundtrip efficiency of the storage ystem
$\acute{\eta}w$	Efficiency of the wind power interface
$\acute{\eta}`pv$	Efficiency of the PV array.
λ	Scale parameter for Weibull distribution
$\Lambda\, k,_3$	Coefficient of skewness for .
μX_K	Expected value of the th input random variable
$£_{K,1}\,£_{K,2}$	Locations of concentrations.
X_K	tandard deviation of the th input random Variable.
T	Gamma function.

I. INTRODUCTION

The.is currently increasing its use of renewable energy and decreasing its reliance on imported fossilfuels. The development of the smart grid will facilitate the integration of renewable energy sources into the power grid.Smart-grid applications include transmission, distribution, and distributed generation [1]. The "smarter" monitoring and control will create a more efficient energy-management system for residential customers. Smart-grid applications in distribution systems include smart metering technologies for efficient integration of distributed renewable generation applications, fair pricing mechanisms, remote monitoring, and home automation and control of electrical power consumption. However, the stochastic nature of PV and wind energy resources complicates theintegration of renewable generation applications. In addition, wind is often not correlated with the load pattern and may be discarded even when abundantly available [2], [3]. The U.S. Department of Energy estimates that HVAC loads account for 40%–60% of the energy consumption in U.S. commercial and residential buildings [4]. Since these time-flexible loads are deferrable for a fewminutes or hours at little or no cost, their energy consumption can be adapted according to the renewable power-supply fluctuation. This demand-side flexibility can counterbalance renewable supply variations and efficiently integrate renewable generation. Energy efficiency can be furtherincreased by storing energy when renewable power generation exceeds the load requirements then releasing it when renewable generation is insufficient to supply the load [5]. The efficiency of a hybrid system is dependent on the renewable generation efficiency,the self-discharge rates, and roundtrip efficiencies of the energy storage units, and on the sizing of the system components [6], [7]. The design, simulation, and optimization of hybrid powersystems have been the subjects of several studies [8]–[18]. Operating concepts, performance evaluation, and economic analysis of such systems were investigated in [8]–[12] where the component sizing is either arbitrary or based on practical and experimental estimates, with no attempt at optimizing their parameter values. References [13]–[17] employed a variety of heuristic optimization techniques for the optimal design and operation of the hybrid systems. However, none of these investigations focused on demand flexibility and HVAC loads,in particular, or on matching HVAC loads with renewable energy sources without the need for supplementary conventionalenerations. Reference [18] presented an optimal component-sizing framework for the hybrid system, but the stochasticnature of wind/PV generation is not considered in the modeling.Emerging smart-grid strategies can provide the distributionsystem with an opportunity to balance renewable generationand HVAC loads for a residential feeder using energy storagesystems. A smart load shifting strategy is proposed in thispaper to shift the HVAC loads based on parameters whichcharacterize the load flexibility, such as the percentage of loadto be shifted, or the deadline by which this load should be met.Unlike [13]–[17], which utilized conventional generation tocomplement a hybrid system, the proposed strategy eliminatesthe need for supplementary generation and meets the HVACload at the desired confidence level. The proposed approachuses FCM to obtain data clusters for characterizing seasonalvariations. This provides a better representation of the system'sbehavior than earlier work [8]–[18]. In addition, the proposedmethodology characterizes the uncertainties of the stochasticvariables (wind speed, solar irradiance, and HVAC load) whichare not addressed in [18]. The combination of the GA andtwo-point estimation enhances the efficiency of the hybridsystem when compared to classical optimization approaches.This paper proposes a smart-grid strategy for matchingrenewable energy generation with HVAC loads using hybridrenewable energy generation and energy storage. Section IIIexplains the new GA optimization and two-point estimationmethodology, reviews FCM clustering, and explains howit is used to cluster historical hourly wind speed/clearness index/load data. It also presents stochastic models of wind and PV generation and HVAC load based on actual data. Different scenarios are studied and their simulation results are given in Section IV. Conclusions are presented in Section V.

II. METHODOLOGY

A. Probabilistic Modeling of Generation and HVAC Load Hybrid generation systems are inherently uncertain because of the stochastic nature of wind speed, solar irradiance, and load characteristics. The uncertainties of wind/solar generation are characterized using the probability density functions (PDFs)whose statistics are obtained from historical data of wind speed and solar irradiance [19], [20]. FCM clustering is used in this paper to account for seasonal variation in the data [21].

Tenyears of historical hourly data are utilized to produce three datasets for: wind speed, solar irradiance, and load [22]. Each datapoint is specified by a membership grade between 0 and 1. Theobjective function of the FCM is to minimize the distance fromany given data point to a cluster center weighted by that datapoint's membership grade. An iterative algorithm is used to updatethe cluster centers and the membership grades for each datapoint, which moves the cluster centers to the most appropriatelocation within the data sets. The elbow method is used to determinethe number of clusters [23]. Accordingly, the days aregrouped into 10 clusters with similar 24-h wind speed, solar irradianceand load data. Maximum-likelihood estimates of thedistribution parameters are calculated for the historical hourlydata within a cluster. Each cluster is then represented by threesets of 24 individual PDFs over the 24-h period.

a) Hourly Wind Power Modeling: Wind speed is statistically modeled using the Weibull distribution [19], [20]. The PDF for a Weibull distribution is given by

$$f_v(v) = \left(\frac{k}{\lambda}\right)\left(\frac{v}{\lambda}\right)^{k-1} e^{-(\frac{v}{\lambda})^k}, \quad 0 \le v \le \infty. \qquad (1)$$

Using curve fitting, maximum-likelihood estimates of theWeibull distribution parameters are calculated for historicalhourly wind speed data. The output power of a wind generator
is a function of wind speed and given by [24]:

$$G'_W = \begin{cases} 0 & v \le v_i, v \ge v_o \\ \frac{v - v_i}{v_r - v_i} G_{W_r} & v_i \le v \le v_r \\ G_{W_r} & v_r \le v \le v_o. \end{cases} \qquad (2)$$

If the power-electronic interface has an efficiency of, $\acute{\eta}_w$ the netwind power output is given by

$$G_w = \eta_w \cdot G'_W. \qquad (3)$$

b) Hourly Photovoltaic Power Modeling: Unlike windspeed, the uncertainty of solar irradiance cannot be directlymodeled using a PDF. This is due to the fact that the solarirradiance has very strong diurnal patterns as at night time; thevalue of solar irradiance is certain to be zero [25]. Hence, thispaper uses the clearness index (k_t) to characterize solar irradiance.The hourly clearness index is defined as the ratio of theirradiance on a horizontal plane*It* (kW/m^2), to the extraterrestrial
total solar irradiance*Io*(kW/m^2)

$$k_t = \frac{I_t}{I_o}. \qquad (4)$$

The clearness index is statistically modeled using the beta distribution[20], [26]. The PDF for a beta distribution over a timeinterval*t* is given by

$$f_{ci}(k_t) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \cdot k_t^{a-1} \cdot (1-k_t)^{b-1}. \qquad (5)$$

Using curve-fitting, maximum-likelihood estimates of thebeta distribution parameters are calculated for historical hourlyclearness index data. Once the hourly clearness index is known,
the irradiance on a surface with inclinationβ to the horizontalplane is$I_\beta$calculated as

$$I_\beta = T \cdot k_t - T' \cdot k_t^2 \qquad (6)$$

where T and T' and are parameters that depend on inclination, declination,reflectance of the ground, latitude, hour angle, and sunsethour angle. The PV power output is a function of the clearnessindex and is given by [19]

$$G'_{PV} = A_c \cdot \eta'_{PV} \cdot I_\beta = A_c \cdot \eta'_{PV} \cdot \left(T \cdot k_t - T' \cdot k_t^2\right). \qquad (7)$$

If the power-electronic interface has an efficiency of ,$\acute{\eta}$pv thenet PV power output is given by

$$G_{PV} = \eta_{PV} \cdot G'_{PV}. \qquad (8)$$

The values for and are calculated using the efficiencycurves of the power converters [27], [28].

c) Hourly Load Modeling: This paper uses a Gaussiandistribution with specific lower and upper limits to model thehourly load variation [20]. Using curve fitting, maximum-likelihood estimates of its parameters are calculated for historicalhourly load data.

B. Optimization Approach Based on the GA Method

Optimization using GAs provides a powerful tool to obtainthe optimal capacity for solar energy, wind energy, and storagein a hybrid system. Generally, a set of initial solutions (initialpopulations), randomly selected from the feasible solutionspace, is used to start the GA. The fitness function is evaluatedfor each solution, and the solutions are consequently ranked.

The population then evolves through several operations, suchas reproduction, crossover, and mutation to optimize the fitnessfunction and obtain the final optimal solution. The processis repeated until a termination criterion is satisfied. This evolutionaryalgorithm is preferred to classical optimization approachesbecause it can handle the nonlinear, nonconvex, andnonsmooth optimization problem of the component sizing forthe hybrid system. The nonconvexity of the problem makes itdifficult for classical optimization methods to obtain a globaloptimum. GAs, on the other hand, globally search the domainof possible solutions for an optimal solution [29]–[31].

Several implementation provisions are considered in thispaper to avoid convergence to local minima. In this regard,the double vector representation rather than the binary oneis used for chromosome codification to guarantee mutationcoherence. Scaling the decision variables and usingmegawatts/megawatt-hours (MW/MWh), instead of kilowatts/kilowatt-hours (kW/kWh) for the components sizingkeeps the feasible solution space smaller and facilitates mutation.

A large population size is selected to increase thepossibility of convergence to the global minimum, but thissignificantly increases the computational burden. Two elitismchildren are maintained for each generation to ensure retainingdesirable solutions. The balance between crossover and mutationoffspring is kept at a desirable level by adjusting thecrossover rate around 78%.

To ensure satisfying the constraints,a large penalty factor is assigned to a solution that violates aconstraint. Enhanced system efficiency as well as the fewernumber of variables provided by the GA make it a bettersolution than classical optimization approaches for optimalcomponent sizing of hybrid systems. The parameters of the GAare given in Table III.Using historical hourly data for wind and PV generation andcooling load, we first normalize the PV and wind generationcurves by dividing them by the maximum PV and wind generation.

Next, we assign the scaling parameters αPV and αWto the normalized PV and wind curves which show the installedcapacities of PV and wind generation. We obtain the optimumscaling parameters αPV and αW as well as the storage capacityby minimizing the cost function

$$\text{Min Cost} = \text{Min}\{C_{\text{PV}} \cdot \alpha_{\text{PV}} + C_W \cdot \alpha_W + C_S \cdot S + C_P \cdot P\}. \tag{9}$$

The last two terms are the capital costs needed for installing the storage system. The total capital cost of the storage system is composed of four components: 1) the capital cost for energy; 2)the capital cost for power; 3) the system energy balance cost; and 4) the system power balance cost. The balance of system energy and power cost can be included in*Cs* and*Cp* , respectively [32].Also, the inverter-based interface cost for connecting the PV and wind to the network is considered part of *Cpv* and *Cw*. The optimization formula given in (9) is subject to severalphysical constraints on the parameters. The first constraint is an energy balance equation to guarantee that the combination of wind and PV generation meets the required HV or coolingload over the optimization period. Note that the efficiency of the storage system is always less than unity due to the losses. To compensate for these losses, additional generation is needed. Hence, the energy balance equation must be changed to the following inequality constraint:

$$\sum_{t=1}^{T} G_{\text{PV}\,t} + \sum_{t=1}^{T} G_{W,t} \geq \sum_{t=1}^{T} L_t \tag{10a}$$

$$E = \sum_{t=1}^{T} EE_t = \sum_{t=1}^{T} G_{\text{PV},t} + \sum_{t=1}^{T} G_{W,t} - \sum_{t=1}^{T} L_t. \tag{10b}$$

The next constraint guarantees an instantaneous balance betweenthe sum of the generated wind energy, PV energy, andstored energy, and the instantaneous load. The storage is charged

When*G*pv,t *+Gw,t − Lt+Ls,t ≥0* and discharged when *Gpv,t+Gw,t −Lt+Ls,t≥o* . The instantaneous energy balancein the storage system is as follows:

a) For charging

$$S_t = (1-d)S_{t-1} + \eta_S(G_{\text{PV},t} + G_{W,t} - L_t + L_{S\,t}) \quad \forall t \in T. \tag{11a}$$

b) For discharging

$$S_t = (1-d)S_{t-1} + (G_{\mathrm{PV},t} + G_{W,t} - L_t + L_{S\,t}) \quad \forall t \in T. \quad (11b)$$

Utilities often have some intelligent control over HVACloads, including agreements with consumers to shift part oftheir HVAC loads during peak load hours, if there is a problemin the operation of the transmission network. For example, NVEnergy's cool share program is associated with anapproximate145-MW remote-controlled air conditioning load. Theseloads can be dispatched by NV Energy through "raise/lower"thermostat commands as needed and may include pool pumps,refrigerators, hot tubes, etc. which "need to run" but their exacttime of operation is not critical. Load shifting can provide someflexibility regarding this problem. Since the hourly generationof wind farms and solar plants is not strictly under human control,load shifting can be useful during periods of insufficientgeneration. Implementing smart load control can reduce themismatch between renewable generation and HVAC load. Load shifting is expressed as

$$L'_t = L_t - L_{S,t} \quad (12a)$$

$$L'_{t+1} = L_{t+1} + L_{S,t}. \quad (12b)$$

To ensure that the shifted load is positive and is less than thespecific percentage of the load at each time , we need

$$0 \le L_{S,t} \le \delta \cdot L_t. \quad (13)$$

Storage systems have a minimum storage level, denoted by, that must be maintained to prolong lifetime. In addition,there is typically a maximum storage capacity that is dictated bythe size of the renewable generation units, which we denote as. The storage at time is thus governed by

$$S_{\min} \le S_t \le S_{\max}. \quad (14)$$

The upper bound is not known *a priori* and is optimallycalculated in our solution.The next constraint ensures that the capacity of the storagesystem is equal to the maximum storage capacity needed tomaintain excess energy at hour*t*

$$S = \max(S_t). \quad (15)$$

Assuming the same charge and discharge rate, the maximumpower rating of the storage unit is given by

$$P_t = G_{\mathrm{PV},t} + G_{W,t} - L_t + L_{S,t} \quad (16a)$$

$$P = \max|P_t|. \quad (16b)$$

The optimization problem can be formulated as follows:

$$\min\{f(x,u)\} \quad (17)$$

$$\text{s.t.} \quad g(x,u) = 0 \quad (18)$$

$$h(x,u) \le 0 \quad (19)$$

where f*(x,u)* is the objective function of (9); the decision variablesare (u) are αPV ,αW ; and the dependent variables(x) are EE,

$L'_t, L'_{t+1}, S_t, S, P_t, P$. The equality constraints of (18) are givenby (10b), (11a), (11b), (12), (15), and (16), while the inequalityconstraints of (19) are given by (13) and (14).We first solve a simplified optimal component-sizing problemwithout load shifting for the hybrid system using a GA mplementedin MATLAB. We then solve the same problem usingdiscontinuous nonlinear programming (DNLP) in GAMS.Table IV shows the simulation results for this problem. Comparing
the GA-based results with the DNLP demonstrates theimproved efficiency of the proposed methodology over theclassical optimization approaches.

C. Probabilistic Optimization

The randomness of wind and PV power output and loads aretaken into account by using stochastic optimization. The latteris performed using analytical methods or simulation methods[33]. Monte-Carlo simulation (MCS) is a simple and accuratesimulation method that uses historical data to determine theirPDFs. Random values from these PDFs are used to quantifythe uncertainties. The large computational effort is the mainobstacle for efficient use of this method. Several approximatemethods have been proposed to reduce the computationalburden including Taylor series expansion [34], first-ordersecond-moment method (FOSMM) [35], cumulants [36], andpoint estimation (PE) [37]. PE is a popular analytical methodbecause of its accuracy, simplicity, and speed. Two-point estimation (2PE), a variation of PE, is applied in this paper to model the uncertainties [38], [39]. Vectors of input and output
random variables and the corresponding nonlinear function are given by (20)–(22).

$$X - [\text{Wind Gen.}, \text{PV Gen.}, \text{HVAC Load}] \quad (20)$$

$$Y = [S_t, P_t, EE_t, L_{S,t}] \quad (21)$$

$$Y = h(X). \quad (22)$$

Two concentrations$f\ x_h(X_k,1,X_{k,2})of$ are used to replace$f\ x_h$by matching its first three moments. The functional relation betweenX_k and$h(X_k)$is then used to produce two estimates of variants
$(Yk,1=h(\mu\ x_1,\mu\ x_2,.....xk,_I,..\mu\ x\ _{xn-1},\mu\ x_m)i=\ 1,2)$from ($x_{k,1,}$ $x_{k,2}$).$P\ k.1$ and P$k,2$scale these estimates to compute the expected value and standard deviation of the output. Fig. 1 shows the flowchart for the proposedmethod. Ten years of historical hourly wind speed, solar irradiance, and load data are the inputs. FCM is then used to cluster these data into clusters of days with similar data points. Next, the scaling parameters (and) are initialized. The parameters of the 2PE shown in Fig. 1 are

$$\zeta_{k,i} = \sqrt{n + \left(\frac{\lambda_{k,3}}{2}\right)^2} \quad i = 1,2 \tag{23a}$$

$$\xi_{k,i} = \frac{\lambda_{k,3}}{2} + (-1)^{3-i}\zeta_{k,i} \quad i = 1,2 \tag{23b}$$

$$P_{k,i} = \frac{(-1)^i \xi_{k,i}}{2n \times \zeta_{k,i}} \quad i = 1,2 \tag{23c}$$

$$x_{k,i} = \mu_{X_k} + \xi_{k,i}\sigma_{X_k} \quad i = 1,2. \tag{24}$$

Once the 2PE parameters are calculated for the input random variables, (2), (3), (7), and (8) are used to calculate these parameters for the normalized net wind and PV power outputs. The
normalized outputs are then multiplied by the scaling parameters to calculate the hourly net PV and wind generation using vector *Z*. Note that$\mu\ x\ _k$inZ is replaced byx_ki(i=1.2), at each iteration. The power rating of the storage system at time$t(Pt)$ is then calculated by the energy-management function (EMF). *Pt* If is positive, more generation is provided, and the storage system is charged. If negative, the load exceeds generation, and the storage system is discharged to supply the excess load. If the energy stored is less than *S* min, part of the load is shifted to the next hour. If the energy stored is less thanafter the maximum-allowable load shifting (a specific percentage of the HVAC load(δ)), new scaling parameters are selected by GA to satisfy this constraint. The first and second momentsof the output variables are then calculated by

$$E(Y) \cong \sum_{k-1}^{n}\sum_{i=1}^{2}(P_{k,i} \times h([\mu_{X_1}, \ldots x_{k,i}, \ldots, \mu_{X_n}])) \tag{25a}$$

$$E(Y^2) \cong \sum_{k=1}^{n}\sum_{i=1}^{2}(P_{k,i} \times h^2([\mu_{X_1} \ldots, x_{k,i}, \ldots, \mu_{X_n}])). \tag{25b}$$

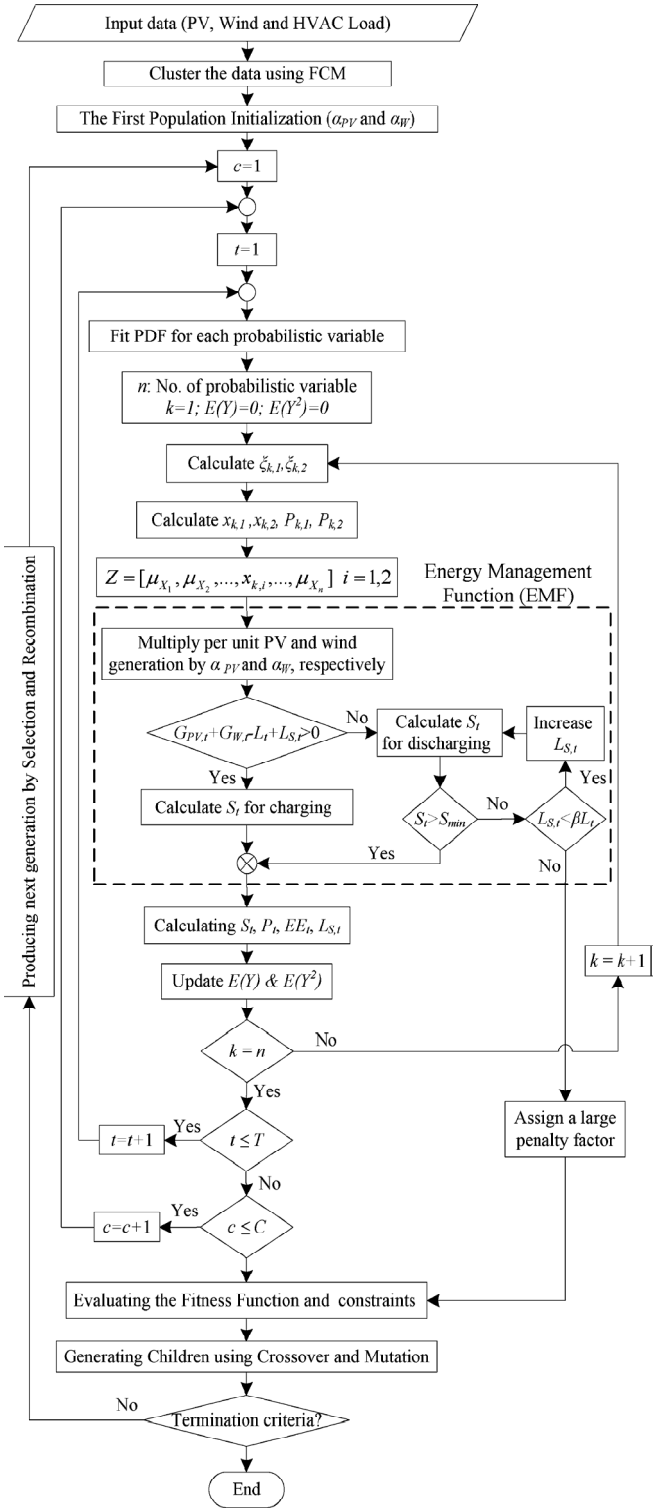
Given E(Y) and$E(Y^2)$, we calculate the mean and standard deviation of the output variables

$$\mu_Y = E(Y) \tag{26a}$$

$$\sigma_Y = \sqrt{E(Y^2) - \mu_Y^2}. \tag{26b}$$

The fitness function is then evaluated, and a confidence coefficient is allocated to the probabilistic constraints

$$P(X \geq X_{\min}) \geq \gamma. \tag{27}$$



Next, the constraints are checked for violation. If there is any violation, the violated constraints are assigned a large penaltyfactor and combined with the fitness function to give

$$f'(x,u) = f(x,u) + \nu[h(x,u)]^2. \qquad (28)$$

This combination assigns higher cost to an infeasible solution candidate than to a feasible one with the same objective valuesImplementing the crossover and mutation operators to the chromosomes, the offspring population is created and then used to produce the next generation by selection and reproduction. This evolutionary algorithm is repeated until reaching the termination
criterion. Eventually, the best chromosome is selected as the optimal solution. The fitness function of the GA is a weighted sum of the hybrid system installation costs for all of the clusters and is given by Fitness Function Cost (29)

$$\text{Fitness Function} = \text{Min}\left\{\sum_{c=1}^{C} w_c \cdot \text{Cost}_c\right\}. \qquad (29)$$

The weighting coefficient for each cluster is defined as the ratio of the number of dayswithin that cluster to the total numberof days (365 10 days). Minimizing the installation cost of the

III. CASE STUDIES

In this section, we examine two scenarios for an energy-management system combining renewable energy generation andenergy storage. The first is a simplified deterministic scenario that allows us to better demonstrate the interplay betweenstorage and renewable energy generation to meet an HVAC load. The second scenario is stochastic and includes the complexityintroduced by the uncertainties of renewable energy generation and cooling loads. We present simulation results forthe optimal GA or GA-2PE solution subject to the constraints (10.b) and (11)–(16).

A. Scenario I: Deterministic Wind/PV Generation and CoolingLoad

Scenario I corresponds to deterministic wind generation, PV generation, and cooling load for a residential feeder over asingle day [40]–[42]. The peak wind generation level is typically significantly less than the generation capacity as observedin this data set [40]. Two different cases are studied using GA-based optimization. Fig. 2 shows the hourly generationof the PV system and wind system normalized based on the maximum-installed capacities of PV and wind generation for asingle day. Fig. 3 shows the hourly cooling load for a residential feeder. Installation costs of the storage system for energy and powerare U.S.$0.2/Wh, and U.S.$0.25/W [32]. Piecewise linear costsingle day.
functions are assigned to the PV and wind eneration to calculate the associated installation costs [43], [44]. These are the averageinstallation costs of the different technologies for utilityscale (hundreds to thousands of kilowatts) systems.

The minimum-allowable charge of the storage system is 3% of its rated capacity [45]. Thisminimum charge, necessary for some storagetechnologies, is for ensuring a longer lifetime.

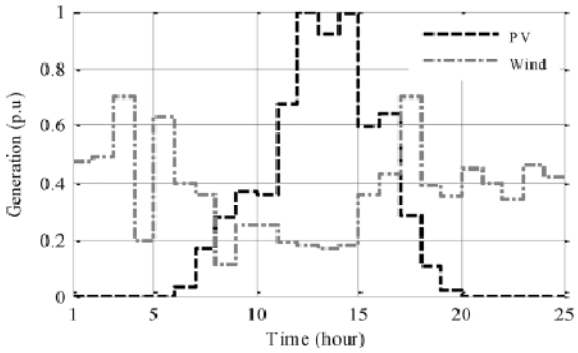


Fig. 2. Normalized hourly PV generation and wind generation.

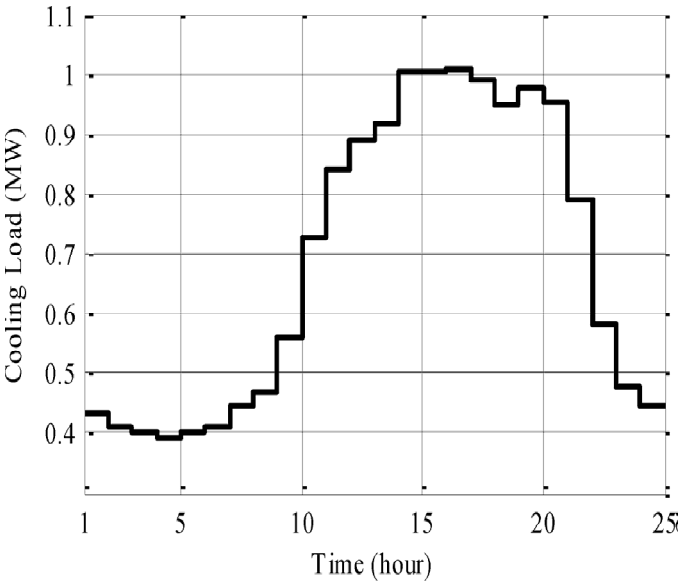


Fig. 3. Hourly cooling load of a residential feeder for a single day

Case Study I: The optimization problem is solved for the normalizedPV generation, wind power, and cooling load as shown in Figs. 2 and 3. The maximum-allowable load shifting is 30%of the load for each hour. The simulation results in Fig. 4 show that in the absence of load shifting, the modified cooling load isthe same as the cooling load during hours 1–15. Storage shows the state of charge of the storage system at each hour. At eachhour, the energy stored in the storage system at time can be calculated by adding two components; the energy stored in thestorage system at time reduced to account for discharge over one hour, and the excess energy given by the differencefunctions are assigned to the PV and wind generation to calculate the associated installation costs [43], [44].

These are the average installation costs of the different technologies for utility scale (hundreds to thousands of kilowatts) systems. The minimum-allowable charge of the storage system is 3% of its rated capacity [45]. This minimum charge, necessary for some storage technologies, is for ensuring a longer lifetime. *Case Study I:* The optimization problem is solved for the normalizedPV generation, wind power, and cooling load as shown in Figs. 2 and 3. The maximum-allowable load shifting is 30%of the load for each hour. The simulation results in Fig. 4 show that in the absence of load shifting, the modified cooling load isthe same as the cooling load during hours 1–15. Storage shows the state of charge of the storage system at each hour. At eachhour, the energy stored in the storage system at time can be calculated by adding two components; the energy stored in the storage system at time reduced to account for discharge over one hour, and the excess energy given by the differencebetween the generation and load over a 1-h period scaled to account for the roundtrip efficiency of the storage system. As shown, wind generation is always included in the optimal solution since wind installation cost permegawatt is less than PV installation cost. The storage system is charged in the early hours of the day when more energy is available and the load is low,

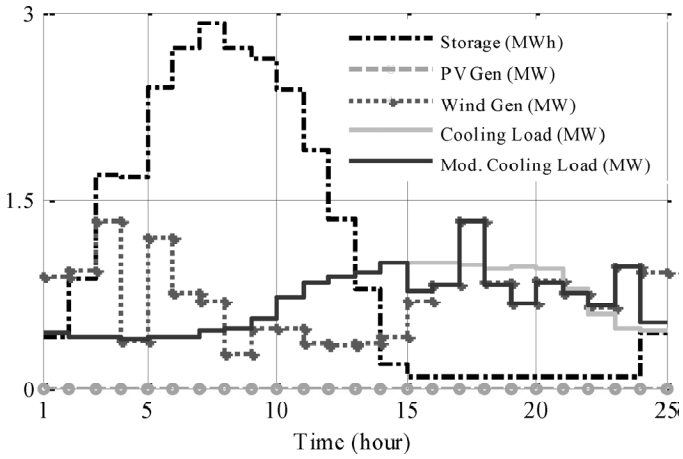


Fig. 4. Simulation result for Case Study I (Scenario I).

then releases the energy stored when the load exceeds generation. During peak hours when the wind is low and the storageis not sufficiently charged, load shifting dispatches the flexible loads to hours when the wind energy is in excess of the load.This is evident for hours 17, 22, 23, and 24 where the shifted loads are fully met. For this case study, the optimum PV, wind installation, and storage capacity are 0.0, 1.9, and 2.92 MWh (with 0.93 MW). The excess energy (i.e., the amount of energy in excess of the load) is 0.85 MWh. Total installation cost of the system is 4.615 10 (3.80 10 for wind and 0.815 10 for storage).

Case Study II:This case study evaluates the possibility of matching HVAC load and PV plants, which is particularlyimportant for regions with poor wind speed profiles and an abundance of solar energy.

The 24-h simulation periodstarts at noon when solar energy is most readily available. The optimum PV and storage capacity are 2.85 MW and 6.4MWh (with 1.81 MW), and the excess energy produced is 4.58 MWh. Total installation cost of the system is minimizedat 13.404 10 (10 for PV 1.733 10 for storage). The simulation results show that by installing more PV capacity and storage capacity, the load can be fully supplied without wind energy generation. Another observation is that the storage capacity needed for this case study is larger than Case Study I where wind energy is available during most hours of the day. This is because solar energy is only available during daylight hours and storage provides energy for the remainder of the day.

B. Scenario II: Stochastic Wind/PV Generation and CoolingLoad

Scenario II corresponds to stochastic models of wind generation, PV generation, and cooling load. PDFs are obtained fromhistorical hourly wind speed and solar irradiance using curve fitting [22]. Wind and PV power are derived based on (1)–(5).

Similarly, we calculate the maximum-likelihood estimates of the normal distribution parameters for historical hourly coolingload data for a residential feeder. GA-2PE stochastic optimization evaluates the efficiency of the hybrid system for 10%, 20%,

30%, 40%, and 50% load shifting (LS).

Case Study I: The GA-based optimization problem is solved considering the probabilistic PV generation, wind generation, and cooling load. Figs. 5 and 6 show the cumulative distribution functions of the storage capacity and of the excess energy (EE) for each LS. For and EE, the cumulative probabilities increase with load shifting. Thus, increasing the load shifting from 10%–50% providesthe system with more flexibility and reduces the storage capacity and excess energy of the system. This leads to a more efficient system with less energy dissipated due to the nonideal characteristics of the storage system.

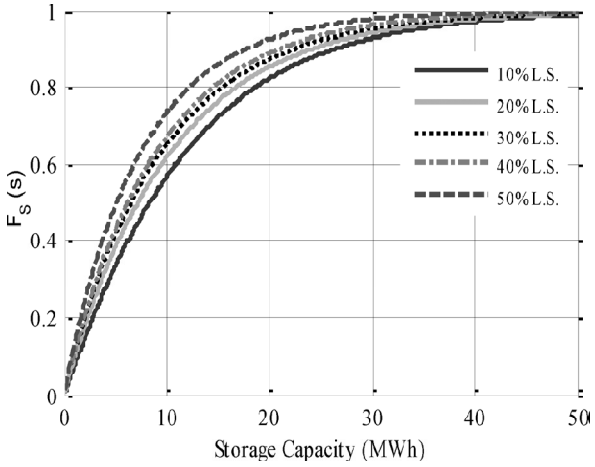


Fig. 5. Cumulative distribution of the maximum capacity of the storage system for different LS percentages (Scenario II, Case Study I).

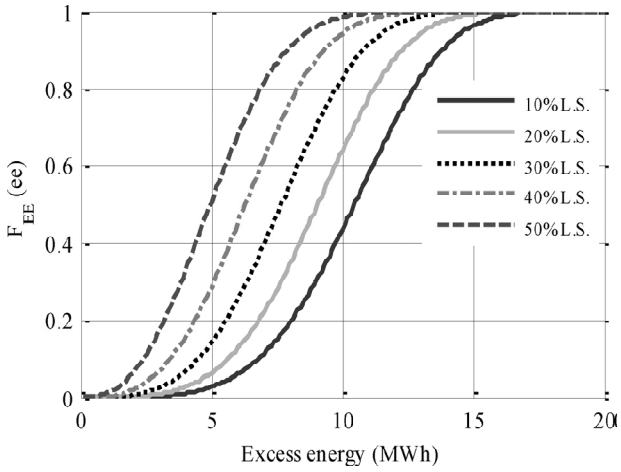


Fig. 6. Cumulative distribution of the excess energy of the system for different LS percentages (Scenario II, Case Study I).

Case Study II*:* This case study evaluates the possibility of matching HVAC load and PV plants for regions with poor wind speed profiles and an abundance of solar energy. The CDFs, of the storage capacity and of the excess energy (EE) for this case study show a similar trend to those of Case Study I and are not provided for brevity. For both S and EE,the cumulative probabilities increase with LS. Thus, increasing the LS from 10 to 50%provides the system with more flexibility. Table I gives the installed wind and PV capacity, the expected value, and standard deviation of storage capacity and excess energy. This table also provides optimal installation cost of the

Table 1: Installed Wind and Pv Capacity, Maximum Storage Capacity, and Excess Energy (Scenario Ii).

Load Shifting		10%	20%	30%	40%	50%
Case Study I	$\alpha_W(MW)$	2.611	2.478	2.347	2.219	2.096
	$\mu_S(MWh)$	11.630	10.309	9.004	7.735	6.576
	$\sigma_S(MWh)$	11.139	10.505	9.891	9.168	7.820
	$\mu_{EE}(MWh)$	10.364	9.000	7.655	6.340	5.068
	$\sigma_{EE}(MWh)$	2.712	2.563	2.421	2.255	2.110
	Wind Cost (M$)	5.222	4.956	4.695	4.439	4.191
	Storage Cost (M$)	2.510	2.232	1.955	1.685	1.441
Case Study II	$\alpha_{PV}(MW)$	3.883	3.844	3.776	3.690	3.542
	$\mu_S(MWh)$	9.114	8.968	8.728	8.429	7.919
	$\sigma_S(MWh)$	4.251	4.208	3.488	3.409	3.274
	$\mu_{EE}(MWh)$	9.131	8.871	8.426	7.855	6.880
	$\sigma_{EE}(MWh)$	2.613	2.799	2.821	2.773	2.801
	PV Cost (M$)	15.922	15.760	15.483	15.128	14.522
	Storage Cost (M$)	2.467	2.429	2.366	2.286	2.151

Table 1 gives the installed wind and PV capacity, the expected value, and standard deviation of storage capacity and excess energy. This table also provides optimal installation cost of the hybrid system for renewable energy generation and storage systems

Table 2: Hybrid System Cost For Different Risk Levels (Scenario Ii).

Risk Level (%)		75	80	85	90	95
Case Study I	Wind Cost (M$)	3.769	4.191	4.799	6.121	9.279
	Storage Cost (M$)	1.059	1.441	2.070	3.471	6.835
Case Study II	PV Cost (M$)	14.341	14.522	15.256	17.265	18.626
	Storage Cost (M$)	2.111	2.151	2.315	2.782	3.102

Table II gives the cost of the hybrid system for different risk levels. Assigning a confidence coefficient to the probabilistic constraints, risk is defined as the percentage of the random variable violating the corresponding constraint

$$\text{Risk } \% = 1-\gamma \qquad (30)$$

As shown in Table I, increasing LS from 10 to 50% decreases the expected value of from 11.630 to 6.576 MWh and decreases the expected value of EE from 10.364 to 5.068 MWh for Case Study I. The same trend is observed for Case Study II, where the expected value of decreases from 9.114 to 7.919 MWh and the expected value of EE decreases from 9.131 to 6.880 MWh as LS changes from 10% to 50%. Note that renewable energy sources have already been installed in many electric utility systems across the U.S. Therefore, the total cost of the hybrid system will be significantly reduced if these resources are already in place. The proposed methodology provides electric utilities with an energy-management tool to optimally utilize these resources and the storage systems to meet the HVAC load of the residential feeders at a desired confidence level.

Table 3: Ga Parameters.

Parameter	Population Size	Max Generation	Crossover Rate	Mutation Rate	Elitism Number
Value	200	150	78%	20%	2

Table 4: Simulation Results For Ga-Based and Classical Optimization Approaches.

Simulation Results	$\alpha_W(MW)$	$\alpha_{PV}(MW)$	*S (MWh)*	*EE (MWh)*	Total Cost (M$)
GA (MATLAB)	1.9325	0	3.383	1.148	4.7792
DNLP (GAMS)	1.9350	0	3.392	1.171	4.786

Case Studies I and II show the economic benefits of using wind power to supply the HVAC load. This is evident from the lower installation costs of the hybrid system in Case Study Iwith respect to Case Study II. In addition, optimal solutions for Case Study I require less wind power capacity than the PV power capacity of Case Study II. The simulation results summarized in Table II provide a quantitative representation of the compromise between cost and risk in the hybrid system.

IV. CONCLUSION

This paper evaluates the efficiency of a hybrid system that combines renewable energy generation and energy storage to meet a controllable HVAC load. Using historical data and curve fitting, wind and PV generation and cooling loads are stochastically modeled. FCM clustering provides ten data clusters that properly represent the effects of seasonal variations. GA-based optimization is proposed to minimize the cost and increase the efficiency. A smart-grid strategy is developed to shift the load and match the renewable energy generation and cooling load. This method is tested on a residential feeder and different case studies are carried out to investigate the factors affecting the energy efficiency of the system. The proposed procedure can be applied for any controllable deferrable load, such as the HVAC load. Simulation results show that increasing the LS percentage gives the system more flexibility and may lead to less excess energy and more efficiency. Our results show the compromise between the risk of failure to meet demand and cost for different wind and PV generation levels. Case studies demonstrate the economic benefits of using wind power to supply the HVAC load. In addition, the proposed methodology provides utility companies with an energy-management tool to optimally utilize the installed renewable energy sources and the storage system to meet the flexible loads of the residential/commercial/industrial feeders. For future work, we will apply the proposed method to matching the renewable energy sources with other controllable loads, such as plug-in electric vehicles.

REFERENCES

[1][Online].Available: http://www.ita.ucla.edu/news/presentations/Ton-UCLA1119-rv.pdfSystem Operator, CAISO report, Nov. 2007.

[2] C. Loutan and D. Hawkins, Integration of renewable resources: Transmissionand operating issues and recommendations for integrating renewable resources on the californiaiso-controlled grid California Independent System Operator, CAISO report, Nov. 2007.

[3] T. Ackermann, *Wind Power in Power Systems*. Hoboken, NJ:Wiley,2005.3

[5] Began and R. Billinton, "Evaluation of different operation strategies insmall stand-alone power systems," *IEEE Trans. Energy Convers.*, vol. **20**, no. 3, pp. 654–660, Sep. 2005.

[6] D. B. Nelson, M. H. Nehrir, and C. Wang, "Unit sizing of stand-alonehybrid wind/PV/fuel cell power generation systems," in *Proc. IEEE Power Eng. Soc. Gen.Meeting*, 2005, pp. 2115–2122.

[7] B. S. Borowy and Z. M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *IEEE Trans. Energy Convers.*, vol. **11**, no. 2, pp. 367–375, Jun. 1996.

[8] O. C. Onar, M. Uzunoglu, and M. S. Alam, "Modeling, control and simulation for an autonomous wind turbine/photovoltaic/fuel cell/ultra-capacitor hybrid power system," *J. Power Sources*, vol. **185**, no. 2, pp. 1273–1283, Dec. 2008.

[9] C. Wang and M. H. Nehrir, "Power management of a stand-alone wind/ photovoltaic/fuel cell energy system," *IEEE Trans. Energy Convers.*, vol. **23**, no. 3, pp. 957–967, Sep. 2008.

[10] S. R. Connors, J. G. McGowan, and J. F. Manwell, "Wind/diesel village-scale electric power systems: The performance and economic analysis of a simulated village system," *Solar Wind Technol.*, vol. **7**, no. 4, pp. 423–439, 1990.

[11] F. Bonanno, A. Consoli, S. Lombardo, and A. Raciti, "A logistical model for performance evaluations of hybrid generation systems," *IEEE Trans. Ind. Appl.*, vol. 34, no. 6, pp. 1397–1403, Dec. 1998.

[12] C. Abbey, J. Robinson, and G. Joos, "Integrating renewable energy sources and storage into isolated diesel generator supplied electric power systems," presented at the 13th Conf. Power Electron. Motion Control, Poznan, Poland, Sep. 2008.

[13] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Trans. Energy Convers.*, vol. **26**, no. 3, pp. 744–756, Sep. 2011.

[14] T. Senjyu, D. Hayashi, A. Yona, N. Urasaki, and T. Fumabashi, "Optimal configuration of power generating systems in isolated island with renewable energy," *Renew. Energy*, vol. **32**, no. 11, pp. 1917–1033, Sept. 2007.

[15] R. Dufo-Lopez and J. L. Bernal-Agustin, "Multi-objective design ofPV-wind-diesel-hydrogen-battery system," *Renew. Energy*, vol. **33**, no. 12, pp. 2559–2572, Dec. 2008.

[16] R. Chedid and S. Rahman, "Unit sizing and control of hybrid windsolarpower systems," *IEEE Trans. Energy Convers.*, vol. **12**, no. 1,pp. 79–85, Mar. 1997.

[17] L. Wang and C. Singh, "Multicriteria design of hybrid power generationsystems based on a modified particle swarm optimization algorithm," *IEEE Trans. Energy Convers.*, vol. **24**, no. 1, pp. 163–172, Mar.2009.

[18] S. Diaf, D. Diaf, M. Belhamel, M. Haddadi, and A. Louche, "Amethodology for optimal sizing of autonomous hybrid PV/wind system," *Energy Policy*, vol. **35**, pp. 5708–5718, Aug. 2007.

[19] G. Tina, S. Gagliano, and S. Raiti, "Hybrid solar/wind power system probabilistic modeling for long-term performance assessment," *Solar Energy*, vol. **80**, pp. 578–588, Jun. 2005.

[20] K. Zou, A. P. Agalgaonkar, K. M. Muttaqi, and S. Perera, "Distributionsystem planning with incorporating DG reactive capability and system uncertainties," *IEEE Trans. Sustain. Energy.*, vol. **3**, no. 1, pp. 112–123,Jan. 2012.

[21] J. C. Bezdek, *Pattern Recognition With Fuzzy Objective Function Algorithms*. New York: Plenum, 1981.

[22] [Online].

[23] D. J. Ketchen and C. L. Shook, "The application of cluster analysisin strategic management research: An analysis and critique," *Strat. Manage. J.*, vol. **17**, pp. 441–458, 1996.

[24] S. Roy, "Market constrained optimal planning for wind energy conversion systems over multiple installation sites," *IEEE Trans. EnergyConvers.*, vol. **17**, no. 1, pp. 124–129, Mar. 2002.
[25] Y.M. Atwa, E. F. El-Saadany, M.M. A. Salama, R. Seethapathy, M .Assam, and S. Conti, "Adequacy evaluation of distribution system including wind/solar DG during different modes of operation," *IEEE Trans. Power Syst.*, vol. **26**, no. 4, pp. 1945–1952, Nov. 2011.
[26] V. A. Graham and K. G. T. Hollands, "A method to generate synthetichourly solar radiation globally," *Solar Energy*, vol. **44**, pp. 333–341,1990.
[27] [Online]. Available: http://www.ecodirect.com/Solar-Power-Inverter-Comparison-s/247.htm
[28] [Online]. http://www.greenworldinvestor.com/topics/solar-renewable-energy-greeninvest/solar-inverters/
[29] T. Weise*, Global Optimization Algorithms—Theory and Application*,2nd ed. Hefei, China: Thomas Weise, Jun. 26, 2009. [Online]. http://www.it-weise.de/projects/book.pdf
[30] Z. Xu, Z. Y. Dong, and K. P. Wong, Transmission planning in a deregulated environment," *Proc. Inst. Elect. Eng., Gen. Transm. Distrib.*, vol. **153**, no. 3, May 2006.
[31] P. Maghouli, S. H. Hosseini, M. O. Buygi, and M. Shahidehpour, "Amulti-objective framework for transmission expansion planning inderegulated environments," *IEEE Trans. Power Syst.*, vol. **24**, no. 2, pp. 1051–1061, May 2009.
[32] T. Mosher, "Economic valuation of energy storage coupled with photovoltaic: current technologies and future projections," M.Sc. dissertation, Dept. Aeronaut. Astronaut., Mass. Inst. Technol., Cambridge, MA, June 2010.
[33] A. Schellenberg, W. Rosehart, and J. Aguado, "Cumulant-based probabilistic optimal power flow (p-opf) with gaussian and gamma distributions," *IEEE Trans. Power Syst.*, vol. **20**, no. 2, pp. 773–781, May2005.
[34] G. J. Hahn and S. S. Shapiro*, Statistical Models in Engineering*. New York: Wiley, 1967.
[35] M. Madrigal, K. Ponnambalam, and V. H. Quintana, "Probabilistic optimal power flow," in *Proc. IEEE Can. Conf. Elect. Comput. Eng.*, May 1998, pp. 385–388.
[36] W.D. Tian, D. Sutanto, Y. B. Lee, and H.R. Outhred, "Cumulant based probabilistic power system simulation using Laguerre polynomials," *IEEE Trans. Energy Convers.*, vol. **4**, no. 4, pp. 567–574, Dec. 1989.
[37] E. Rosenblueth, "Point estimation for probability moments," *Proc. Nat.Acad. Sci. United States Amer.*, vol. **72**, no. 10, pp. 3812–3814, Oct. 1975.
[38] C. Su and C. Lu, "Two-point estimate method for quantifying transfercapability uncertainty," *IEEE Trans. Power Syst.*, vol. **20**, no. 2, pp. 573–579, May 2005.
[39] G. Verbic and C. A. Canizares, "Probabilistic optimal power flow inelectricity markets based on two-point estimate method," *IEEE Trans. Power Syst.*, vol. **21**, no. 4, pp. 1883–1893, Nov. 2006.
[40] [Online]. http://transmission.bpa.gov/business/operations/wind/
[41] [Online]. http://www.nrel.gov/eis/pdfs/uwig_spring_2011_speckman.pdf
[42] Alternative sectoral load shapes for NEMS, Aug. 2001.
[43] G. Barbose, N. Darghouth, R. Wiser, and J. Seel, Tracking the Sun
[44] R. Wiser and M. Bolinger, U.S. Dept. Energy, "2010 Wind Technologies Market Report," Jun. 2011.