Management of Distributed Generation Units under Stochastic Load Demands using Particle Swarm Optimization

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Abstract—**This paper presents a Particle Swarm Optimization (PSO) approach to optimize the daily electricity and heat generation in proton exchange membrane (PEM) fuel cells for residential applications under electrical demand uncertainties. The stochastic load processes are modelled as scenario trees using adaptive PSO. The resulting multistage nonlinear stochastic cost model aims to minimize the average operating costs over this scenario tree. Adaptive PSO is used to solve this model and the results are compared with the deterministic model.**

Keywords - **Distributed generation, particle swarm, stochastic optimization, uncertainty modeling**

I. INTRODUCTION

DUE to the deregulation of the energy market, distributed generation (DG) has a huge impact on electric power market. The main idea behind the use of DG [1] for residential applications is to supply electricity to customers at a competitive price. The other benefits include efficient use of electrical and thermal energy, improved power quality, increased reliability and reduced emission. Out of the many DG units such as micro turbines, wind turbines, photovoltaic cells, combustion engines and diesel engines, fuel cells have become the most competitive [2]. As fuel cells are capable of generating electrical as well as thermal energy they are a good choice for residential applications. However the high cost of electricity generated by fuel cell has restricted its use in DG. Many researchers have proved that the operating costs of the fuel cells can be drastically decreased by appropriate settings of the unit for optimal operation.

This paper presents an approach to reduce the daily total operating costs of a proton exchange membrane (PEM) fuel cell supplying a residential load under electrical demand uncertainty. A cost model [3] is developed to minimize the daily total operating costs of a fuel cell taking into account the various operating and technical constraints associated with the unit. The major issue in developing such a cost model is the representation of the underlying uncertainties. The significant uncertainties in the cost model include the electrical demand, thermal demand, cost of purchased electricity and cost of sold electricity. In this paper the fuel cell is modelled taking into account just the stochastic electrical demand. Even a slight variation of the temperature results in a huge variation of the electrical demand. So the electrical load demand cannot be forecasted accurately and is therefore a random process. The evolution of this random process i.e. all future realizations of the electric demand, is modelled as a scenario tree [4], where each scenario represents an instance of the future realizations. The scenario tree is visualized as a set of nodes. It starts with a root node at stage one. The information at this node is completely defined. The root node then branches of into several successor nodes. The tree progresses until the end of the planning horizon. The nodes at this stage are called the leaf nodes. The number of scenarios corresponds to the number of leaf nodes. The scenarios together with the node probabilities thus form a good discrete approximation of the uncertain load demand. The conventional scenario tree generation methods pose a restriction on the number of branching stages and the number of samples at each stage. Due to the restriction on these key parameters the stochastic model does not replicate the real model and there is a huge modelling error. To overcome these barriers a new approach of generating scenario trees using adaptive Particle Swarm Optimization (PSO) is presented. The conventional methods start with an initial bulk tree and then reduce the insignificant branches to reduce the tree. In the new approach the tree generation starts with a single scenario and then adds the best branches to generate the scenario tree. There is no need for the initial bulk tree and hence no restrictions on the key parameters.

The scenario tree modelling transforms the cost model to a stochastic multistage nonlinear mixed integer model. Such a model can be solved without decomposition using adaptive PSO technique. PSO is an efficient tool for handling nonlinear, non-differentiable and multi-model problems. It can handle continuous as well as discrete variables. It has been successfully tested on numerous applications such as function minimization, training Neural Network weights etc.

The paper is organized as follows. The next section presents the deterministic economic model of the PEM fuel cell. A PSO algorithm is introduced in section III. In section

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IV, fuel cell modelling under stochastic load demands is discussed. The optimization results are presented in section V.

II. PEM Fuel Cell: Deterministic Economic Model

A. Objective Function

The following fuel cell model has been taken from [3]. The objective function aims to minimize the daily total operating costs of a fuel cell taking into account the following assumptions:

- The fuel cell will supply both electrical and thermal power to the load
- There is a possibility to sell back the excess electricity at different tariffs. These tariffs are always lower than those of the purchased electricity
- A part of the generated power is utilized by the auxiliary devices.

The objective function is developed according to the above mentioned assumptions in the following form.

$$DOC=DFC+DCPE-DISE+DCPG+O\&M+STC \qquad (1)$$

Where:

DOC :Daily total operating cost ($)
DFC :Daily fuel cost for the fuel cell ($)
DCPE :Daily cost of purchased electricity if the demand exceeds the produced electrical power ($)
DISE :Daily income on sold electricity if the unit electrical output power exceeds the electrical demand ($)
DCPG :Daily cost of purchased gas for residential loads if the produced thermal power is not enough to meet the thermal demand ($)
O&M :Daily operating and maintenance cost ($)
STC :Daily start up cost ($)

The daily fuel cost is a function of generated electrical power and efficiency and is given as:

$$DFC = C_{nFC} T \sum_J U_J \frac{P_J + P_a}{\eta_J} \qquad (2)$$

Where:

C_{nFC} : Natural gas price for fuel cell ($/kWh)
T : Time duration (h)
P_J : Net electrical power produced at interval “J” (kW)
P_a : Power for auxiliary devices (kW)
η_J : Cell efficiency at interval “J”
U_J : Unit commitment at interval “J”

The efficiency of the fuel cell depends on the active power [5] and hence, a typical efficiency curve (3) is developed as a function of the electrical power and is used in (2).

$$\eta_J = 0.4484 - 0.05359 P_J + 0.01267 P_J^2 - 0.00182 P_J^3 \qquad (3)$$

The fuel cell model has a backup from the main grid system. So whenever the generated power is less than the demand, power is taken from the grid and power is fed back to the grid only when the generated power exceeds the demand. The daily cost of purchased electricity and daily income on sold electricity is given by:

$$DCPE = C_{elp} T \sum_J U_J \max(D_{el,J} - P_J, 0) \qquad (4)$$

$$DISE = C_{els} T \sum_J U_J \max(P_J - D_{el,J}, 0) \qquad (5)$$

Where:

C_{elp}, C_{els} : Tariffs of purchased and sold electricity respectively ($/kWh)
$D_{el,J}$: Electrical demand at interval “J” (kW)

The thermal output power from the fuel cell bears a nonlinear relationship with the electrical power. The thermal demand is supplied by the thermal power generated by the fuel cell and the deficit is met by burning natural gas. Therefore the daily cost of purchased natural gas for residential applications when the thermal power from the fuel cell is not enough to meet the thermal load requirements is given as:

$$DCPG = C_{nRL} T \sum_J U_J \max(D_{th,J} - P_{th,J}, 0) \qquad (6)$$

Where:

C_{nRL} : Fuel price for residential loads ($/kWh)
$D_{th,J}$: Thermal load demand at time interval “J” (kW)
$P_{th,J}$: Thermal power produced at interval “J” (kW)

The operating and maintenance (O&M) cost is assumed to be constant per kWh and hence O&M is proportional to the produced energy. The start up cost depends on the temperature of the unit and hence on the time the unit has been switched off before start up:

$$STC = \sum_J U_J (1 - U_{J-1})(\alpha + \beta(1 - e^{\frac{-T_J^{off}}{\tau}})) \qquad (7)$$

Where:

α, β : Hot and cold start up costs respectively
T_J^{off} : The time the unit has been switched off till current interval J(h)
τ : The fuel cell cooling time constant (h)

B. Constraints

The economic model of the fuel cell is subjected to the following operational and technical constraints.

Unit capacity constraints : $P_J^{\min} U_J \le P_J \le P_J^{\max} U_J \qquad (8)$

Ramp rate constraints : $P_J U_J - P_{J-1} U_{J-1} \le \Delta P_U \qquad (9)$

$$P_{J-1} U_{J-1} - P_J U_J \le \Delta P_D \qquad (10)$$

In the above equations, $P_J^{\min}$ and $P_J^{\max}$ are the minimum and maximum limits of the generated power, ΔP_U and ΔP_D are the upper and lower limits of the ramp rate, and P_{J-1} is the power generated at interval (J-1). The constraints associated with minimum up/down time limits are as follows:

$$(T_{J-1}^{on} - MUT)(U_{J-1} - U_J) \geq 0 \quad (11)$$
$$(T_{J-1}^{off} - MDT)(U_J - U_{J-1}) \geq 0 \quad (12)$$

Where T_{J-1}^{on}, T_{J-1}^{off} are the unit on and off times at interval (J-1), MUT, MDT are the minimum up and down time limits and U is the unit commitment or the on/off status. U=1 for running mode and 0 for stop mode. Finally, the total number of start-stop ($n_{start-stop}$) should not exceed a certain maximum number (N_{max}).

$$n_{start-stop} \leq N_{\max} \quad (13)$$

III. Particle Swarm Optimization

Particle swarm optimization [6]-[7] is an evolutionary computational technique developed by Kennedy and Eberhart in 1995.Unlike the other search algorithms PSO finds the optimal solution not by survival of the fittest but by a process motivated by the simulation of social behavior such as fish schooling and birds flocking in search of food. It is a population based search algorithm. It is initialized by a population of random solutions called particles and the group of particles is called a swarm. Each particle in the swarm moves over the search space with a certain velocity. The velocity of each particle as given by (14) is influenced by the particles own flying experience as well as its neighbors flying experience. The velocity of each particle depends on three terms. The first term is the inertia velocity which carries information regarding the particles previous history of velocities. The second term is the cognitive part which reflects the particles behavior with respect to its own previous experiences. The final term is the social parameter which indicates the particles behavior with respect to the experience gained from the other members of the swarm. This velocity when added to the previous position generates the current position of the particle (15). PSO solves a highly constrained problem as an unconstrained one by adding a suitable penalty function to the main objective function.

$$V_i^{k+1} = \chi(wV_i^k + c_1 r_1(P_i - X_i^k) + c_2 r_2(P_g - X_i^k)) \quad (14)$$
$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (15)$$

Adaptive particle swarm optimization technique [8] is used for all the simulations presented in this paper. An adaptive version of PSO is used for uncertainty modeling to generate the scenario tree and is also used for solving the multi-stage stochastic optimization problem. The significant feature of this algorithm is that the optimization algorithm can be used as a black box; the user has to specify just the search space, the objective function to be minimized and stopping criteria for the algorithm. The user is totally free from parameter tuning and also from the burden of selecting the most appropriate swarm (population) size.

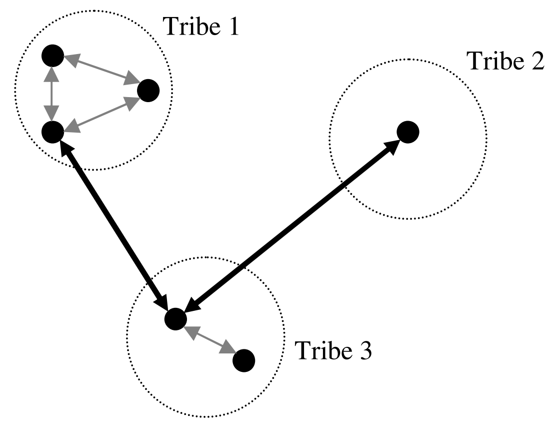

Fig. 1. Tribes of different sizes and the information links among them.

In this algorithm, different sized groups of particles called "Tribes" move about in an unknown environment in search of an optimal solution. Information links exist among the particles in a tribe. These particles collectively explore the search space to find a local minimum. Each such tribe succeeds in finding a local minimum. Information links also exist among the different tribes through which they exchange information regarding their local minimums to collectively decide the global minimum. The optimization process starts with a single particle representing a single tribe .After a few iterations if this particle does not improve its fitness, it generates a new particle forming a new tribe .After further iterations if neither of these particles improve their fitness ,each of these particles generate a particle simultaneously forming a new tribe with two particles. The process of evolution continues until the stopping criterion is met.

PSO has been chosen because it has many prominent merits over the other evolutionary algorithms. It has a high probability of finding a global minimum. The search process is faster and robust. It does not require parameter tuning.

IV. PEM Fuel Cell: Stochastic Economic Model

A. Uncertainty Modeling

The first step in solving the stochastic cost model of the fuel cell is to model the underlying stochastic electric load demands. In this case study the fuel cells supplies power to a small residential load. One cannot exactly predict when the resident will switch on the air-conditioner (peak load) or for how long the lights will be switched on. These utilizations depend totally on the weather conditions. Therefore the electric load demands of a residential utilization shows huge variations even with minute changes in the weather conditions. Hence while forecasting such load demands, they have to be analyzed quite frequently (Three to four times an hour). The uncertainty in the electrical demand increases with time. We assume that the increase is as shown in the following figure.

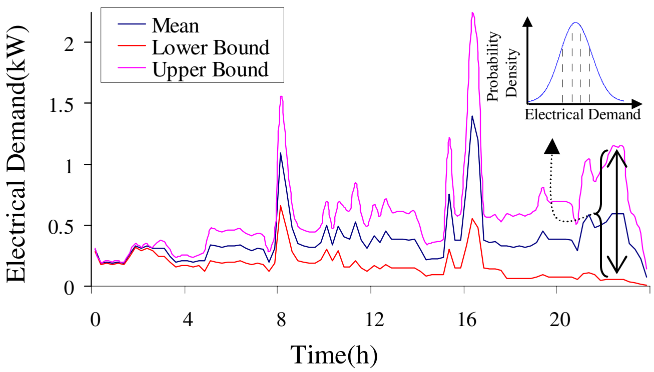

Fig. 2. Evolution of uncertainty over time.

We assume that the uncertainty evolve as a discrete random process. The evolution of this random process over time i.e. all possible future demands is realized in the form of a scenario tree with finite set of nodes as shown below.

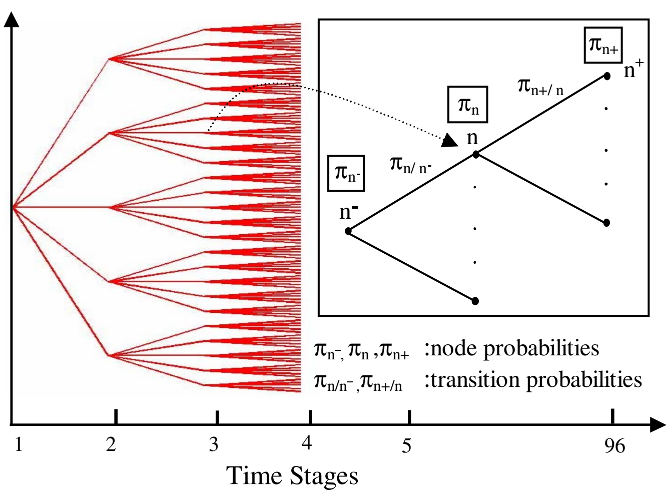

Fig. 3. Standard scenario tree with 95 branching stages and 5 branches at each stage.

Each node of the scenario tree is a decision making point. A decision involves in selecting one of the discrete approximation (e.g. the number of approximations are five for time period t=2) of the stochastic random process (Electric load demand) at that time stage. Once a decision is made at time t, the information regarding the uncertainty at time t is known only at the beginning of the next time stage t+1.The decision making process over the whole planning horizon is presented as a scenario tree. Each node (n) of the scenario tree has a unique predecessor node (n^-) and a transition probability π_{n/n^-}>0, which is the probability of n being the successor of n^-. The probability π_n of each node n is given recursively by $\pi_1=1$, $\pi_{n/n^-}*\pi_{n^-}$ for $n\neq1$.The probabilities of all the nodes at any given time stage add to one. The future research will try to associate appropriate transition probabilities for each of these samples. For the optimal operation of the fuel cell, the settings have to be updated every 15 minutes and hence for a planning horizon of 24 hours, there are 96 decision making stages. We assume that the information at stage 1(root node) is completely known. Hence there are 95 decision making stages. The uncertainty at each stage is approximated to a Gaussian distribution as shown below.

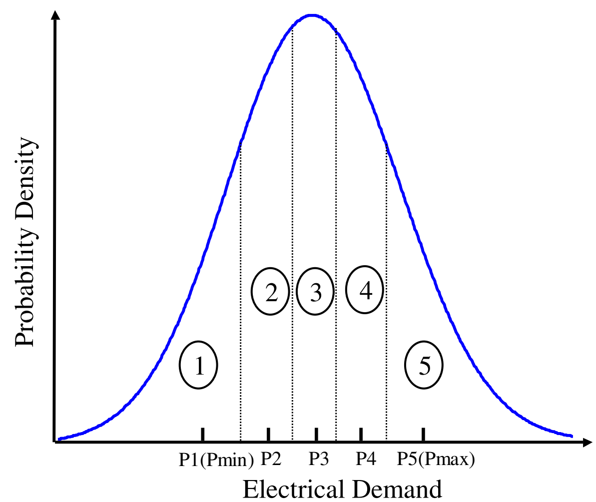

Fig. 4. Gaussian distribution of the stochastic electrical demand at a given time stage.

The distribution has a mean equal to the mean electrical demand at that stage and standard deviation corresponds to that shown in Fig. 2. The Gaussian distribution is normalized so that the sum over all possible instances of the electrical demand gives a probability of 1. The area under the curve is divided into five equal blocks. All values of the electrical demand in one region are approximated to their corresponding P value (mean value of that region) as shown in Fig. 4. For example all the values in region 2 are approximated to P2. Therefore the random electrical demand at any given node of the scenario tree is discretized into five samples of equal probability. The scenario tree therefore consists of 5^{95} scenarios. Although this huge number of scenarios completely represents the randomness of the stochastic variable, it is quite cumbersome to solve the stochastic model. The conventional scenario reduction schemes can be used to prune the original tree but as there are more branching stages, the process is very complex and time consuming. Hence a method which is totally free from such restrictions is presented in this paper.

Adaptive PSO is used to generate the scenario tree. The particle represents a scenario. The particle is a 95 dimensional vector where each dimension represents a branching stage. The tree generation process is considered as an ordinary optimization problem whose objective is to maximize the fitness of each particle given by the following equation.

$$objective = \max_{m \in N_p} fitness(particle^m) \quad (16)$$

$$fitness(particle^m) = \min_{q \in N_p} \pi_m \left\{ \sum_{k=0}^{N_T} (\pi_k^m D_k^m - \pi_k^q D_k^q)^2 \right\}^{\frac{1}{2}} \quad (17)$$

Where:

N_p :Total number of particles in the swarm
N_T :Total number of branching stages
π_m :Total Probability of particle m from root to leaf node
π_k^m :Probability of particle m at time stage k.
D_k^m :Electrical demand corresponding to particle m at stage k

The process of generating the scenario tree can be explained by the following flowchart.

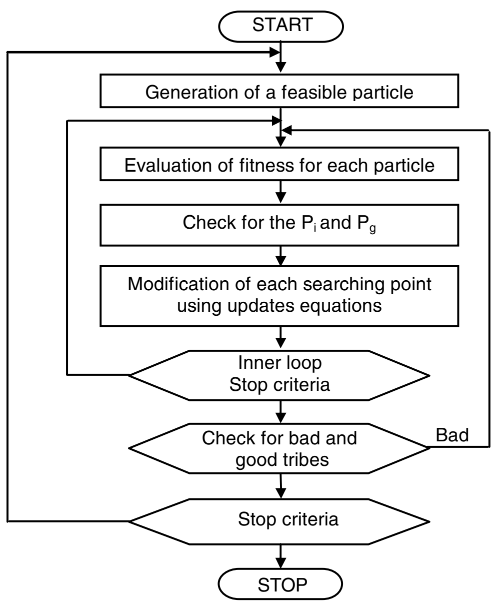

Fig. 5. Flowchart for generating the scenario tree using adaptive particle swarm approach

The process starts with the random generation of a single particle within the admissible range. The particle then enters the inner loop where a fitness value is assigned based on (17).The fitness value of a particle is the minimum weighted euclidian distance from the other particles in the swarm. Since the swarm initially has a single particle, the fitness of this particle is assumed to be the distance from a dummy particle i.e. particle representing the mean load. The best position vector (P_i) represents the best position encountered by the particle and the global best position vector (P_g) represents the best among all the particles in the swarm. Initially these vectors are set to the current searching point. In the next step the particle searching point is updated based on (14)-(15).

The inner loop is checked for the termination condition. Outside the inner loop the tribe is evaluated. During these evaluations either a new tribe is added or an existing tribe is deleted based on the performance of the existing tribes. The tribe is considered good if it has a greater number of good particles and is considered bad if it has a greater number of bad particles. A particle is considered good if any of its previous two performances are improvements and is considered bad if neither of its previous two performances are improvements. Such an adaptation creates competition among the particles of a tribe as well among the tribes. If a tribe happens to be bad, none of its particles could converge to local minima and therefore the tribe requires more particles to find an optimal solution. Therefore the tribe identifies the best particle in it and this particle would generate a new particle representing a new tribe. On the other hand a good tribe would identify the worst particle in it and removes it since this particle does not carry any significant information about the tribe. The outer loop is executed until the stopping criterion, which is usually the maximum number of function evaluations, is met. The probability of the deleted particle is added to its nearest neighbor. Towards the end of the process only those particles with significant fitness value survive. Since the particles represent the scenarios, we are left with only the distinct scenarios.

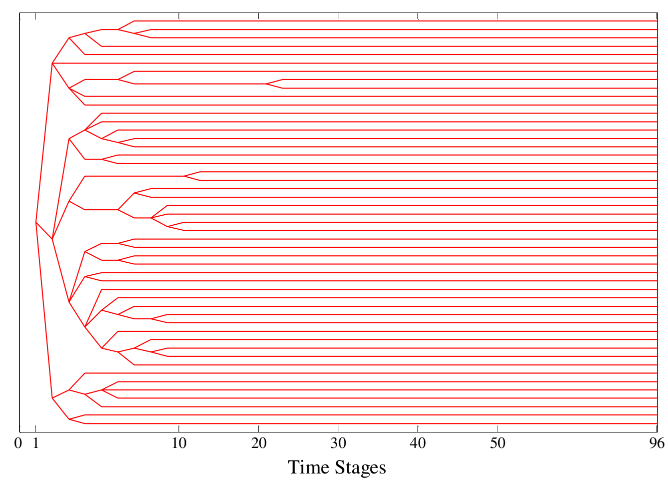

Fig. 6. Scenario tree generated by PSO for 95 branching stages and 5 branches at each stage.

B. Stochastic Optimization

With the scenario tree approach described above, the uncertainty is incorporated into the cost model of the fuel cell. The cost model is solved using multistage stochastic optimization programming. The objective of the multistage stochastic optimization problem is to minimize the expectation of the daily total operating costs of a fuel cell as shown below.

$$\min E\begin{Bmatrix} C_{nFC}T\sum_{J}U_{J}\dfrac{P_{J}+P_{a}}{\eta_{J}}+C_{elp}T\sum_{J}U_{J}\max(D_{el,J}-P_{J},0) \\ C_{els}T\sum_{J}U_{J}\max(P_{J}-D_{el,J},0)+K_{O\&M}T\sum_{J}U_{J}P_{J} \\ C_{nRL}T\sum_{J}U_{J}\max(D_{th,J}-P_{th,J},0)+ \\ \sum_{J}U_{J}(1-U_{J-1})(\alpha+\beta(1-e^{\frac{-T_{J,off}}{\tau}})) \end{Bmatrix} \quad (18)$$

The objective can be realized by minimizing the average operating costs over the scenario tree.

$$\min\sum_{n\in N}\pi_{n}\begin{Bmatrix} C_{nFC}T\sum_{J}U_{J}^{n}\dfrac{P_{J}^{n}+P_{a}}{\eta_{J}^{n}}+ \\ C_{elp}T\sum_{J}U_{J}^{n}\max(D_{el,J}^{n}-P_{J}^{n},0)+ \\ C_{els}T\sum_{J}U_{J}^{n}\max(P_{J}^{n}-D_{el,J}^{n},0)+K_{O\&M}T\sum_{J}U_{J}^{n}P_{J}^{n}+ \\ C_{nRL}T\sum_{J}U_{J}^{n}\max(D_{th,J}-P_{th,J}^{n},0)+ \\ U_{J}^{n}(1-U_{J-1}^{n^{-}})(\alpha+\beta(1-e^{\frac{-T_{J}^{n,off}}{\tau}})) \end{Bmatrix} \quad (19)$$

Where:

N :Total number of nodes

P_J^n :Electrical power produced at interval "J" and node n (kW)

$$\text{Unit capacity constraints}: P_{J}^{n,\min}U_{J}^{n}\le P_{J}^{n}\le P_{J}^{n,\max}U_{J}^{n} \quad (20)$$

$$\text{Ramp rate constraints}: P_{J}^{n}U_{J}^{n}-P_{J-1}^{n^{-}}U_{J-1}^{n^{-}}\le \Delta P_{U} \quad (21)$$

$$P_{J-1}^{n^{-}}U_{J-1}^{n^{-}}-P_{J}^{n}U_{J}^{n}\le \Delta P_{D} \quad (22)$$

$$(T_{J-1}^{n^{-},on}-MUT)(U_{J-1}^{n^{-}}-U_{J}^{n})\ge 0 \quad (23)$$

$$(T_{J-1}^{n^{-},off}-MDT)(U_{J}^{n}-U_{J-1}^{n^{-}})\ge 0 \quad (24)$$

$$n_{start-stop}\le N_{\max} \quad (25)$$

Note that the cost function (19) and constraints of (20-25) correspond directly to (1)-(13). The tree based model for N nodes involve N binary, N continuous decision variables, N bounds and 5N inequality constraints. TABLE I shows how the size of the mixed integer nonlinear problem of the scenario tree model increases with the number of scenarios.

TABLE I
SIZE OF THE SCENARIO TREE MODEL DEPENDING ON THE NUMBER OF SCENARIOS (S) AND NODES (N)

S	N	Variables		Constraints	Bounds
		Continuous	Binary		
1	96	96	96	480	96
15	504	504	504	2520	504
46	978	978	978	4890	978
125	1548	1548	1548	7740	1548

The stochastic cost model is solved using adaptive particle swarm optimization approach. Each node of the scenario is associated with two decision variables (1:optimal power generation, 2:unit commitment). Hence for a N node scenario tree, the particle represents a 2N-dimensional vector. The fitness of each particle is given by (19). The objective of the optimization process is to minimize the fitness of each particle.

$$objective=\min_{m\in N_{p}} fitness(particle^{m}) \quad (26)$$

The optimization process is the same as described by the flowchart in Fig. 4. Towards the end of the optimization, the fitness of the best particle in the swarm gives the optimal production costs of the fuel cell under demand uncertainty.

V. RESULTS OF THE OPTIMIZATION PROCESS

The adaptive PSO for scenario tree generation and stochastic optimization was implemented using visual C language. The results were computed on an Intel Pentium 4 CPU 3.00 GHz 1GB RAM. The basic C program for adaptive PSO was taken from http://clerc.maurice.free.fr/pso/#Tribes. In order to evaluate the performance of the scenario tree generation using the evolutionary algorithm, several numerical tests were conducted. Since it is quite difficult to solve the stochastic model with 5^{95} scenarios, the dominant (peak demand) branching stages t_1=33, t_2=66, t_3=90 are considered. These accounts to 5^3 scenarios. The stochastic model was solved with this standard tree and the results are compared to the scenario tree generated by PSO. The results are presented in TABLE II. The results show that the pruned tree performs similar to the initial tree .Hence the approach is a good alternative to the conventional method.

TABLE II
COMPARISON OF THE INITIAL TREE WITH THE PRUNED TREE

Type	S	N	Objective
Pruned Tree	7	294	2.165
Pruned Tree	15	504	2.180
Pruned Tree	22	624	2.200
Pruned Tree	46	978	2.252
Initial Tree	125	1548	2.327

The deterministic cost model of a 4 kW fuel cell unit was solved for the load curve in Fig. 2. The tests were carried out with C_{nFC} =0.05$, C_{elp} =0.16$, C_{els}=0.10$,$C_{nRL}$=0.09$. Under the optimal operation, the daily operating costs amount to 2.098$ while non-optimal operation (operating at 4 kW) costs 7.623$. There is a reduction of 5.525$ per day which amounts to 2016.6$ per year. In order to check the influence of uncertainty on the operating cost, the stochastic model was solved for the same set of conditions. The uncertainty was modeled as a scenario tree with 95 branching stages and 5 branches at each stage. The initial scenario tree with 5^{95} scenarios is reduced to a tree with 49 scenarios and 4468 nodes as shown in Fig. 6. The stochastic model is solved over the scenario tree. The operating cost under these conditions was 2.757$.The reduction is approximately 4.866$ per day and 1776.1$ per year. The value of stochastic solution which measures the advantage of using the stochastic model is 240.5$/year.

TABLE III
COMPARISON OF THE PRODUCTION COSTS FOR DIFFERENT MODELS

Model	Production Cost($/day)
Full capacity generation model	7.623
Deterministic mean model	2.098
Stochastic model	2.757
Non-optimal generation to meet electrical demand	2.585

The results show that considerable reduction can be made in the operating costs of the fuel cell. Hence fuel cells can be a competitive energy source for distributed generation. More over by modeling all the uncertainties prevailing in the economic model of the fuel cell, the mathematical model replicates the real fuel cell. Hence the production costs calculated in this research are approximately the same as those of the real fuel cell.

VI. CONCLUSION

This paper presented an evolutionary based approach to model the uncertainties prevailing in the cost model of the fuel cell. A new scenario tree generation algorithm using adaptive PSO is proposed. This approach is proved to be more efficient than the conventional tree generation as it has no restriction on the evolution of the scenario tree. For computational simplicity, the current model considered only the electrical demand as an uncertain variable. However the proposed approach can be extended to any number of uncertainties.

Secondly, adaptive particle swarm optimization was successfully applied to solve the multistage mixed-integer nonlinear cost model without any decomposition techniques. PSO algorithm is more efficacious in handling mixed-integer nonlinear problems. It was observed that the uncertainties had a significant impact on the daily operating costs. The computational results of such a tree based stochastic cost model were very close to the true model. Further research is required to investigate the effect of all the other uncertainties on the operating costs.

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VIII. BIOGRAPHIES

Venkata Swaroop Pappala (1981) received the B.E degree in electrical engineering from Faculty of Electrical engineering, S.V.H College of engineering, 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.