Multi-Objective Optimization for Hybrid Fuel Cells Power System Design

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Abstract

The design and optimization of fuel cells in hybrid power systems is a complex problem involving integration of various components. At conceptual level, fuel cell power system consists of four components: (1) fuel processor, (2) fuel Power system, (3) power conditioner, and (4) a co-generation or bottoming cycle to reduce utilize rejected heat. The problem involves multiple objectives such as cost, pollutant emissions and process efficiency. The conflicting nature of these objectives makes the handling of this problem an even more formidable task. The solution of a multi-objective problem is not a single solution but a complete non-dominated or Pareto set, which includes the alternatives representing potential compromise solutions among the objectives. This makes a range of choice available to decision makers and provides them with the trade-off information among the multiple objectives effectively. We present a new and efficient approach to design optimal fuel cell hybrid power systems to address this problem. This methodology for multi-objective process design consistent with almost any simulation environment is based on an algorithmic approach, which formulates the synthesis tasks as a multi-objective optimization problem. A new efficient algorithm MINSOOP has been used which results in considerable computational savings. The Pareto optimal set for a SOFC-PEM hybrid power plant have been obtained which has designs with up to 55% savings in cost, 5% reduction in CO_2 emissions and up to 12 times higher SOFC current density than the base case. This provides a great deal of flexibility to decision makers by giving an effective knowledge of the trade-offs involved.

1. Introduction

Fuel cells are an important technology for a potentially wide variety of applications including micropower, auxiliary power, transportation power, stationary power for buildings and other distributed generation applications, and central power. These applications can be used in a large number of industries worldwide. Research efforts are being made to design fuel cell plants with low emissions, high efficiencies, high performance and low costs. High efficiency hybrid fuel cell power plants are being conceptualized in order to meet the great expectations from this technology. Also, a large number of materials need to be considered in the fuel cells for obtaining the desired properties for electrolyte issues, electrode performance issues, and for different configurations. Moreover, the development in the area of new materials and other technologies where the performance and economic data is scarce and/or incomplete, calls for consideration of uncertainties in the design and optimization. Furthermore, the problem involves multiple objectives such as cost, process efficiency and pollutant emissions. The conflicting nature of these objectives makes the handling of this problem an even more formidable task. The solution of a multi-objective problem is a complete non-dominated or Pareto set, which includes the alternatives representing potential compromise solutions among the objectives. This makes a range of choice available to decision makers and provides them with the trade-off information among the multiple objectives effectively. Also, the array of materials, configurations, and other operating windows can result in a combinatorial explosion, which makes it impossible to conduct even the laboratory scale experiments to determine the limits and feasibility of technology. Hence, an integrated framework is required with the ability to, (1) model cost and environmental performance of the new technological developments, (2) integrate various components on a single platform, (3) evaluate and analyze multiple objectives and trade-offs involved and, (4) handles uncertainties and forecast system performances.

In this paper, we present the first step towards this integrated approach where we model the cost and performance of a new SOFC-PEM hybrid power plant and evaluate and analyze the trade-offs between the multiple objectives. In section 2, we discuss the salient features of the new SOFC-PEM hybrid power plant. In section 3, a novel multi-objective optimization approach is presented which is based on a new and efficient algorithm MINSOOP for multi-objective optimization and implemented in Aspen Plus simulator. This approach finds the set of Pareto optimal designs for the process where trade-offs are explicitly identified, unlike cost-benefit analysis, which deals with multiple objectives by identifying a single fundamental objective and converting all other objectives into this single currency. The results have been discussed in section 4 followed by the final conclusions of the study.

2. SOFC-PEM Hybrid Power Plant

A solid oxide fuel cell, proton exchange membrane hybrid power plant was chosen as our case study. This is a conceptual design being focus of the current research and development program at NETL [6]. As shown in Figure 1, this plant contains two fuel cells combined with a heat recovery steam generation cycle. This use of two fuel cells makes the cycle up to 37.8% more efficient than the case where only SOFC is used (maximum efficiency of 52.4%). Natural gas is used as the fuel. It is processed in a fuel pre reformer and fed to the SOFC, which acts as both electricity producer as well as a fuel reformer for PEM. The exhaust fuel from the SOFC is cooled and shifted in a low temperature

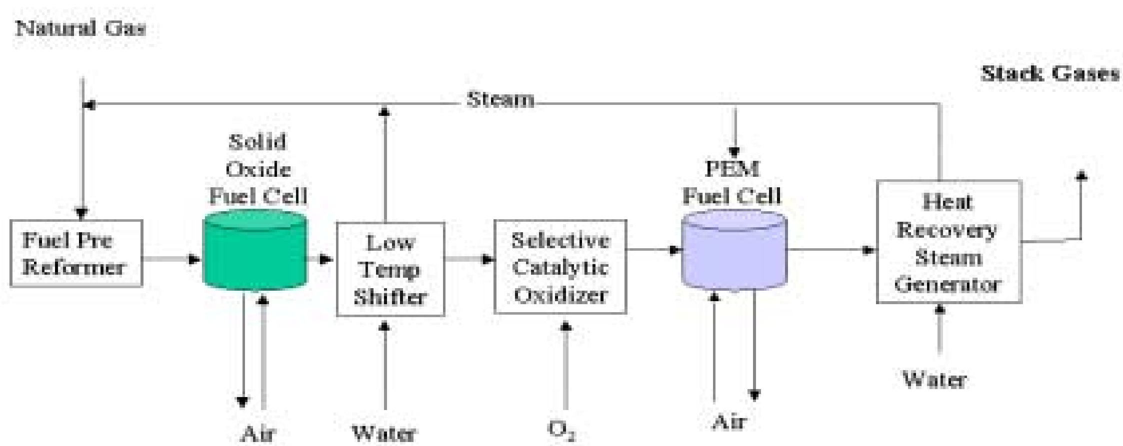

Figure 1: SOFC-PEM Hybrid Power Plant

shifter that also functions as a low-pressure steam boiler. Shifted fuel gas is then treated with pure oxygen in a selective catalytic oxidizer to reduce CO from several hundred parts per million (ppm) to below 10 ppm. The utilization of this reformed fuel is completed in the PEM where more favorable thermodynamics apply. The exhaust from the PEM cell goes to waste hydrogen burner and heat recovery steam generator to utilize the waste heat of the exhaust stream to make steam from water. This steam produced in the low temperature shifter and the heat recovery steam generator is used in both the SOFC and PEM. In the SOFC, steam is used as a reactant for the reforming and downstream shift reactions and to control against the carbon. In the PEM, steam is used to humidify fuel and air streams to maintain water balance in the electrolyte and electrodes. Design and performance for the system are summarized in Table 1.

Power Rating	1472 kW	*Overall Efficiency*	72.6 %
Capital Cost	1773 $/kW	*CO_2 Emissions*	5.61 kg/kWh
Cost of Electricity	6.35 c/kWh		
SOFC		***PEM***	
Temperature	1750 °F	*Temperature*	176 °F
Pressure	20 psi	*Pressure*	25 psi
Current Density	75 mA/cm^2	*Current Density*	190 mA/cm^2
Fuel Utilization	70%		
Equivalence Ratio	1.25		

Table 1: Base Case Design and Performance of the SOFC-PEM Hybrid Plant

Key assumptions in the advanced technology model are that staged cells can be manufactured and installed at the same cost as unstaged cells, and that a sufficient number of cells can be staged so as to closely approach the limiting case performance for staged cells.

3. Multi-objective Optimization Framework

The economic objectives along with CO2 emissions, power rating, overall system efficiency and fuel cell current densities form the set of multiple objectives to be optimized simultaneously for which multi-objective optimization is required [2,5]. Multi-objective problems appear virtually in every field and in a wide variety of contexts [1]. The problems solved vary from designing spacecrafts, aircraft control systems, bridges, vehicles, and highly accurate focusing systems, to forecasting manpower supplies, selecting portfolios, blending sausages, planning manufacturing systems, managing nuclear waste disposal and storage, allocating water resources, and solving pollution control and management problems. The solution of a multi-objective problem is not a single solution but a complete non-dominated or Pareto set, which include the alternatives representing potential compromise solutions among the objectives. This makes a range of choice available to decision makers and provides them with the trade-off information among the multiple objectives effectively.

A simple linear multi-objective optimization example is presented to illustrate the effectiveness of this method more clearly.

$$\begin{aligned} &Max \quad Z_1 = 6x_1 + x_2 \\ &Max \quad Z_2 = -x_1 + 3x_2 \end{aligned}$$

subject to :

$$\begin{aligned} 3x_1 + 2x_2 &\leq 12 \\ 3x_1 + 6x_2 &\leq 24 \\ x_1 &\leq 3 \\ x_1, x_2 &\;/\; 0 \end{aligned}$$

In Figure 2, we have plotted the two objective functions against each other. Point C on the objective space is better than B with respect to both objectives Z_1 and Z_2. However, D although has a higher value of Z_2 than C but has a lower value for Z_1. In fact, all the points on the blue line from C to D to E are not better than any other point on the line in terms of both the objective functions. This is the non-dominated or the Pareto optimal set of solutions for this

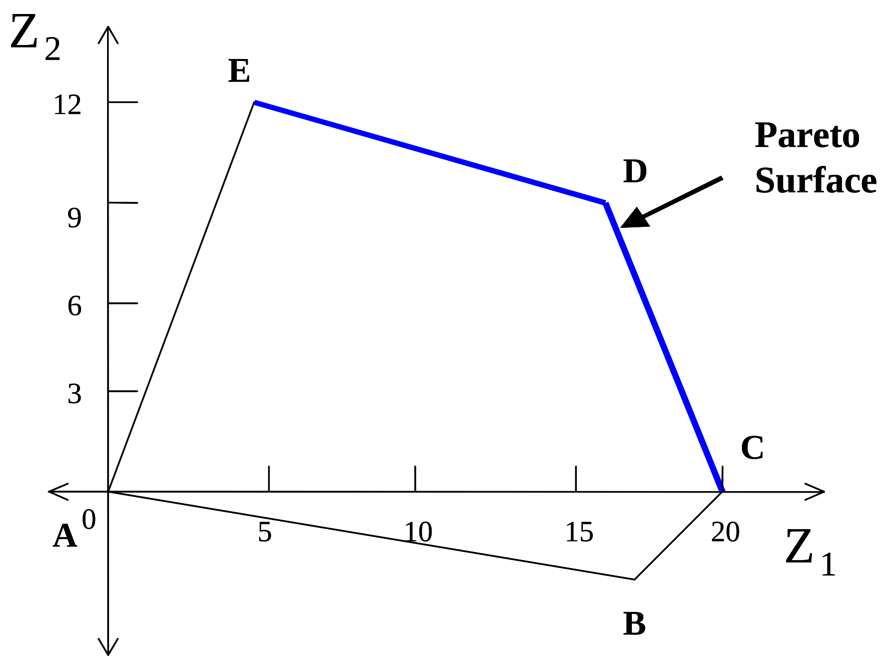

Figure 2: Multiple objectives plotted on the objective space

problem. It gives additional makers additional insights into the trade-offs among different objectives so that, depending on the preferences and existing conditions the point of operation can be chosen. This was a simple linear example but in real life situations we often encounter highly non-linear problems, which may require solving of a large number of Non-Linear Programming (NLP) problems. This can be very computationally extensive and the costs may offset the benefits provided by this approach. We have used a new efficient multi-objective optimization algorithm MINSOOP (Minimizing Number of Single Objective Optimization Problems)[3, 4]. As shown in Figure 3, in the conventional methods the number of NLP problems to be solved scales exponentially with the number of objective functions involved but it

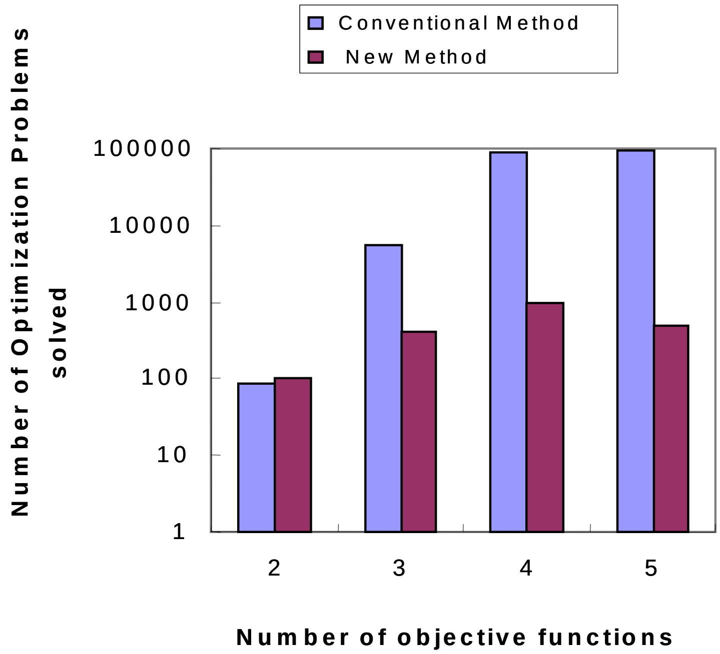

Figure 3: Conventional method vs new efficient MINSOOP algorithm

is not so with MINSOOP algorithm where we can get a good approximation of the Pareto set by solving only about 100 NLP problems. Below is the multi-objective optimization problem formulation for the current study,

Min Capital cost
Min Cost of electricity
Min CO_2 emissions
Max Current density SOFC
Max Current density PEM
Max Overall efficiency
Max Power rating
s.t. Mass & energy balance constraints
(modeled in Aspen Plus)

We have used the following multi-objective (Figure 4) to address the current problem with 7 objective functions. We give the inputs to the multi-objective optimizer, which, formulates single objective NLP optimization problems and pass them on to the NLP optimizer. The NLP optimizer gives the optimal value of the objective functions and the decision variables that is passed back to the multi-objective optimizer. This step is repeated about a 100 times until we get a good approximate of the Pareto optimal set of solutions to the problem.

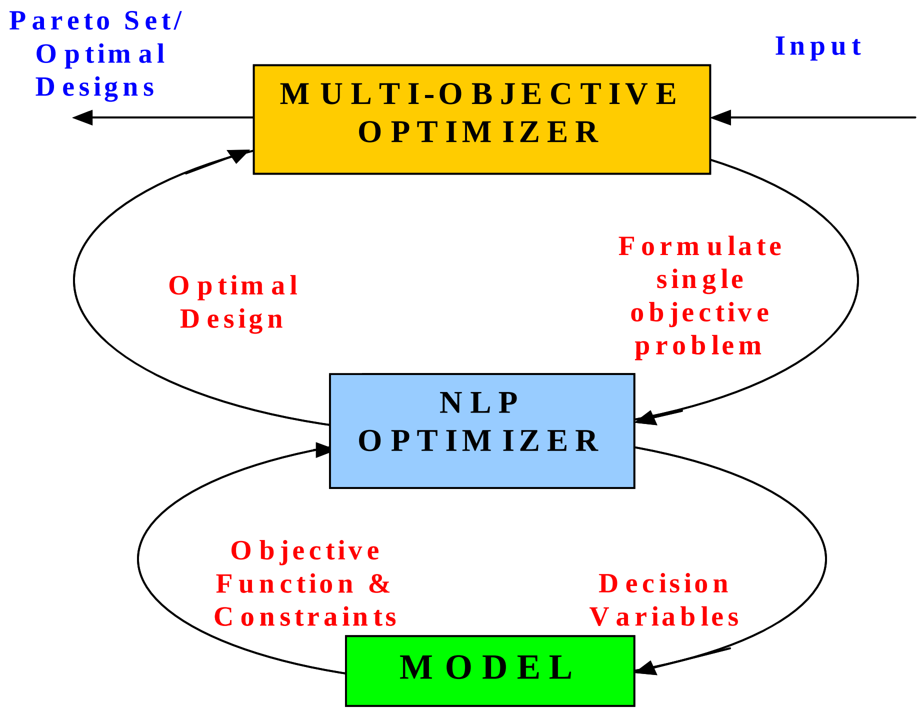

Figure 4: Multi-objective Optimization Framework

4. Results and Discussion

Figures 5-7 show the objective values of 12 different designs, which were obtained by maximizing and minimizing each of seven objectives using NLP optimizer (duplicate designs were removed). As we can see in Figure 5, both capital cost and the cost of electricity follow the same trend. They are both maximized and minimized at the same set of decision variables and hence we dropped one of the objectives and considered only one in the next stage of multi-objective optimization to reduce the problem complexity. Similarly, power rating and overall efficiency (Figure 6) follow the same trend and hence we considered only efficiency in the next stage. Although, the value of SOFC current density shows a lot of variation (Figure 7) but PEM current density remains relatively constant showing little sensitivity to the change in decision variables. Hence, we do not need to optimize it. Finally, we carry four objectives (capital cost, overall efficiency, SOFC current density and CO_2 emissions into the next stage) to the next stage of multi-objective optimization.

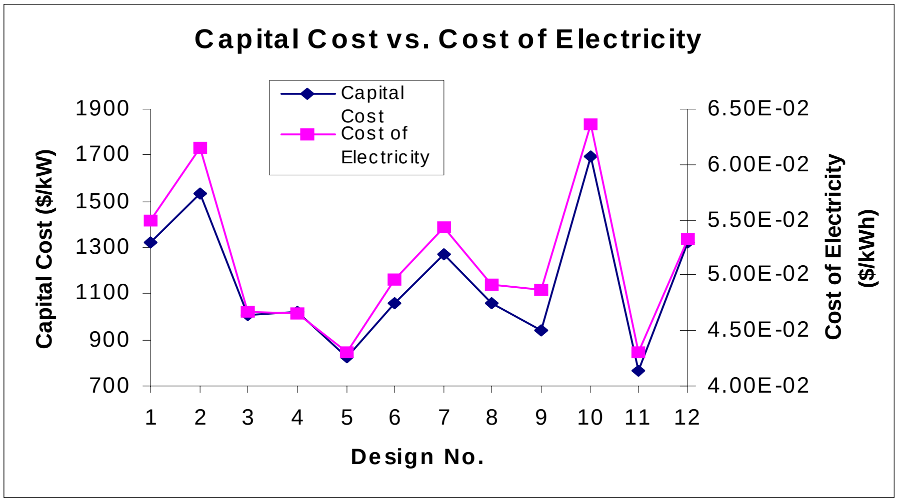

Figure 5: Capital cost and cost of electricity different SOFC-PEM hybrid plant designs

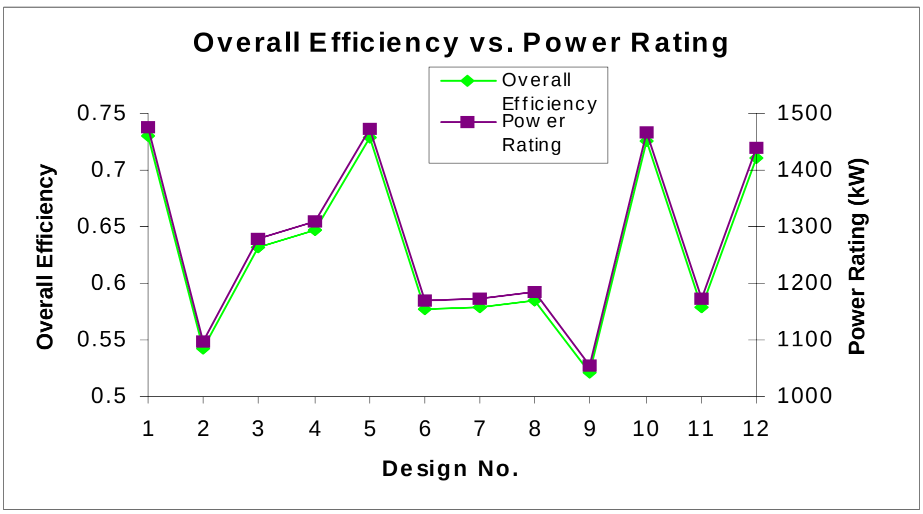

Figure 6: Overall efficiency and power rating for different SOFC-PEM hybrid plant designs

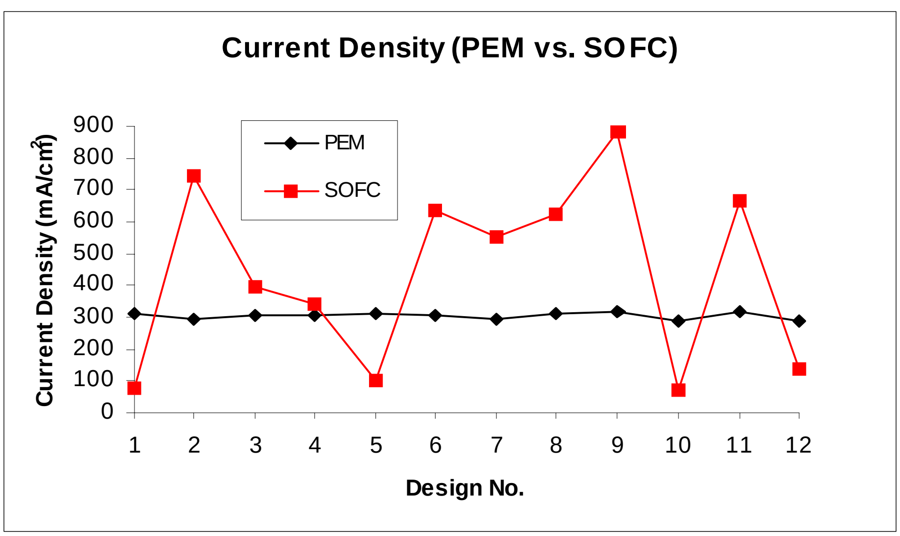

Figure 7: SOFC and PEM current density for different SOFC-PEM hybrid plant designs

The four objectives were put into the multi-objective optimization framework to obtain the approximate Pareto set of solutions. The contour plot (Figure 9) gives a representation of the trade-off solutions in the Pareto set. CO_2 emissions and SOFC current density have been plotted on the two axes of the plot and the contours represent different values of capital cost required to obtain a design with the emissions and current density values at the corresponding point. By this study we were able to obtain designs with up to 54% savings in capital cost, SOFC current density as high as up to 12 times and with up to 5% less CO_2 emissions than the base case.

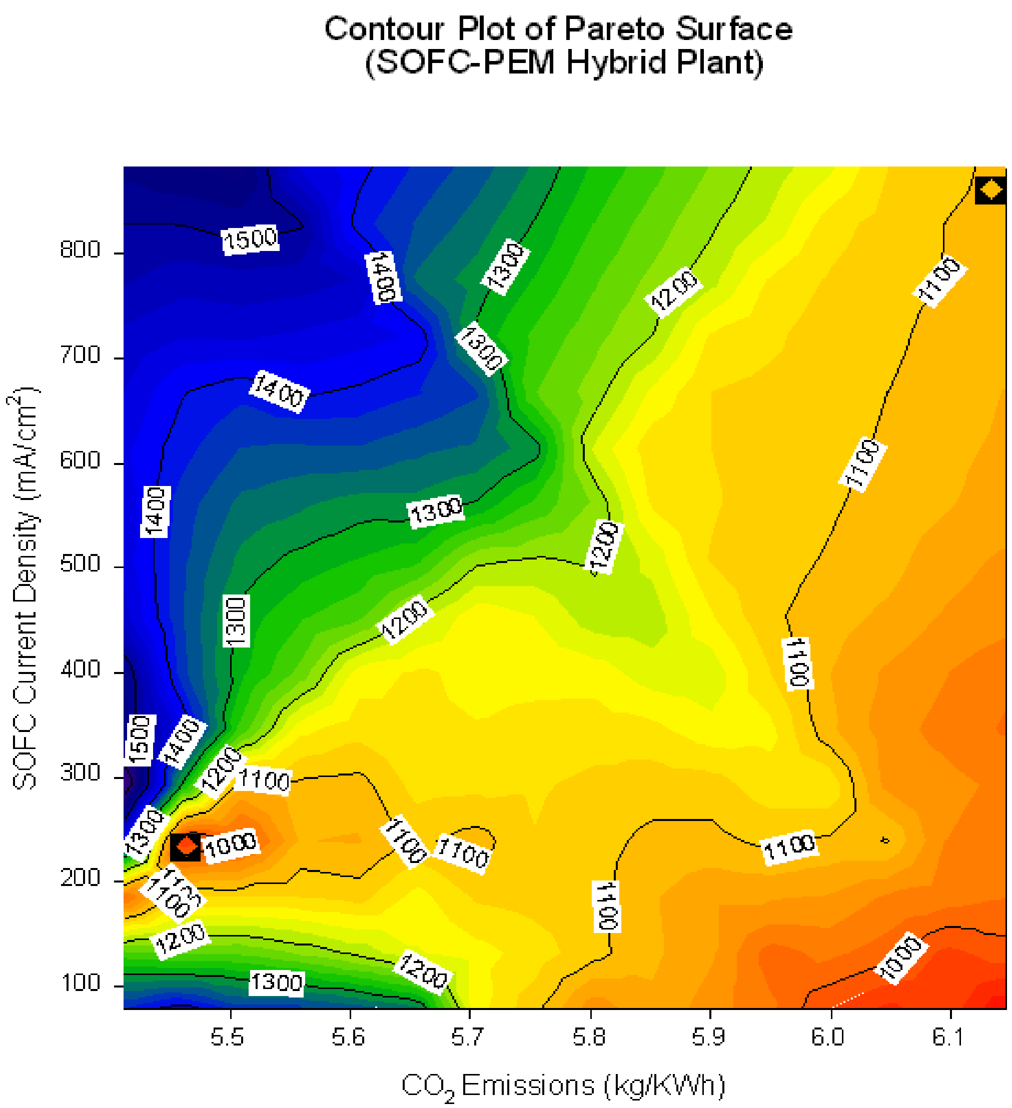

Figure 8: Contour plot of Pareto trade-off designs for SOFC-PEM hybrid power plant

This plot represents the trade-off solutions and helps in identifying several regions of operations that may not be evident intuitively. We see that it is possible to operate the plant at a low capital cost of less than $1000 /kW and still get CO_2 emissions as low as 5.46 kg/kWh of electricity produced. However, we will then have to compromise on current density. The maximum cost regions quite understandably are the ones with a high value of SOFC current density and low CO_2 emissions. However, again we can see several regions where we have a moderate capital cost $1100-1200 /kW and still get relatively good values of current density (300-700 mA/cm^2) and CO_2 emissions (5.6-6.0 kg/kWh). The little white regions near the lower left corner and the upper right corner of the plot indicate the minimum capital cost designs (54% lower than the base case). But again we can see that in one case we have to compromise heavily on SOFC current density and in the other case on emissions. The best part about this kind of representation is that given a particular value of current density or CO_2 emissions, we can easily identify the minimum cost, minimum emission or the maximum possible SOFC current density that we can achieve through this configuration. Then we can backtrack and find the values of the decision variables where we need to operate to get this kind of performance. Also, the advantage of including CO_2 emissions in our multi-objective framework is that it gives the decision maker an additional flexibility in case the emission standards change. By doing this exercise just once we can also get an idea of the different amounts of capital cost involved and achievable current densities in different geographical locations, as every location has different emission standards. Although, this picture gives several insights into the current problem but it is far from a complete representation as we can only visualize 3 objectives out of the four in our framework [7].

For getting the complete trade-off representation we normalized all the objectives to get a value between 0 and 1, such that the lower the value of the normalized objective function the better the design.

If we want to maximize objective Z, then:

$$Z_{normalized} = (Z_{UB} - Z)/(Z_{UB} - Z_{LB})$$

If we want to minimize objective Z, then:

$$Z_{normalized} = (Z - Z_{LB})/(Z_{UB} - Z_{LB})$$

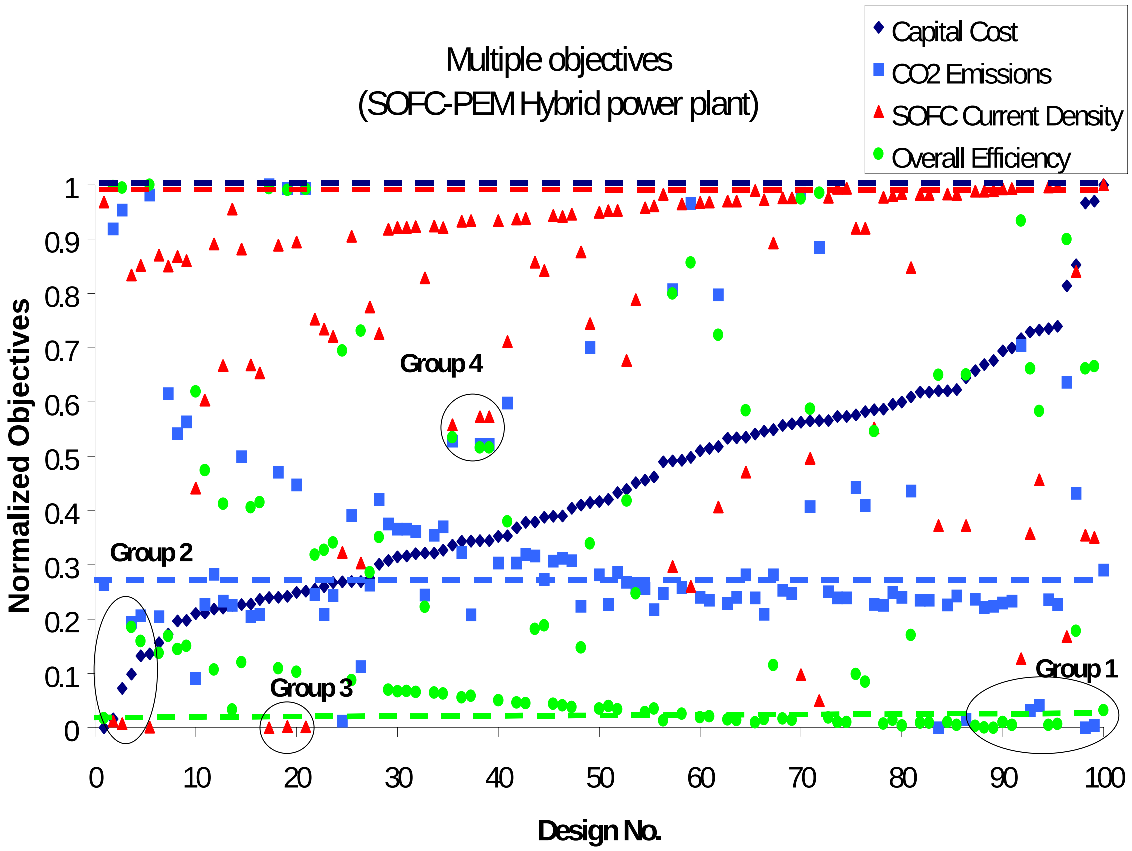

Figure 9: Normalized Objectives for Design of SOFC-PEM Hybrid Power Plant

So, we have plotted the normalized objective values (capital cost, CO_2 emissions, SOFC current density and overall efficiency) of the 100 optimal designs that we have obtained through our multi-objective optimization framework in Figure 9. The dashed horizontal lines indicate the normalized values of the objectives corresponding to the base case. Here, we can identify several groups of designs with similar objective values. We have identified four such groups and presented their comparison with the base case. The corresponding objective functions and decision variables values for various groups and base case is presented in Table 2. Group 1 has

	Base Case	Group 1	Group 2	Group 3	Group 4
Objective Functions					
Capital cost ($/kW)	1773	1450-1650	815-880	1025-35	1120-30
Power rating (kW)	1472	1200-1230	1055-1095	1055-75	1260
CD SOFC (mA/cm^2)	75	500-600	875-880	870-880	400-420
CD PEM (mA/cm^2)	190	310	315	310	300
Overall efficiency	72.6%	60-70%	50-52.1%	52.2-54%	62-62.3%
Cost of elec. ($/kWh)	6.35	6.05-6.20	4.70-4.85	5.17-5.27	4.95-5.0
CO_2 emission (kg/kWh)	5.61	5.4-5.45	6.0-6.1	6.14	5.6-5.79
Decision Variables					
SOFC fuel utilization	0.7	0.4-0.43	0.4-0.42	0.4-0.43	0.53-0.56
PEM pressure (psi)	25	62-65	70-75	70-75	40-45
Equivalence ratio SOFC	1.25	1.25-1.4	4.5-5.0	5.5-6.0	2.0-2.15

Table 2: Comparison of objective function and decision variable values for base case and different groups

lower CO_2 emissions (up to 5%) and capital cost (up to 25%) than the base case. There also is a higher value of SOFC current density but we lose in power rating and efficiency of the system. These types of designs are recommended for places with strict CO_2 regulations. Group 2 presents designs with maximum capital cost savings (up to 50%) and high current density (875-880 mA/cm^2). But again we have to compromise on efficiency, power rating and CO_2 emissions (9% higher). These designs are recommended when emission standards are not that stringent and cost is the single most important objective. Group 3 designs gives slightly better values for current density and plant efficiency than Group 2 designs but are compromised with increase in cost and emissions. These give a clear-cut representation of the trade-off involved in the design process. Finally, Group 4 designs have a middle range for efficiency, SOFC current density and CO_2 emissions. The capital cost and power rating are also on the better side. A decision maker might want to choose such a design if he wants his process to run at "moderate" conditions as it requires a moderate pressure in PEM.

5. Conclusion

We have shown in this paper that SOFC-PEM hybrid plant design is a multi-objective optimization problem and presented a methodology to handle these problems by using the new efficient MINSOOP algorithm. The optimization framework presented allows for an efficient determination of the non-dominated or Pareto set for the problem. The Pareto surface provides an effective to assess the trade-offs amongst the multiple objectives. We have shown that multi-objective optimization framework can help in identifying designs, which are more cost effective as well as environmentally benign. This paper provides a first step towards an integrated approach to synthesis of new and more efficient fuel cell hybrid power plants. However, several material issues need to be considered in the fuel cells for obtaining the desired properties for electrolyte and electrode performance issues. Moreover, the development in the area of new materials and other technologies where the performance and economic data is scarce and/or incomplete, calls for consideration of uncertainties in the design and optimization. In the future, the framework will be extended to address these issues.

6. Acknowledgements

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