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Multi-objective trade-offs for fuel cell-based auxiliary power units: case study of South California Air Basin

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Abstract

Auxiliary power units (APUs) are energy devices that complement the main internal combustion engine of a vehicle providing power for the non-propulsion needs. There are several goals or objectives that need to be achieved for designing and operating fuel cell-based APUs. The system should have as high efficiency as possible, but also be economically viable with cost or profits competitive with the existing technology. Not only should the environmental impacts of the chemicals released during the process be as low as possible, but also the human health impact has to be minimum. This becomes an extremely challenging multi-objective problem and its solution leads to the quantification of the trade-offs between the different objectives. The fact that these multiple objectives are often conflicting in nature and can have completely different trends with respect to multiple process variables makes the representation and analysis of the trade-off information an extremely formidable task. The solution of the multi-objective optimization of the system, which comprehends sensitivity analysis, payoff table and optimal trade-off surfaces, is illustrated. The case study that was chosen for the simulations is South California Air Basin and the assumptions that were taken to model this region are briefly discussed.

Keywords: SOFC-based APUs; South California Air Basin; Multi-objective optimization; Optimal trade-off surfaces

1. Introduction

Auxiliary power units (APUs) are devices that can provide all or part of the non-propulsion power for vehicles (space conditioning/heating, refrigeration, lighting, etc.) offering a high-efficiency (equivalent to low consumption), low emission, and low-noise alternative that would supplant the need for engine idle. Idling of large-displacement diesel engines is in fact an extremely inefficient and polluting way to generate heat and electricity. There is a good fit between APU requirements and fuel cell system characteristics in terms of efficiency, load requirement, and physical size and weight. Among the different fuel cell types, the Solid Oxide FC technology is considered the most favorable. APU applications are predicted to be the first fuel cell penetration in the transportation sector, in the market of heavy-duty trucks and luxury vehicles (recreational vehicles and limos).

In previous publications [1,2], an integrated framework that can automatically identify and quantify trade-offs between cost effectiveness, efficiency and environmental and health impacts of solid oxide fuel cell (SOFC) power systems has been introduced. In this paper, the results of the multi-objective optimization of the system considering South California Air Basin in 2010 as case study are presented and discussed.

A multi-objective optimization problem is any decision problem that involves a set of objectives instead of a single one. In this case the objectives to be achieved simultaneously are maximum efficiency, minimum environmental impact (considered as total output Potential Environmental Impact (PEI)), minimum total cost and minimum health im-

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pact, which involves three independent effects (carcinogenic, chronic and acute).

As already discussed in [1], MINSOOP algorithm [3], which is based on constraint method, was applied in the framework to solve the multi-objective problem. The basic strategy of constraint method [4] is to transform the multi-objective optimization problem into a series of single-objective optimization problems. The idea is to pick one of the objectives to minimize (say Z_l) while each of the others (Z_i, i =1, ..., k, $i \neq l$) is turned into an inequality constraint with parametric right-hand sides (ε_i, i =1, ..., k, $i \neq l$). The problem takes the form:

$$\text{Minimize :}\quad Z_l = f_l(\boldsymbol{x})$$

$$\begin{aligned}\text{Subject to :}\quad & Z_i = f_i(\boldsymbol{x}) \leq \varepsilon_i, \quad i = 1, \ldots, k, \quad i \neq l \\ & h_I(\boldsymbol{x}) = 0, \quad I \geq 0 \\ & g_J(\boldsymbol{x}) \leq 0, \quad J \geq 0 \\ & l_j \leq x_j \leq u_j, \quad j = 1, \ldots, n \\ & \boldsymbol{x} = (x_1, \ldots, x_n)\end{aligned}$$

Summarizing, the solution of a multi-objective optimization problem with k objectives (to be minimized) using MINSOOP algorithm involves the following basic steps:

I. Performing a sensitivity analysis using Partial Correlation Coefficients (PRCCs) [5] to select the decision variables
II. Solving k single-objective optimization problems with the original constraints of the multi-objective problem to find the optimum point of each of the individual k objectives.
III. Computing the value of each of the k objectives at each of the k individual optimal solutions. In this way, the potential range of values for each of the k objectives is determined and saved in a table (called payoff table).
IV. Selecting a single objective to be minimized. Transform the remaining $k-1$ objectives into inequality constraints ($\leq\varepsilon$ for minimization) with parametric right-hand side.
V. Selecting a desired number of single-objective optimization problems to be solved to represent the Pareto set and using the Hammersly Sequence Sampling, HSS [6] technique to generate the combinations of the inequality constraint values within the range determined in Step II.
VI. Solving the constrained problems set up in Step IV for every combination of the right-hand-side values. The feasible solutions form an approximation for the Pareto set.
VII. Analyzing the trade-off surfaces.

It should be remembered that for a non-convex problem like the problem at hand, this procedure needs to be repeated for different initial values of the decision variables.

In the next section the case study that was used for simulations is presented followed by the results of the multi-objective optimization and conclusions sections.

2. Case study: South California Air Basin (SoCAB)

Because of the well-known pollution problem and the abundance of data, Los Angeles Air Basin (SoCAB) has been chosen as case study for simulations. Moreover, in California there is a law proposal [7] that would require, starting 2007, the installation of a non-adjustable idle reducing system on all new on-road heavy-duty diesel engines in vehicles with a gross vehicle weight rating (GVWR) greater than 14,000 pounds. This clearly shows the interest in that region for the idling emission problem.The time period that we considered is 2010 and beyond, when the SOFC technology will be widespread.

According to ARB estimates [8], in 2010 in Los Angeles Basin there will be 152,800 medium and heavy-duty trucks (gross vehicle weight greater than 14,000 lb) and 4980 motor homes. Fuel cell APU candidates are those trucks with an average trip of 500 miles or more [9]. In California in 1997 according to the U.S. Census Bureau [10], 4.24% of the trucks (excluding pickups, panels, vans, sport utilities, and station wagons) had this range of operation. Assuming that the same percentage can be applied to the specific case of SoCAB, in 2010 there will about 6500 trucks that are fuel cell based APU candidates. Considering the about 5000 motor homes, it makes a total of 11,500 vehicles candidates. For lack of more detailed data we assumed that APUs installed on trucks and RVs work the same amount of time. It is expected that the qualitative results will not be different for RVs.

Since trucks and RVs are supposed to idle mainly in rest areas along the communication routes [9], the stop areas in Los Angeles Basin were detected and placed on the map of the region. Table 1 shows the position of the 27 stop areas retrieved from reference [11] (subsequently aggregated into 20) in terms of longitude, latitude and altitude and with respect

Table 1
Position of the truck stop areas

No.	X (m)	Y (m)	Z (m)	Latitude	Longitude	Notes
1	91500	58300	228.3	34	−117.9	
2	24200	107800	146.2	34.5	−118.6	
3	62500	112600	410.7	34.5	−118.2	
4	69400	56000	36.1	34	−118.1	
5	89800	43000	39.2	33.9	−117.9	
6	24200	112400	479.5	34.5	−118.6	
7	59800	69600	151	34.1	−118.2	
8	71900	58600	205	34	−118.1	Two sources
9	106300	63200	346.3	34	−117.7	
10	61200	34200	89.2	33.8	−118.2	
11	60900	39700	74.8	33.8	−118.2	
12	131000	56000	445	34	−117.5	Two sources
13	61700	59700	151	34	−118.2	
14	55300	47200	74.8	33.9	−118.3	
15	44100	85900	348.5	34.2	−118.4	Two sources
16	62700	47500	20.9	33.9	−118.2	Two sources
17	118200	71700	336	34.1	−117.6	Two sources
18	145900	70100	496.2	34.1	−117.3	Two sources
19	136700	66000	445	34.1	−117.4	
20	127500	69600	336	34.1	−117.5	Two sources

Table 2
Position and classification of the receptor points

No.	*X* (m)	*Y* (m)	*Z* (m)	Classification[b]
1	15000	75000	432.0	A
2	30000	90000	705.5	R
3	45000	30000	98.5	R
4	45000	45000	56.2	R
5	45000	60000	255.0	R
6	45000	75000	266.5	R
7	45000	90000	747.0	R
8	45000	105000	715.0	R
9	60000	45000	32.0	R
10	60000	60000	151.0	I
11	60000	75000	151.0	R
12	75000	30000	17.5	R
13	75000	45000	216.1	R
14	75000	60000	205.0	I
15	75000	75000	205.0	I
16	90000	15000	31.9	R
17	90000	30000	25.5	R
18	90000	45000	228.3	R
19	90000	60000	225.4	I
20[a]	90000	70000	225.4	R
21	105000	15000	160.8	R
22	105000	30000	370.8	A
23	105000	60000	346.3	I
24[a]	105000	70000	346.3	R
25	120000	15000	372.0	R
26	120000	45000	303.0	I
27	120000	60000	336.0	A
28[a]	120000	70000	336.0	R
29	135000	30000	873.6	R
30	135000	45000	355.5	A
31	135000	60000	445.0	A
32[a]	135000	70000	445.0	A
33	150000	15000	496.5	R
34	150000	30000	576.2	R
35	150000	45000	691.4	A
36	165000	0	634.0	R
37	165000	15000	634.0	A
38	165000	30000	616.0	A
39	165000	45000	728.9	A
40	180000	45000	740.0	A
41	180000	60000	1013.3	R
42	195000	0	1173.0	A
43	195000	60000	1093.0	A
44[a]	66000	34000	53.0	R
45[a]	146600	69600	496.2144	I
46[a]	160000	68000	548.1828	R
47[a]	32000	107000	479.5	R

[a] Out of the uniform grid.
[b] A—agricultural; R—residential; I—industrial.

to the arbitrary axis showed in Fig. 1. The use of arbitrary axis is necessary to input positions in the dispersion modeler. Data on the actual terrain conformation (altitudes) were retrieved from map databases [12]. It was assumed that the vehicles are evenly distributed among the stop areas and that one candidate out four is idling at the same time. This makes a total of 2700 vehicles.

For dispersion modeling, a grid of receptors has to be established. A grid with 15 km spacing that uniformly covers the region (with a few exceptions in order to include urban areas) was used. Table 2 and Fig. 1 show the position of

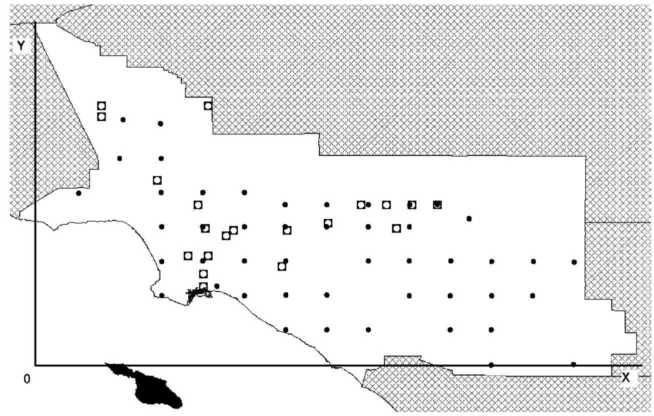

Fig. 1. South California Air Basin (SoCAB). The squares represent the source points (truck stop areas) while dots are the receptors. The lines are the arbitrary reference axis.

the receptor points. The receptor points were classified in three different scenarios: agricultural, industrial and residential. The classification was made looking at aerial pictures and does not have any official connotation. Receptors in mountainous regions were neglected for the human health impact assessment.

3. Multi-objective optimization

The formulation of the multi-objective optimization problem is as follows:

Min	Total cost
Max	Efficiency
Min	Total output potential environmental impact
Min	Carcinogenic risk
Min	Chronic hazard quotient
Min	Acute hazard index
Varying	Diesel intake, system pressure, reformer temperature, fuel utilization, cathode air stoichiometric ratio, air preheating temperature,

s.t. Mass and energy balances Net power = 5 kW.

3.1. Sensitivity analysis

A statistical analysis based on stochastic modeling has been carried out to quantify the sensitivity of the different objectives to various input parameters in order to identify the decision variables for the optimization. The effect of an original set of nine system parameters on efficiency, cost, total environmental impact, carcinogenic effect through inhalation, chronic effect through inhalation, and acute health effect has been studied. The original set of variables included diesel intake, system pressure, fuel cell cathode stoichiometric ratio, air preheating temperature, reformer temperature, fuel utilization in the fuel cell, steam/diesel ratio, SOFC temperature, and steam temperature.

The variables were sampled using the Hammersley Sequence Sampling [4,6], which ensures multi-dimensional uniformity. After all samples have gone through the cycle for a specified number of times (500 in this case), the outputs (various objectives) were analyzed using statistical techniques (Partial Correlation Coefficient calculated on Ranks, PRCC). The process has been completely integrated in Aspen Plus using the stochastic simulation capability that was added to the process simulator with the work of Diwekar et al. [13] later modified by Diwekar and Kim [14].

The absolute values of the PRCCs referring to each objective are sorted and a weight is given to each variable according to the position that its PRCC has in the rank. The weighting scheme used in this work is as follows. The variable that has highest value of absolute value of PRCC (not accounting for the sign) for a particular objective is given the weight of 6. A weight of 5 is assigned to the variable with the second highest PRCC and so on. Variables with higher sum of the weights over all the objectives are considered to be the most important. The results of this analysis can be seen in Table 3.

From the PRCC analysis, it was possible to infer that air pressure and diesel intake are the variables influencing most of the objectives. The only objective that is not influenced much by diesel intake is, as expected, the system efficiency. Fuel utilization in the fuel cell and cathode stoichiometric ratio (the ratio between the air flux to the cell and the stoichiometric amount) are other variables with strong effect on the objectives. The air preheating temperature (for its effect on efficiency and cost) and reformer temperature are also included in the set. These parameters were already identified as important in other studies performed in the past [15].

3.2. Payoff table

The pay off table contains the value of each of the six objectives at each of the six individual optimal solutions. Therefore, it provides an approximation of the potential range of values for each of the objectives. This represents the first approximation to the complete Pareto set. The optimum value of each objective is given in Table 4. The bounds of the decision variables were chosen according to physical constraints and knowledge of the problem: diesel intake 0.0001–0.01 kmol h^{-1}; reformer temperature 700–900 °C; air-preheating temperature 500–900 °C; system pressure 1.2–6 bar; cathode stoichiometric ratio: 3–12; fuel utilization 0.5–0.9. 1-D diesel was used as fuel because it is more similar to the fuel that will likely be used in 2010 (even if the sulfur content will probably be lower). The net power output of the cell was constrained to 5 kW, the cell temperature is 800 °C, steam temperature is 270 °C and the mass Steam/Diesel ratio is 0.69. The carcinogenic and non-carcinogenic health impacts refer to adult population through inhalation of outdoor air. The total output Potential Environmental Impact (PEI) is computed as the summation with equal weight over all the categories and it is multiplied times 2700 (total number of vehicles considered to idle at the same time). The "base case" design is similar to reference [16].

All the single-objective optimizations of this study were solved using the SQP inbuilt in Aspen Plus [17,18].

The payoff table is the first approximation of the trade-off surface. From the payoff table, it can be seen that chronic

Table 3
Partial correlation coefficients (PRCCs) and weights for the considered variables with respect to each objective

	Efficiency		Cost		Total out PEI	
	PRCC	Weight	PRCC	Weight	PRCC	Weight
System pressure	−0.526502	6	−0.242553	4	−0.053499	3
SOFC temperature	−0.212681	2	−0.197424	1	0.093814	5
Air preheating	0.414649	4	0.446421	5	−0.036981	1
Steam temperature	−0.006873	0	0.012237	0	−0.01685	0
Fuel utilization	0.27194	3	0.237192	3	−0.044903	2
SOFC air stoichiometric ratio	−0.468977	5	−0.085495	0	−0.022859	0
Diesel intake	0.186359	1	0.544112	6	0.912453	6
Steam/diesel ratio	−0.041105	0	0.105201	0	0.009053	0
Reformer temperature	0.023463	0	0.23656	2	0.064281	4
	Cancer risk		Chronic hazard quotient		Acute hazard index	
System pressure	0.612471	6	0.148579	3	0.696533	6
SOFC temperature	0.046586	1	0.019108	0	0.034428	0
Air preheating	−0.02575	0	0.011615	0	−0.066524	1
Steam temperature	0.010989	0	−0.007612	0	−0.000861	0
Fuel utilization	−0.07386	2	0.272664	4	−0.10433	2
SOFC air stoichiometric ratio	−0.029891	0	0.52092	6	−0.144878	3
Diesel intake	0.409863	4	0.478339	5	0.3573	4
Steam-Diesel ratio	−0.147142	3	−0.118317	1	0.375379	5
Reformer temperature	0.421347	5	−0.134635	2	−0.014774	0

Table 4
Payoff table

	Base case	Max efficiency	Min cost	Min PEI	Min cancer risk	Min chronic hazard quotient	Min acute hazard index
Efficiency	0.37	0.65	0.47	0.65	0.63	0.52	0.59
Cost ($)	13919	22336	12038	22323	20579	24744	18109
Total PEI out (s^{-1})	0.0102	0.0585	0.0790	0.0585	0.0602	0.0720	0.0636
Carcinogenic risk	6.65E−12	2.73E−11	4.43E−12	2.22E−12	2.22E−12	4.43E−12	4.43E−12
Chronic hazard quotient	1.33E−05	3.39E−06	3.76E−06	3.63E−06	4.84E−06	3.34E−06	3.79E−06
Acute hazard index	1.16E−04	5.87E−05	6.95E−05	6.01E−05	7.09E−05	4.27E−05	3.83E−05
System pressure (bar)	1.29	1.20	1.20	1.20	1.20	1.20	1.20
Reformer temperature (°C)	800	788.34	821.82	773.68	743.60	899.78	900.00
Fuel utilization	0.9	0.89	0.79	0.88	0.90	0.77	0.90
Air preheating (°C)	650	900.00	626.61	890.73	896.82	887.02	829.84
Diesel intake (kmol h^{-1})	0.00621	0.00358	0.00484	0.00358	0.00368	0.00443	0.00391
SOFC air stoichiometric ratio	7.6	3.11	3.01	3.03	4.49	3.00	3.41
Cell voltage (V)	0.69	1.03	0.9	1.03	1.01	1.02	1.00
Cell current density (A m^{-2})	6103.8	216.5	1967.7	216.5	264.1	200.2	339.5

hazard quotients and acute hazard indexes are far below unity and cancer risk is far below 10^{-6} (considered as the safety limit [19]). This fact means that no level of danger is posed by SOFC-based APUs in the receptor points in which concentrations were computed. It should be noted that the grid of 47 receptors that was considered covers uniformly the wide territory of SoCAB but does not guarantee to detect the point with maximum risk.

All the designs that minimize PEI and health impacts (HIs) have a very high efficiency, but the opposite is not true. The design that maximizes efficiency, in fact, minimizes PEI but not HIs. This is probably due to the different optimal reformer temperatures and it is a consequence of the fact that this problem is non-convex and has multiple solutions (same efficiency but different decision variables). As expected, the designs with high efficiency have also very high cost. In order for the fuel cell to be more efficient, in fact, it has to operate in a region of high voltage [20] and so low current density. Lower current density means that higher cell area is required with the consequence of higher cost. So the lower operating cost (lower fuel consumption) is not enough to compensate the higher fuel cell cost. However, the efficiency is defined as overall efficiency and not just efficiency of the cell. That is why the design that minimizes chronic health effects can have high-cell voltage (so high-cell efficiency and highest cost) but efficiency 0.52.

The design that minimizes cost, instead, has a trade-off in environmental and health impacts. This design has a very low-manufacturing cost but quite a high-operating cost due to a higher fuel intake. This explains the high PEI and HIs.

The design with minimum PEI does not minimize HIs (with the exception of the chronic effects). This shows the importance of considering environmental impacts and health impacts separately. Carcinogenic, chronic and acute effects minimization results in different solutions so they need to be considered as independent objectives.

The greater contribution to the total PEI comes from the Aquatic Toxicity Potential, primarily due to the emissions of carbon dioxide and NO_x. Health effects, instead, are a consequence of the emission of NO_x, ammonia, carbon monoxide and formaldehyde (which is the only emitted species with carcinogenic effect).

All the decision variables have a certain range of variation inside the bounds with the exception of the system pressure. All the optimum designs, in fact, predict a system pressure equal to the lower bound (1.2 bar). This means that even if system pressure is the most influential variable, increasing it goes against the objectives to be achieved. Higher system efficiency is promoted by high fuel utilization in the fuel cell and high-air preheating. However, increasing the air temperature has a negative effect on costs. The formation of components with carcinogenic effects is inhibited at low-reforming temperature, while the formation of components with chronic and acute effects is inhibited at high-reforming temperature: it is necessary to find a trade-off between these two behaviors.

From the payoff table, it is possible to retrieve the approximate bounds of each objective. These are presented in Table 5.

3.3. *Optimal trade-off surfaces*

First issue before applying the constraint method is to choose the objective that is remaining as objective and is

Table 5
Bounds of the objectives

	Max	Min
Efficiency	0.65	0.47
Cost ($)	24744	12038
Total PEI out	0.0790	0.0585
Carcinogenic effect	4.43E−12	2.22E−12
Chronic effect	4.84E−06	3.34E−06
Acute effect	7.09E−05	3.83E−05

not converted into an inequality constraint [6]. For a convex problem, any objective can act as the main objective. However, for non-convex problem this choice is not trivial. In the payoff table exercise, we found that we can get multiple solutions to the same problem (e.g. same efficiency with different designs). Therefore, efficiency was initially chosen as the main objective. Managing a non-convex constraint is in fact numerically difficult and may lead to convergence problems. After several tests, it came out that the constraint on cancer risk was particularly difficult to be satisfied. Therefore, it was decided that the minimization of cancer risk had to be the objective of the optimization.

Hundred samples of the parametric right-hand side of the constraints were generated and the set of optimizations was run from four different starting points. This way we got the convergence of 52 optimizations problems, totaling 58 optimal designs (adding the 6 design of the pay off table). This number is not very high but sensitivity analysis showed that it is enough for the first cut analysis of the trade-off surfaces.

The values of the objectives at the optimal designs were smoothed using an "inverse distance" smoother with sampling proportion 0.5 and exponent 3. This operation was done with the help of the software SigmaPlot [21]. The values of the smoothing parameters were chosen accordingly to other studies performed in the past on the same problem [15].

The contour plots in Figs. 2–4 give a representation of the trade-off solutions in the Pareto set. Although these contour plots provide several insights into the current problem, they are far from a complete representation as we can only visualize three objectives at a time.

Fig. 2 shows the trade-offs between costs (*x*-axis), environmental impact (*y*-axis) and efficiency (contours). As expected, the designs in the region with highest efficiency (red contour) have also the highest cost but they are good designs in terms of environmental impact. Therefore, it is possible to have high efficiency and low-environmental impact at the same time, but you are trading off with cost values. There is a good region of operation in terms of these three objectives close to the lower left corner, where costs and total PEI are at their minimum and efficiency is around 0.60–0.62 (the base case was 0.374). The designs in the up-right part of this graph are bad in terms of these three objectives, but since they are in the Pareto set they necessarily have to be optimal for some other objective.

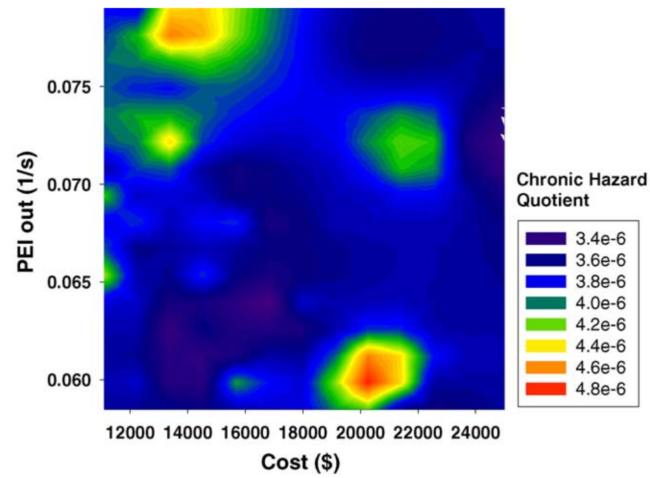

Fig. 3. Contour plot of Pareto trade-off designs for SOFC based APU. Costs (*x*-axis) refer to one single APU, while the total output PEI (*y*-axis) and chronic hazard quotient (contours) refer to 2700 vehicles.

Fig. 3 shows the trade-offs between costs (*x*-axis), environmental impact (*y*-axis) and chronic effects (contours). The upper-right corner, which seemed to be not optimal in Fig. 2, is actually a region of minimum chronic hazard quotient. The designs close to the lower left corner, which were identified as good operating region in Fig. 2, have also very low chronic hazard quotient. However these designs do not perform well in terms of cancer risk and acute effects (Fig. 4).

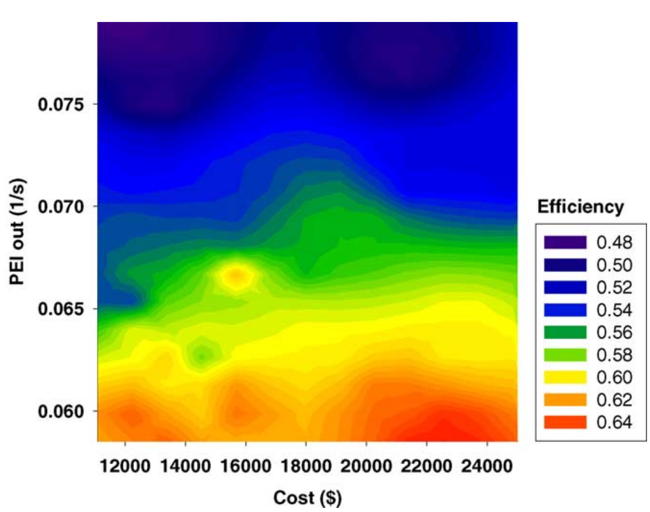

Fig. 2. Contour plot of Pareto trade-off designs for SOFC based APU. Costs (*x*-axis) refer to one single APU, while the total output PEI (*y*-axis) refers to 2700 vehicles.

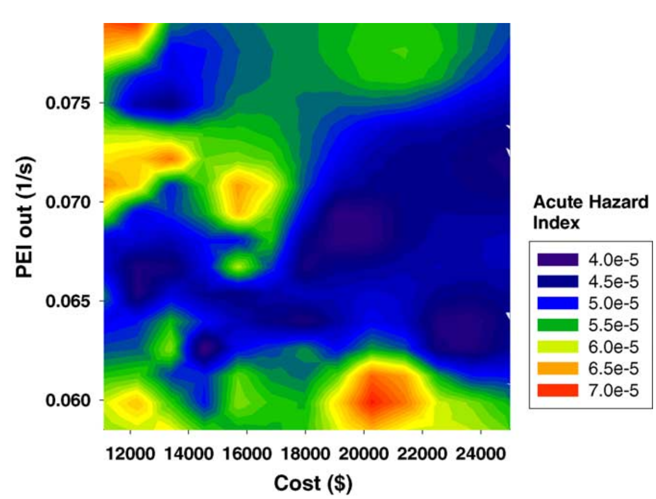

Fig. 4. Contour plot of Pareto trade-off designs for SOFC based APU. Costs (*x*-axis) refer to one single APU, while the total output PEI (*y*-axis) and acute hazard index (contours) refer to 2700 vehicles.

Table 6
Qualitatively similar design groups

	Base case	High efficiency designs			Low health effects designs	
		A	B	C	D	E
Efficiency	0.37	0.60	0.60	0.65	0.55	0.58
Cost ($)	13919	13337	14568	22336	12409	15709
Total PEI out (s^{-1})	0.10161	0.06277	0.06050	0.05850	0.06867	0.06481
Carcinogenic risk	6.65E−12	4.43E−12	4.43E−12	2.73E−11	4.43E−12	4.43E−12
Chronic hazard quotient	1.33E−05	3.33E−06	3.39E−06	3.39E−06	3.40E−06	3.59E−06
Acute hazard index	1.16E−04	5.85E−05	4.57E−05	5.87E−05	4.04E−05	4.25E−05
System pressure (bar)	1.30	1.20	1.20	1.20	1.20	1.20
Reformer temperature (°C)	800.00	811.99	857.10	788.34	900.00	880.41
Fuel utilization	0.90	0.90	0.90	0.89	0.88	0.89
Air preheating (°C)	650.00	738.22	725.73	900.00	798.21	754.19
Diesel intake ($kmol\,h^{-1}$)	6.21E−03	3.85E−03	3.71E−03	3.58E−03	4.22E−03	3.98E−03
SOFC air stoichiometric ratio	7.60	3.00	3.29	3.11	3.00	3.14

Fig. 4 shows the trade-offs between costs (*x*-axis), environmental impact (*y*-axis) and acute effects (contours). The most relevant information that can be retrieved from this contour plots is that it is possible to operate with very low acute effects (dark blue contour) at the entire range of costs, but the environmental impact will never be minimum for these designs. If the objective is to operate at low-health effects (carcinogenic, chronic, and acute simultaneously), it is possible to do it at low cost but moderate environmental impact and efficiency.

The fact that Figs. 3 and 4 are tremendously different is another proof of the independence between the various health impacts and the necessity of considering them as different objectives.

It has to be noticed that since the surface is highly non-convex, it is easy for the optimizer to reach a relative optimum instead of the global one. This problem has been faced also during the calculation of the payoff table and calls for further improvement towards a global optimizer.

Table 6 summarizes, in comparison with the base case, the different groups with similar objective values that have been identified. As it was already noticed, each of these groups represents a region of good operation depending, on which objective is considered particularly important.

High-efficiency designs are possible to obtain with wide range of design variable values (Table 5 designs A–B–C). These designs guarantee also minimum potential environmental impact. However, in order to obtain the highest efficiency value (65%), one has to pay a steep penalty in terms of cost (US$ 22336). Maximum efficiency, which is intended as overall and not just cell efficiency, is achieved through low-diesel intake and high-fuel utilization (low-fuel utilization would be optimal just for the cell efficiency). Moreover the air preheating temperature is high (880–900 °C), while the reformer temperature is moderately low (around 780 °C). Air-preheating temperature seems to be in our model the key parameter to achieve maximum efficiency (design C). The trade-off is in terms of costs, since higher temperature requires higher exchange area. The cathode air stoichiometric ratio is about 50% lower than the base case.

The second group that has been identified has the common characteristic of low-health impacts (Table 5 designs D–E). Chronic and acute effects are around their minimum, while carcinogenic effect is about 34% lower than the base case. The drawbacks are in terms of efficiency and environmental impact, but the values are always better than the base case (efficiency is at least 0.13 more and output PEI at least 33% less). These performances are obtained mainly thanks to high-reformer temperature (close to the upper bound of 900 °C), which seems to be in our model the key parameter to decrease the health effects (at least chronic and acute effects, since the value of cancer risk is almost flat). Stoichiometric ratio is about 50% lower and air preheating temperature about 15% higher than the base case design. Design D has lower cost but higher environmental impact than design E.

4. Conclusions

In this paper, the results of the multi-objective optimization of an auxiliary power unit system considering South California Air Basin in 2010 as case study have been presented and discussed. An MOP is any decision problem in which more than one objective needs to be achieved simultaneously. In this case, the goals are maximum efficiency, minimum environmental impact, minimum cost and minimum health impact, which involve three independent effects (carcinogenic, chronic and acute). The solution is not a single design but a set of alternatives, which represents the optimal trade-offs between the objectives.

South California Air Basin (SoCAB) has been chosen as case study mainly because of the well-known pollution problem and the relatively abundance of data. 2700 APUs have been assumed to be working simultaneously in the truck stop areas of this region.

First step towards the optimization is finding the parameters of the system that affect the objectives most. A statistical analysis based on PRCCs showed that diesel intake, temperature of the reformer, system pressure, cathode air stoichiometric ratio, air preheating temperature and fuel utilization in the fuel cell are the most influent parameters and so the most suitable decision variable for the optimization.

The optimum values of each objective has been computed and saved in the so-called payoff table. From that table, the approximate bounds of each objective are retrieved. This is necessary in order to find the optimal trade-off surfaces using MINSOOP algorithm.

The analysis of the trade-off surfaces shows that high efficiency (above 60%) can be achieved at any range of cost and with minimum environmental impact. However, in order to obtain the highest efficiency value (65%), one has to pay a steep penalty in terms of cost (about US$ 22000). If the main objective is to operate at low-health effects (carcinogenic, chronic, and acute simultaneously), it is possible to do it at low cost but moderate environmental impact and efficiency. It has to be noticed that all the values for the health effects that have been computed, even at their maximum, are far below the safety limits. This means that no level of hazard is posed by this kind of devices in the points in which concentration of pollutants were calculated.

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