OPTIMAL OPERATION OF HYBRID PV/FUEL CELL SYSTEM WITH FOCUS ON UNCERTAINTY MODELLING

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Abstract – This paper presents a stochastic programming approach for calculating the operating cost of an autonomous photovoltaic-fuel cell power system with battery storage under uncertainties. The significant uncertainties include the electrical and thermal demand of a single household and the power generation capability of the photovoltaic. A new uncertainty modeling technique using particle swarm optimization is proposed to improve the quality of the stochastic solution. The system is modeled as a multi-stage nonlinear mixed-integer stochastic cost model and is solved using adaptive particle swarm optimization.

Keywords: Autonomous Power System, Hybrid PV-Fuel Cell System, Particle Swarm Optimization, Random Process, Scenario Tree, Stochastic Programming, Uncertainty Modeling

1 INTRODUCTION

The growing concern about global warming and the huge incentives for renewable energy generation from government policies have prompted residential consumers to opt for the most elegant and environmentally benign energy sources like photovoltaic and the fuel cell. This paper proposes an optimization approach to reduce the daily operating costs of an autonomous hybrid PV/Fuel cell system with energy storage device supplying a residential load under demand and generation uncertainties. An economic model describing the various production costs of energy and the associated operating constraints of the hybrid system is developed. The uncertainties associated with the economic model are the electrical & thermal demand of the single residential house and the generation capacity of the PV.

The generation capacity of the PV depends to a great extent on the insolation and temperature. The electrical & thermal demand is very sensitive to climatic changes. The total daily energy consumption of a single household can be estimated to some extent from historical data. But the daily load profile is highly unpredictable. The average load profile depends on the type of the day, the number of inhabitants and their availability at each hour and also on their life style. Since these dependencies can not be mathematically modeled, the evolution of these variables should be considered as random processes. All possible outcomes of these random processes should be taken care while planning for the optimal operation of the hybrid system. The evolution of these random processes which represents the future realizations of the uncertainties is modeled as a suitable scenario tree [1]. Each scenario is an instance of the future realizations for the uncertainties. This tree gives the complete information of the uncertainties prevailing in the cost model. The better the scenario tree, the better will be the stochastic solution for the cost model.

A very huge number of scenarios are required to completely describe the stochastic nature of these uncertain variables. This huge set of scenarios should first be reduced without losing the information. The currently available scenario reduction techniques [2] could not handle this enormously huge number of initial scenarios. Hence a new method is proposed to solve this problem and also to improve the quality of the scenario tree, reduce the modeling error and improve the stochastic solution.

This method starts with a fixed number of scenarios and explores the entire search space until it finds the best set of scenarios. The reduction technique is formulated as an optimization problem and is solved using the particle swarm optimization method (PSO). PSO [3], [4] is a population based searching algorithm. It consists of particles (solution to a given problem) which explore the entire search space until it finds the global solution. But for scenario reduction technique, the objective of the optimization is to maximize the fitness of each particle. Here each particle represents a scenario. The fitness of each particle is the minimum weighted Euclidean distance from the other particles in the swarm. The particle's flight is influenced by its own performance as well its nearest neighbour. The particles are guided so as to move away from their neighbours and thereby increasing their fitness value. Towards the end of the optimization process, the particles are distributed in the search space so that the distance from their neighbours is significant. Since the particles represent the scenarios, we are left with only the distinct scenarios.

The scenario tree modeling transforms the cost model into a multistage nonlinear stochastic cost model. The aim of this stochastic model is to minimize the average operating costs over this scenario tree. The resulting stochastic model is solved without decomposition [5], [6] by stochastic programming approach using adaptive particle swarm optimization technique [7].

2 PROBLEM FORMULATION

2.1 Deterministic Model

The deterministic cost model consists of a photovoltaic (PV), fuel cell, gas boiler and a lead acid storage battery supplying both electrical and thermal energy to a single household. The planning horizon is of 24 hours and is split into 24 equal subintervals. The operation cost of the system consists of the daily fuel cost (DFC), start-up cost (STC), maintenance cost (MC) of the fuel cell and the cost of gas (CG) for the boiler. The boiler operates only then the fuel cell could not meet the thermal demand. There are no costs involved in the operation of the PV and the battery storage.

The daily fuel cost (DFC) includes the natural gas price (C_{FC}) for generating active power P and the cost of the power used by the auxiliary devices (P_a) and is formulated as shown below:

$$DFC = C_{FC} U_t \frac{P_t + P_a}{\eta_t} \quad (1)$$

Here $U_t \in \{0, 1\}$ indicates the commitment decision (1 if on, 0 if off) variable of the unit at time t. The fuel cost [8] is dependent on the efficiency (η) of the fuel cell which is a polynomial function of the active power generation.

$$\eta = 0.4484 - 0.05359 P_t + 0.01267 P_t^2 - 0.00182 P_t^3 \quad \text{for all} \quad P^{min} \le P_t \le P^{max} \quad (2)$$

The start-up cost, STC (3) depends on the hot and cold start-up costs (α, β) and the off time of the unit. The maintenance cost, MC (4) is proportional to the power generation and is therefore constant for kWh.

$$STC = U_t (1 - U_{t-1})(\alpha + \beta(1 - e^{\frac{-T_{t,off}}{\tau}})) \quad (3)$$

$$MC = K_{MC} P_t \quad (4)$$

The operation cost, CG of the boiler is modeled as follows:

$$CG = C_G \max(D_{th,t} - P_{th,t}, 0) \quad (5)$$

Where C_G is the gas price, $D_{th,t}$ is the thermal demand and $P_{th,t}$ is the thermal power generated by the fuel cell.

$$P_{th,t} = \begin{Bmatrix} -0.0715 + 1.15 P_t - 0.0236 P_t^2 \\ + 0.0442 P_t^3 - 0.0037 P_t^4 \end{Bmatrix} \quad (6)$$

$$\text{for all} \quad P^{min} \le P_t \le P^{max}$$

The aim of the optimization is to find an operating schedule for the system with minimum operation costs. The objective function is as follows:

$$\min \sum_{t=1}^{T} (DFC + STC + MC + CG) \quad (7)$$

The unit constraints include

- The minimum and maximum unit rated capacities

  The operation levels of the fuel cell and battery are limited by the lower bounds P^{min}, BL^{min} and upper bounds P^{max}, BL^{max}.

$$P^{min} U_t \le P_t \le P^{max} U_t \quad (8)$$

$$BL^{min} \le BL(t) \le BL^{max} \quad (9)$$

- Ramp rates

$$P_t U_t - P_{t-1} U_{t-1} \le \Delta P_U \quad (10)$$

$$P_{t-1} U_{t-1} - P_t U_t \le \Delta P_D \quad (11)$$

  ΔP_U and ΔP_D are the upper and lower limits for the ramp rate.

- Minimum up/down time limits of the units

$$(T_{t-1}^{on} - MUT)(U_{t-1} - U_t) \ge 0 \quad (12)$$

$$(T_{t-1}^{off} - MDT)(U_t - U_{t-1}) \ge 0 \quad (13)$$

  Where T_{t-1}^{on}, T_{t-1}^{off} are the unit on and off times at interval (t-1), MUT, MDT are the minimum up and down time limits.

- Switching frequency of the fuel cell

  The maximum number of times the fuel cell can be switched on /off is controlled by the following constraint.

$$n_{start-stop} \le N_{max} \quad (14)$$

- Initial and final charge levels for the battery

$$BL(0) = BL^0 \quad (15)$$

$$BL(T) = BL^T \quad (16)$$

The charge and discharge of the battery [9] can be calculated from the following equations.

$$BL(t+1) = BL(t) - BD(t) * \eta_C \quad (17)$$

$$BL(t+1) = BL(t) - BD(t) / \eta_D \quad (18)$$

where BL_t and BL_{t-1} are the battery levels at the beginning and end of the interval t respectively, $BD(t)$ is the power delivered to/from the battery. It is positive if power is delivered from the battery and is negative if power is delivered to the battery. η_D and η_C are the battery discharging and charging efficiencies respectively.

To meet the electrical load (P_L), the system has to optimally operate in one of the following modes.

(a) Fuel cell only

$$P_{L,t} = P_t \quad (19)$$

(b) PV only

$$P_{L,t} = P_{PV,t} \quad (20)$$

(c) Battery only

$$P_{L,t} = BD(t) \quad (21)$$

(d) Fuel cell and PV supplying load

$$P_{L,t} = P_t + P_{PV,t} \quad (22)$$

(e) Fuel cell and Battery supplying load

$$P_{L,t} = P_t + BD(t) \quad (23)$$

(f) Battery and PV supplying load

$$P_{L,t} = BD(t) + P_{PV,t} \quad (24)$$

(g) Fuel cell, battery and PV supplying load

$$P_{L,t} = P_t + P_{PV,t} + BD(t) \quad (25)$$

2.2 Stochastic Extension

The deterministic model described above assumes that the information regarding the load profile and PV generation can be either estimated or forecasted. However in real time these variables can not forecasted accurately. For instance the electrical power utilization of a single household over a 24 hour planning horizon is highly unpredictable. The inhabitants may follow regular activities that involve the use of stove, oven, coffee maker, refrigerator, dishwasher, television, computer, lighting etc but the time when these devices will be used during the day can't be estimated with any degree of precision. This depends on the life-style and personal behavioral characteristics [10] of the inhabitants. These characteristics can not be mathematically modeled. The only way to model this uncertainty is to use the scenario tree analysis where all possible occurrences of the uncertainty are considered. The basic cost model has to be reformulated as a multistage stochastic cost model.

$$\min \sum_{t=1}^{T} \mathrm{E}\left(DFC + STC + MC + C_G \max(D_{th}(\omega) - P_{th,t}, 0)\right) \quad (26)$$

Where ω indicates stochasticity. The stochastic load balance equation is as follows:

$$\mathrm{PL}(\omega) = \mathrm{P_t} + \mathrm{P_{PV}}(\omega) + \mathrm{BD(t)} \quad (27)$$

This model aims at minimizing the expectation of the operating costs of the system.

3 SCENARIOS

3.1 Initial Scenarios

The significant uncertainties associated with the above cost model are the electrical, thermal demand and PV generation. They are considered as a multi-variant random process. The uncertainty is assumed to increase with time. The increase in uncertainty of electrical demand and PV generation is as shown in the following figures.

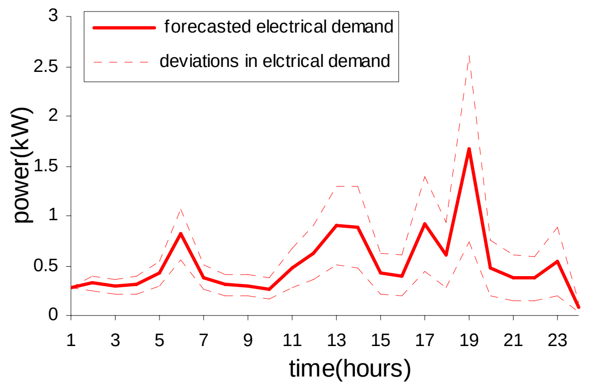

Figure 1: The evolution of the electrical demand with time

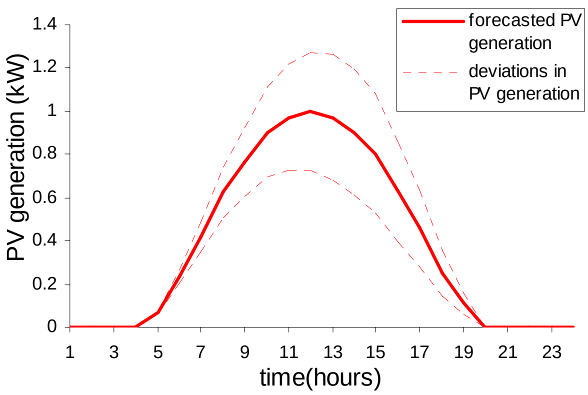

Figure 2: The evolution of the PV generation with time

The deviation of the forecasted uncertain variables (electrical, thermal demand and PV generation) is 20% and increases to 45% of the forecast with time. The bold curve in figure 1 shows the forecasted electrical demand. The other two curves show the confidence interval of the forecasted demand. The marginal distribution for each of these variables is assumed to be uniform distribution. For simplicity, each marginal distribution is approximated to five discrete samples at every time step. Hence the random process has 125 samples at each time stage. Each of these samples has equal probability. The information regarding the three random variables is completely defined at t=1. The evolution of the random process for the next 23 hours has to be modeled using scenario analysis. Hence there are 23 branching stages and the random process evolves into 23^{125} scenarios. Each of these scenarios represents a future realization of the random process. This type of uncertainty modeling results in a multistage scenario tree with 23 branching stages and 125 samples at each stage. So each node (n) of the scenario tree has 125 equally probable successor nodes (n^+). To solve this stochastic model, the random process with huge set of scenarios has to be approximated to a simple random process with finite set of scenarios and should be as close as possible to the original process.

The currently available scenario reduction techniques use heuristic methods to select the best scenarios from initial set using some probabilistic metrics. These methods could not handle the models with extremely huge number of scenarios. Hence a new technique to develop a scenario reduction algorithm for huge models is suggested. By considering all possible outcomes of the random process, the stochastic nature of the multivariate random process can be completely captured. This will help to develop better stochastic cost models which will help in planning and operation of the system. Hence there is a need to develop such algorithm which could handle extremely huge number of scenarios.

3.2 Optimal Scenario Reduction

The scenario reduction is formulated as an optimization problem and is solved using the particle swarm optimization (PSO) technique. PSO simulates the social behavior of bird flocking or fish schooling in search of food. During their search process, the birds/fish interact with its neighbors and exchange information regarding their personal performances and behavior which helps them to find an optimal solution. PSO is initialized by a population of random solutions called particles and the population is called a swarm. The particles explore the multidimensional search space in search of an optimal solution. Their flight is guided by their own experiences and also by the social behavior of its neighbors. PSO is an evolutionary algorithm. At each iteration the position x_{jk} and velocity v_{jk} of the particles are updated by equations (28) and (29).

$$v_{jk}(t+1) = \chi(w v_{jk}(t) + \phi_1(pbest_{jk} - x_{jk}) + \phi_2(gbest_k - x_{jk})) \quad (28)$$

$$x_{jk}(t+1) = x_{jk}(t) + v_{jk}(t+1) \quad (29)$$

The velocity of particle j at k^th^ dimension depends on its previous velocity $v_{jk}(t)$, its best performance so far ($pbest_{jk}$) and on the performance of its best neighbor ($gbest_{jk}$). The inertia weight *w* controls the impact of the previous velocity on the current velocity. This is assumed to be a linear decreasing function to provide a good balance between local and global exploration capability of the particles. φ_1 and φ_2 are the acceleration coefficients which regulate the relative velocity towards local and global best particle. The constriction factor χ enables faster convergence and better exploitation of the search space. The newer versions of this algorithm are parameter free, can adapt the optimal swarm size and quite simple to implement. This makes it the best global search algorithm for engineering applications.

The scenario reduction process is formulated as an integer optimization problem. The standard optimization problems aim to find a global optimal solution. But this special optimization problem has to explore the given search space in order to improve the fitness of each particle in the swarm. The problem formulation looks similar to multi-objective optimization. For a swarm of size N_P, there are N_P objectives. The N_P objectives are the fitness values of the N_P particles. The fitness of the particle is the minimum aggregated normalized multivariate Euclidean distance from the other particles in the swarm. Which implies that as one particle changes its position; its update will affect the fitness of other particles in the swarm.

The three random variables considered in this paper are measured to the same unit but have different scales. The electrical demand has larger values compared to PV generation or thermal demand. If real coded fitness function is used for solving the problem then the distance measure will be biased. Hence the distance metric of a random variable has to be normalized by a suitable factor so that the distance measures of all the three random variables are equally valued. In real coded PSO, after the particle position is updated, each dimension of the particle has to be discretized. This discretization is much simple with integer coding.

The multivariate scenario is a realization of three random variables i.e. each node of the scenario tree represents a three dimension vector corresponding to the three random variables. The particle represents a scenario. Each dimension *p* of the scenario corresponds to *p*, *T + p* and *2T + p* dimension of the particle. Hence if the scenario happens to be *N* dimension, the corresponding particle will be *3N* dimension vector. The five discrete samples of a random variable at every time stage are normalized to integers between one and five. The lower and upper bound of the random variables at all stages corresponds to one and five respectively. The process of scenario reduction can be explained by the following steps.

Step1: Initialize the swarm

The swarm size which represents the number of preserved scenarios is fixed before the start of the reduction process. The position and velocity of each particle in the swarm is randomly initialized between the normalized lower and upper bound. The particles best performance so far measured, *pbest* is initialized to the current position.

Step2: Calculate scenario probability

Each node of the initial scenario tree has 125 successor nodes. Each successor has a transition probability of 0.008. The current swarm is visualized as a reduced scenario tree and is compared to the initial tree. If any of the successor is missing then the transition probability of that missing successor is added to its nearest neighbor. The probability of the successor node is its transition probability multiplied to its parent node probability. The node probability of the leaf node or the successor nodes of the last branching stage gives the scenario or particle probability.

Step3: Fitness evaluation

A fitness value is assigned to each particle based on its distance with its neighboring particles. Convert the position vector back to measured scale. Calculate the Euclidean distance corresponding to particle *m* from the other particles in the swarm as shown below.

$$fitness(particle^m) = \min_{q \in N_p} \pi_m \left\{ \frac{1}{N_D} \sum_{i=1}^{N_D} \frac{\left(\sum_{j=1}^{N_T} (A_{i,j}^m - A_{i,j}^q)^2 \right)^{\frac{1}{2}}}{N_i} \right\} \quad (30)$$

Here N_T is the total number of branching stages, N_P is the swarm size, $A_{i,j}^m$ is the value of the random variable *i* corresponding to particle m at j^{th} dimension in measured scale. The Euclidean distance is then normalized by N_i. Similarly the distance corresponding to other random variables is also calculated. The sum is again normalized by N_D, the total number of random variables. The aggregated distance is weighted by the scenario or particle probability π_m. The fitness of the particle will be the aggregated multivariate Euclidean distance with its nearest neighbor weighted by its probability.

Step4: Evaluate pbest and gmin

If the current fitness value of a particle is better than the current *pbest* of the particle, the *pbest* value is replaced by the current value. The position and fitness of the nearest neighbor to a particle is stored in *gmin*.

Step5: Update position and velocity

The update equations are similar to the standard PSO update equations as in (28) and (29). But the social information term in the velocity update equation is modified as shown below.

$$v_{jk}(t+1) = \chi(w v_{jk}(t) + \phi_1(pbest_{jk} - x_{jk}) - \phi_2(g\min_k - x_{jk}) \quad (31)$$

The particle's velocity is guided in the direction of its previous velocity (v_{jk}), its previous best performance ($pbest_{jk}$) and in the direction opposite to its nearest neighbor ($gmin_k$). By doing so, the particle will move farther away from its nearest neighbor. This will improve the Euclidean distance and also its fitness value. The calculated velocity is then added to the current position to obtain the new position for the particle. The real valued position vector is rounded of to its nearest integers.

Step6: check for the boundaries

Make sure that the particle is in the designated search space. If a particle crosses the boundaries, then make the particle to stay on the search space boundary.

Step7: Turbulence

During the early process of the optimization, turbulence is added in the form of velocity to each particle to avoid premature convergence. After a particles position has been updated, check if this update has degraded the fitness of the worst member of the swarm. If it does so, then the velocity of that particle is randomly initialized.

Step8: Check the exit condition

If the current iteration number reaches the maximum iteration number, then exit. Otherwise go to Step2.

The particle's fitness is improved at each iteration and towards the end of optimization process we are left with particles with best fitness values. It means we are left with best particles or distinct scenarios. The optimization process explores the entire search space or the huge set of initial scenarios to find the best set of N_p scenarios.

4 SOLUTION PROCEDURE

The deterministic cost model is solved using the adaptive particle swarm optimization (APSO). Using the above mentioned scenario tree modeling for the uncertainties, the basic cost model can be remodeled using stochastic programming approach [12], [13] as shown below.

$$\min \sum_{n \in N} \pi_n \left(\begin{aligned} & C_{FC} U^n \frac{P^n + P_a}{\eta^n} + U^n (1 - U^{n-})(\alpha + \beta (1 - e^{\frac{-T^n_{off}}{\tau}})) \\ & + K_{MC} P^n + C_G \max(D^n_{th} - P^n_{th}, 0) \end{aligned} \right) \quad (32)$$

Where, N represents total number of nodes of the reduced scenario tree. The above model is subjected to the constraints (8)-(18). The stochastic load balance equation reads as follows.

$$\mathrm{PL}^n = \mathrm{P}^n + \mathrm{P}^n_{\mathrm{PV}} + \mathrm{BD}^n \quad (33)$$

The aim of this model is to find a unit commitment schedule for the fuel cell common to all scenarios, to find an optimal operation mode (19)-(25) for the hybrid system at each time step and to minimize the expectation of the operation cost of the model over the whole scenario tree. This model is solved by stochastic programming approach using APSO. This solution technique requires a decision variable at each node of the scenario tree. Therefore the size of the optimization increases with the size of the scenario tree. APSO solves above problem without using the decomposition technique.

5 NUMERICAL RESULTS

5.1 *Deterministic Model*

The test system consists of a fuel cell (1.5kW), PV (1.5kW), gas boiler (2.5kW) and a storage battery (5kW) supplying a residential load. The objective of this deterministic optimization problem is to use the basic cost model to find the solution vectors of the fuel cell commitment schedule U, the power output levels of the fuel cell P and the battery schedule BD. There is no thermal storage, so the gas boiler will operate only when the fuel cell thermal output is unable to meet the thermal demand. The optimization is carried out at each time step of one hour, over a scheduling period of 24 hours, so that the total operating costs are minimized subjected to unit and system operating constraints. The charging and discharging efficiency of the battery is assumed to be 66%. The load profiles correspond to a single household on a working day in July at Baden-Württemberg, Germany. The insolation profile is for the month of July. The PV generation is available from 5AM to 7PM.

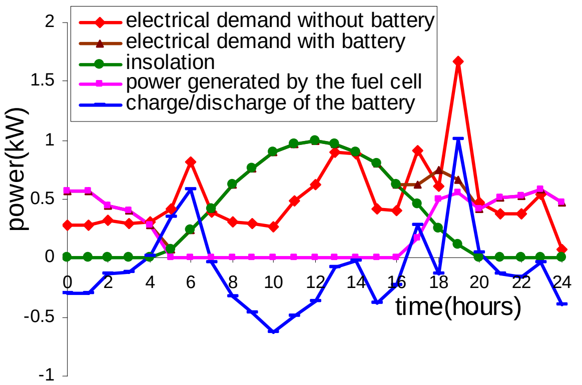

Figure 3: Hourly scheduling of PV/Fuel cell/Battery units based on deterministic optimisation

The hourly scheduling of PV/Fuel cell/ Battery system is shown in figure 3. In this figure, positive discharge BD corresponds to hours when battery is discharging, while negative discharge corresponds to charging hours of the battery. The fuel cell charges the battery during the off-peak period. The excess PV generation during the day also charges the battery. The battery supports the peak demand in the morning and evening. The use of battery smoothens the load profile. The new load profile has no peaks. This is shown by the curve with triangle bullets. The fuel cell operates in the early hours of the morning when there is no PV generation to supply the load and also to charge the battery. It is switched off when PV is in operation. In the evening when the load is high and PV generation is scarce, the fuel cell is again switched on. The total operating cost for the whole day amounts to 2.09euro or 0.16euro/kWh.

5.2 *Scenario reduction*

Unlike the conventional scenario reduction methods, the proposed method does not go through each and every scenario in picking the best scenarios. The particles use the experience gained from their exploration to select the scenarios. The algorithm needs only 100 iterations to pick the best N_p scenarios from a set of 23^{125} scenarios.

The evolution of the uncertainties is modeled as a multistage scenario tree with 23 branching stages. The scenario reduction algorithm is run with a swarm size equal to five. The performance of the particles during the evolutionary process is shown in figure 4. During

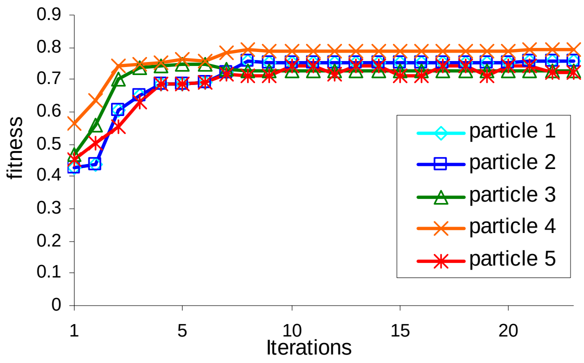

Figure 4: Performance of the particles

the first few iterations, the particle have huge improvements in their fitness value. The performance of particle 1 coincides with that of particle 2. This means that particle one is always the closest neighbor to particle two. The fitness of the particles never deteriorate. This implies that each particle has sufficient knowledge regarding the direction of motion of its neighbors and is capable of moving in a direction away from its neighbors. Thereby improving their individual performances. This algorithm therefore has the ability to select the best scenarios from a huge collection of initial scenarios.

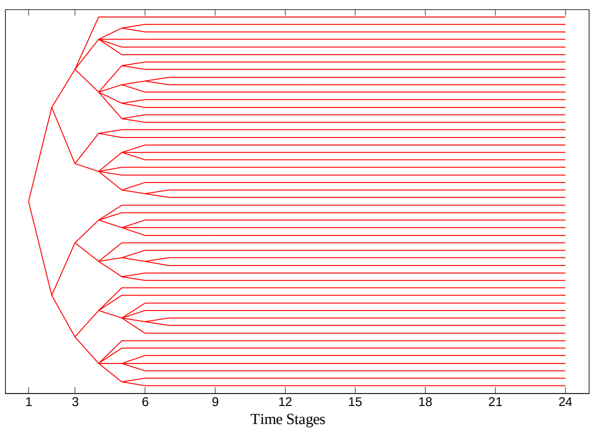

Figure 5: Scenario tree for stochastic electrical, thermal demand and PV generation generated by PSO for 24 branching stages and 5 branches at each stage.

5.3 Stochastic Extension

Multistage stochastic programming approach is used to solve the stochastic cost model. The optimization was solved using adaptive particle swarm optimization. The initial set of scenarios was reduced to fifty scenarios as shown in figure 5 using the proposed scenario reduction algorithm. This reduced set of scenarios is used in the stochastic model to represent the uncertainties. Table 1 shows the increased problem size for stochastic model. Huge forecast errors about 45% are considered for all the random variables. For this reason we need a higher rated battery and boiler although not required for the basic cost model. The unit commitment schedule of the fuel cell for the stochastic model is depicted in Table II.

	Deterministic Model	Stochastic Model
Scenarios	1	50
Binary variables (U)	24	24
Decision variables (P)	24	990
Bounds	24	990
Constraints	146	4899

Table 1: Problem dimensions

	State (Hours 1-24)
Deterministic Model	111100000000000011111111
Stochastic Model	000111000000110000111111

Table 2: Unit commitment results for basic and stochastic model

In stochastic model a single UC schedule has to satisfy all the load profile scenarios. For a scenario that has high load profiles and low PV generation, the fuel cell has to operate at high levels whereas for a scenario with low load profile, the fuel cell has to use the same UC schedule but should operate at low operating level. The operating cost associated with this model amounts to 3.06euro. The effect of uncertainties on the cost model has increased the costs by 33%. So ignoring the influence of the uncertainties would drastically effect the planning and operation of the system.

6 CONCLUSION

The proposed uncertainty modeling algorithm is a new method for handling huge number of scenarios. This provides the basis for the development of new robust modeling tools that can handle enormously huge number of scenarios. This modeling technique does not impose any restriction on the number of branching stages and number of samples at each stage. Hence this method can be used to capture the complete stochastic nature of the random process.

This paper presented a solution for a day-ahead operation of a PV-Fuel system with battery storage considering the electrical & thermal demand and PV generation uncertainties. The stochastic cost model can be used to predict a unit commitment schedule for the optimal operation of the system with unpredictable uncertainties.

The uncertainty modeling and stochastic programming approach presented in this paper can be very useful for planning and operation of the power system subjected to the influence of many uncertainties.

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BIOGRAPHIES

Venkata Swaroop Pappala received the B.E degree in electrical engineering from Faculty of Electrical engineering, Nagarjuna University, India in 2002, and M.Sc. degree in electrical engineering with emphasis on power and automation from University Duisburg-Essen, Germany in 2005. He is currently a Ph.D. student at the University of Duisburg-Essen, Germany. His research interests include stochastic optimization under uncertainty using evolutionary algorithms.

Istvan Erlich (1953) received his Dipl.-Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen/Germany. His major scientific interest is focused on power system stability and control, modelling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and senior member of IEEE.