Kasetsart J. (Nat. Sci.) 48 : 474 - 486 (2014)

Optimal Operation of Tubular Solid Oxide Fuel Cell Based on Efficiency and Environmental Impact

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ABSTRACT

Solid oxide fuel cell (SOFC) technology dominates other fuel cell technologies because it is a highly efficient form of electric energy generation from natural gas, with both simple fuel cell plants and with integrated cogeneration power plants. This study proposed a tubular SOFC stack with methane gas feeding, internal reforming of hydrocarbons and internal air preheating. To achieve this goal, 'optimal' operating conditions for enhanced unit performance were identified. Thus, the genetic algorithm (GA) technique with the min-max method was employed to perform a multi-objective optimization on the unit performance. Simultaneous maximization of efficiency and minimization of environmental impact were considered as the two objective functions. Pareto-optimal sets of operating conditions were successfully obtained by GA with the min-max method for different process conditions and were used to achieve the effective operation of a tubular SOFC stack power generator with the diameter, the thickness of the cathode, anode and electrode, and the length being 22.0×10^{-3}, 2.0×10^{-3}, 1.0×10^{-4}, 4.0×10^{-5} and 1.5 m, respectively. The fixed current density model produced the optimal solution with 75.52% efficiency and 16.35×10^{-2} g.s^{-1}.kW and an environmental impact score of 221.28 kW. The fixed outlet temperature option prodcued 50.41% system efficiency, 31.15×10^{-2} g.s^{-1}.kW and an environmental impact score of 38.22 kW.

Keywords: tubular solid oxide fuel cell, modified genetic algorithm, multi-objective optimization, environmental impact

INTRODUCTION

Following the increased demand for electricity, the development of a high efficiency power generator has been widely researched with the proposed technology required to be commercial, environmentally friendly and highly efficient, so that fuel cells (devices that convert chemical energy directly into electrical energy) have been promoted as a promising solution (Singhal, 2000). Each cell in a fuel cell consists of an electrolyte layer contacted with an anode and cathode. Fuel cells can be classified by temperature operation, by the electrolyte, by

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Received date : 08/08/13 Accepted date : 24/04/14

the fuel or by the geometric configuration of the cells. Among these, a simple method involves temperature operation where low-temperature fuel cells normally operate below 250°C such as in a polymer electrolyte fuel cell, an alkaline fuel cell and a phosphoric acid fuel cell (Inui, 2003). High temperature fuel cells include designs such as a molten carbonate fuel cell operating at 600-700°C, and a solid oxide fuel cell (SOFC) with an operational range of 650-1,000°C and these can support 'internal reforming' reactions (that is, hydrocarbon to hydrogen), and also their faster kinetics allow for CO in the electrochemical reaction (Inui, 2003). However, SOFC is the most acceptable technology for stationary electricity and heat production because of its internal reforming potential (Singhal, 2000). SOFC is separated into two types by geometric configuration—tubular and planar.

The study of the tubular SOFC model covers a zero-order model method, with a simple model, characteristics of the parameters in a tubular SOFC and a co-generation system. A tubular SOFC and its parameters were modeled and calibrated on a prototype plant working at atmospheric pressure and running on natural gas (Campanari, 2001). The cell voltage can be derived from the Nernst equation, as a function of pressure, temperature, cathodic flow composition and anodic flow composition. A model of a hybrid system (HS) was developed by combining an SOFC stack and a micro gas turbine where the thermodynamic voltage was calculated under open-circuit conditions; this hybrid system fixed 240 Kw from the SOFC stack and 50 kW from the micro gas turbine (Costamagna *et al.,* 2001). A simple, natural-gas-fed and a hybrid SOFC gas-turbine (GT) power generation system was developed by Chan *et al*., (2002). Following their previous work, they developed a model that emphasized reduced dependence on the experimental data and extend the code for part load simulation in the future. A part-load operation of SOFC-GT followed their previous configuration. Study of the output characteristics, such as the current distribution, the gas component distribution and temperature distribution of tubular SOFC with an internal reformer was proposed by Nagata *et al*., (2001). Another comparison focused on three mass transport models—Fick's model, the dusty-gas model and Stefan-Maxwell's model)—which were used to calculate the concentration of the over potential on an SOFC anode (Suwanwarangkul *et al*., 2003). A combined power generation system with liquefaction recovery of CO_2 was proposed (Inui *et al*., 2003), where SOFC was combined with the combustor and gas turbine cycle and methane was used as the fuel and the oxidant was pure oxygen. A framework for impacts assessment and tread-off of the fuel cell system were integrated (Baratto *et al.,* 2005a; Baratto *et al.,* 2005b). This framework could classify and quantify the trade-off between cost effectiveness and the environmental and health impacts of fuel cell power systems and focused on using an auxiliary power unit in heavy-duty trucks and luxury vehicles. Subramanyan *et al.* (2004) reported on the modeling of fuel cell behavior that emphasized multi-objective optimization under the uncertainly of SOFC-PEM hybrid fuel cell power. This work used the minimized number of single objective optimization problems (the MINSOOP algorithm). Diwekar (2003) presented an integrated framework for a greener environmental design, where the goal considered not only profitability but environmental and economical objectives also. This work still used the SOC-PEM hybrid system and the Pareto set used only 150 single optimization problems based on the MINSOOP algorithm. Because there are only a few well known model studies of tubular SOFC, this article proposed to predict the optimal operating conditions by maximizing the system efficiency and minimizing the environmental impact score.

METHODOLOGY

Solid oxide fuel cell system configuration and description

An SOFC operates at the highest temperature of all fuel cells using a solid-state electrolyte. Its single unit consists of two electrodes separated by the electrolyte. Its fuel, usually H_2 or CH_4, is supplied at the anode where it reacts with O^{2-}, the charge carrier in the electrolyte. Since the operation occurs at high temperature, the internal reforming is most complete at the start of the cell:

Internal reforming $CH_4 + H_2O \longleftrightarrow 3H_2 + CO$

Hence, there are two other reactions along the cell at the anodes:

Water gas shift reaction $CO + H_2O \longleftrightarrow H_2 + CO_2$

Electrochemical reaction $H_2 + 1/2\ O_2 \longleftrightarrow H_2O$

Thus, the products of an SOFC are not only electricity from ion movement but also steam and CO_2 gas. The high operation temperature is an advantage because an SOFC can handle fuels that contain some impurity without additional cost. At present, SOFC applications have been demonstrated in cars, boats, buses and power generation at levels from 1 KW to 10 MW (Singhal, 2000).

Multi-objective optimization using the genetic algorithm

Many engineering problems can be defined as multi-objective optimization problems. Each single optimization may not provide the solution that is the best with respect to all objectives. Genetic algorithms (Gas) can be used instead of a single optimum and can solve a set of alternative trade-offs, generally known as Pareto-optimal solutions (Wasanapradit *et al*., 2010). They are based on the natural processes of selection that exists in the genetics of the species (Nagata *et al*., 2001). The algorithm was developed at the University of Michigan in the 1960s and was published in 1975 (Subramanyan, *et al.*, 2004), from which time GAs have become a popular method because they do not focus on a local optimum. In order to determine the optimum, GAs will present alternative solutions that are very close to the global optimum. Moreover, they are able to solve discontinuous functions without requiring the derivative (Subramanyan *et al.*, 2004). The GAs propagated by Goldberg (1989) reduced the data-structure used for representing the genetic structure to bit strings. Currently, this is considered to be one of the main-characteristics of GAs (Goldberg, 1989). A GA starts the initial set of random solutions (population or feasible candidate solution) to form a new population. In so doing, the selection involves a process of keeping and deleting some solutions from both parents (the current solutions) and offspring (the new solutions) to be the next population with the same number of populations. Moreover, selection also involves the process of choosing some parents to generate offspring. The solutions are selected according to their objective function values (fitness). The suitable fitness must be calculated on each chromosome and a new population proposed by genetic operators (crossover and mutation). The algorithms continue until a termination condition is satisfied. The best solution is returned to represent the optimum solution.

Therefore, selection plays an important role in GAs. Wuttikun (2003) and Wasanapradit *et al.* (2010 proposed modifications of the algorithm based on the same concept as in selection (crossover and mutation) but using the min-max method in the optimal evaluation and the cross-generation probabilistic survival selection method (CPSS) in the generation of the next population. The chromosomes in both the offspring and parent are selected using random numbers based on a selection probability curve as shown by Equation 1.

$$P_s = \left\{ (1-s)\frac{h}{L} + s \right\}^{\alpha} \quad (1)$$

where,Ps is the selection probability, h is the distance between the best fitness chromosome and the candidate chromosome in the population, L is the maximum distance between the best fitness chromosome and the candidate chromosome and *s* is the shape coefficient. There are two intersected points, $h=0$, $P_s=s^{\alpha}$ and $h=L$, $P_s=1$ because of the real number representation, h is calculated using the Euclidean distance from Equation 2:

$$h=\sqrt{\left(v_1-v_1^*\right)^2+\ldots+\left(v_i-v_i^*\right)^2+\ldots+\left(v_n-v_n^*\right)^2} \quad (2)$$

where v_i is the ith gene of candidate chromosome, v_i^* is the ith gene of the best fitness chromosome and L is the maximum distance between the fittest chromosomes and the others in that generation and can be calculated using Equation 3:

$$L = \text{Max}\ (h_j) \quad (3)$$

Arithmetic crossover is used in the crossover step. The parents are combined as a linear combination of two vectors. The new chromosomes are defined using Equations 4, 5 and 6:

$$v_1' = r\cdot v_1+(1-r)\cdot v_2 \quad (4)$$

$$v_2' = r\cdot v_2+(1-r)\cdot v_1 \quad (5)$$

The next step is mutation which requires a single parent (v) and produces a single offspring (v'). Initially, the operator selects a random component $i \in (1,\ldots,n)$ of vector $v = [v_1,\ldots,v_i,\ldots,v_n]$ and produces $v' = [v_1,\ldots,v'_i,\ldots,v_n]$ where v'_i is a random value from the range $[v_i^L, v_i^U]$ where v_i^L, v_i^U are the lower and upper bound of variable v_i, respectively.

$$v_i' = v_i^L + r\left(v_i^U - v_i^L\right) \quad (6)$$

Following Wuttikun (2003), this method is called multi-position mutation using the mutation rate to set the amount and position of the genes.

Min-Max method

The single optimum in the multi-objective optimization problem was evaluated using the min-max method coded in the MATLAB software (2006A; The MathWorks Inc.; Natick, MA, USA). This method applies the comparison of relative deviation from attainable optima. Considering the i^{th} objective function, the relative deviation is calculated using Equation 7 or from Equation 8:

$$z_i'\left(\bar{x}\right)=\frac{\left|f_i\left(\bar{x}\right)-f_i^o\right|}{\left|f_i^o\right|} \quad (7)$$

$$z_i''\left(\bar{x}\right)=\frac{\left|f_i\left(\bar{x}\right)-f_i^o\right|}{\left|f_i\left(\bar{x}\right)\right|} \quad (8)$$

where $Z_i'(\bar{x}), Z_i''(\bar{x})$ are the first and second order differential of the component of the vector respectively $f_i^o = \min f_i\left(\bar{x}\right)$.

Then, minimization and maximization were applied for every in the feasible region. Let $\bar{z}\left(\bar{x}\right)=\left[z_1\left(\bar{x}\right),\ldots,z_k\left(\bar{x}\right)\right]^T$ be a vector of the relative increments. The component of the vector $z\left(\bar{x}\right)$ can be evaluated from Equation 9 which defines the relative increment, while Equation10 works conversely:

$$z_i\left(\bar{x}\right)=\max\left\{z_i'\left(\bar{x}\right),z_i''\left(\bar{x}\right)\right\} \quad (9)$$

$$v_1\left(\bar{x}^*\right)=\min_{x\in X}\max_{i\in I}\left\{z_i\left(\bar{x}\right)\right\} \quad (10)$$

Minimization of environmental impacts

In this process, environmental impacts were divided into the two categories of global warming and acidification. The global warming effect potential was estimated by calculating the products of the amount of emitted greenhouse gas per kilowatt hour of produced electricity. The impact scores were calculated using Equations 11 and 12:

$$IS_{GW}=\sum_{i=1}^{n}\left(GWP_i\times INVGW_i\right) \quad (11)$$

where IS_{GW} is the global warming impact score for greenhouse gas chemical i (measured in kilograms CO_2 equivalents per kilowatt hour), GWP_i is the global warming potential for greenhouse gas chemical i (in CO_2 equivalents, 100 year time horizon) adapted from Intergovernmental Panel on Climate Change (1996) and $INVGW_i$

is the inventory output amount of greenhouse gas chemical i released to air (in kilograms per kilowatt hour).

$$IS_{Acid} = \sum_{i=1}^{n} (ARP_i \times INVA_i) \quad (12)$$

where IS_{Acid} is the acidification impact score for greenhouse gas chemical i (in kilograms SO_2 equivalent per kilowatt hour), ARP_i is the acid rain potential for greenhouse gas chemical i (in SO_2 equivalents, 100 year time horizon) and $INVA_i$ is the inventory output amount of acidification chemical i releases to air (in kilograms per kilowatt hour).

Maximization of cell efficiency

The thermal efficiency of an energy conversion device was defined as the amount of useful energy produced relative to the change in stored chemical energy (commonly referred to as thermal energy) that is released when fuel is reacted with an oxidant. The most widely used efficiency of a fuel cell is based on the change in the standard Gibbs free energy (ΔG^o_{rxn}) for the cell reaction as calculated using Equation 13, given by Hess's Law (Nagata, *et al*, 2001):

$$\Delta G^o_{rxn} = G^o_{H_2O} - G^o_{H_2} - \frac{1}{2} G^o_{O_2} \quad (13)$$

where G^o_i is standard Gibbs free energy of component (i is H_2O,H_2,O_2). Because the SOFC is operated at a high temperature (over 1000 K), ideal efficiency cannot be calculated under standard conditions (25 ^oC, 1 atmosphere pressure). In order to calculate the enthalpy (ΔH^o) at the operating temperature, the heat capacity (Cp) of each component is required as shown in Equations 14, 15, 16 and 17:

$$C_{pH_2}\ Cp_{H2} = ((6.9469 *(T - 298)) + (0.5 *(-1.999 *10^{-4})* (T^2 - 298^2)) + ((1 / 3) *(4.808*10^{-7})(T^3 - 298^3))) / (T - 298) \quad (14)$$

$$C_{pO_2}\ Cp_{O2} = ((6.148 *(T - 298)) + (0.5 *3.102 *10^{-3} * (T^2 - 298^2)) + ((1 / 3) *(-9.23 *10^{-7})*(T^3 - 298^3))) / (T - 298) \quad (15)$$

$$C_{pH_2O}\ Cp_{H2O} = ((7.256 * (T - 298)) + (0.5 *2.298 * 10^{-3}*(T^2 - 298^2)) + ((1 / 3) *2.83 *10^{-7} * (T^3 - 298^3))) / (T – 298) \quad (16)$$

$$\Delta H^o = (-242.6 *10^6) + (-- (0.5) +)* (TOUT - 298) *10^3 / 4.2 \quad (17)$$

where T is the temperature measured in Kenvine and TOUT is the solid oxide fuel cell temperature outlet Thus, the thermal efficiency of an ideal fuel cell (η_{ideal}) operating reversibly on pure hydrogen and oxygen under standard conditions would be represented by Equation 18:

$$\eta_{ideal} = \frac{\Delta G^o}{\Delta H^o} \quad (18)$$

where ΔG^o can be calculated using Equation 19:

$$\Delta G^o = -239113 + 7.53\ T \ln (T) + 8.568*10^{-3}\ T^2 - 6.64*10^{-6}\ T^3 + 2.34*10^{-9}\ T^4 - 3.37*10^{-13}\ T^5 - 10.794\ T \quad (19)$$

However, the efficiency of an actual fuel cell (η) can be expressed in terms of the ratio of the operating cell voltage (V_{act}) to the ideal cell voltage (V_{ideal}) which can be calculated using Equations 20 and 21.

$$E^o = x\ 1{,}000/ (-2*F) = V_{ideal} \quad (20)$$

where F is the Faraday constant.

$$\eta = \frac{\text{Useful Energy}}{\Delta H} = \frac{\text{Useful Energy}}{\Delta G / \eta_{ideal}} = \frac{V_{act} \times \text{Current}}{V_{ideal} \times \text{Current} / \eta_{ideal}} = \frac{\eta_{ideal} V_{act}}{V_{ideal}} \quad (21)$$

The actual cell voltage is less than the ideal cell voltage because of the losses associated with cell polarization and the iR loss. Nevertheless, the overall system efficiency can be calculated from the useful energy produced which is the sum of power from the fuel cell and turbine in the Rankine cycle less the power consumption of the compressor in the Rankine cycle (Equation 22):

System efficiency = Useful energy produced/ Higher heating value of the fuel (22)

Modeling and simulation

This work consisted of two parts: the SOFC model and optimization. In the first part, the UESR2 model block in the Aspen Plus software (Aspen Plus® 11.1; Aspen Technology Inc.; Burlington, MA, USA) was used as the stack of the SOFC, with the calculations to determine the temperature, cell voltage, power and efficiency written in the FORTRAN programming language (FORTRAN 77; IBM; Armonk, NY, USA), combining the Rankine cycle to recover heat from the exhaust gas. The second part was concerned with the efficiency of the SOFC and CO_2 concentration optimization. The Visual Basic programming language (2005VB8.0; Microsoft; Albuquerque, NM, USA) was used as the interface containing the genetic algorithm for optimization.

Following the SOFC characteristics, two spacific subroutines were developed by FORTRAN: 1) Fixed current density model; and 2) Fixed temperature model. The flow diagrams in the flow sheet of Aspen Plus were combined with the Rankine cycle (Figure 3).

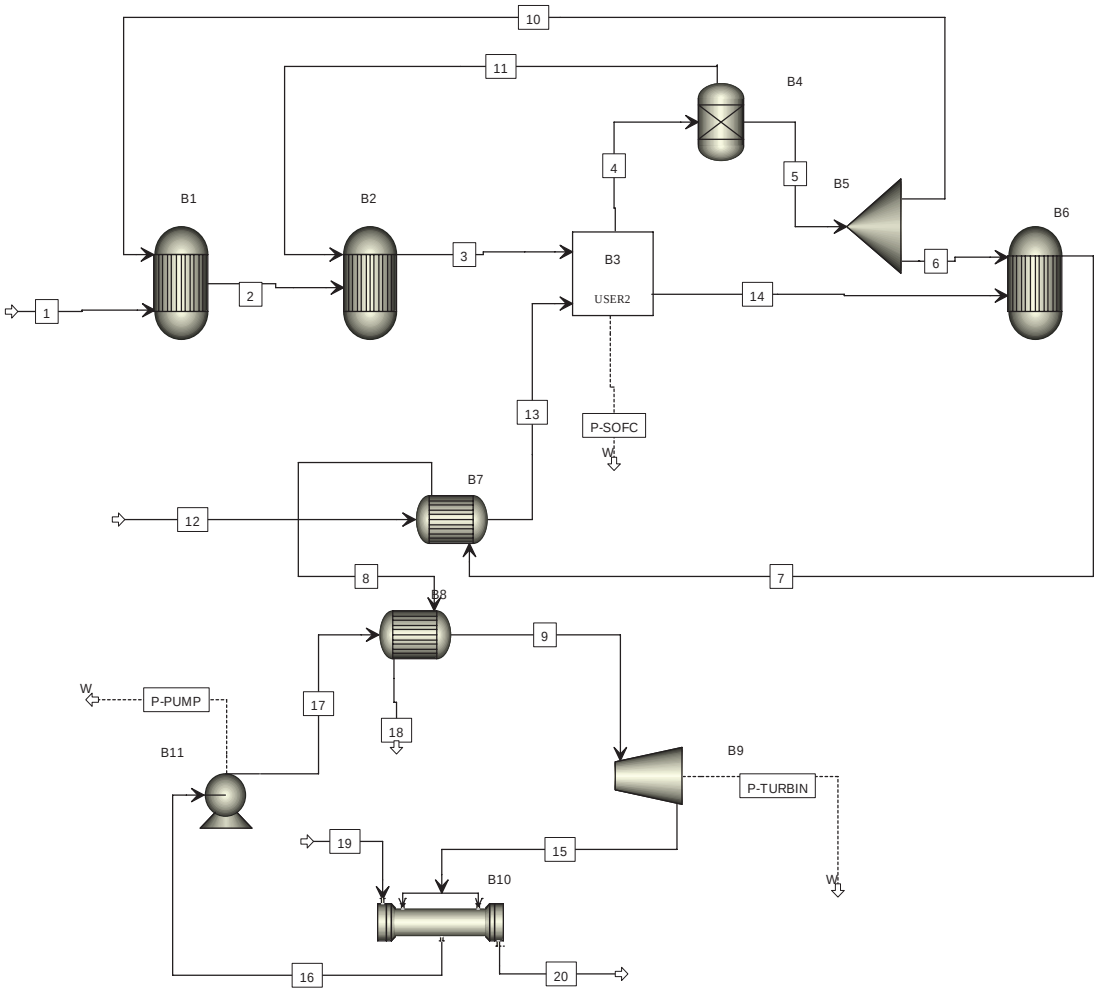

Figure 3 Aspen model based on SOFC-Rankine cycle.(B1 = Pre-reformer, B2 = Reformer, B3 = SOFC (USER2 was used in this block with FORTRAN programming language), B4 = Separator, B5 = Splitter, B6 = Combustor, B7 = Pre-heater, B8 = Heater, B9 = Turbine, B10 = Condensor, B11 = Pump, W = Work of block, P-SFOC = Power of SOFC block, P-PUMP = Power of pump block, P-TURBIN = Power of turbine).

This process consisted of polar non-electrolyte compounds, where NRTL-RK is the equation of state used as the property method. However, the three blocks in the Rankine cycle used STEAMNBS (The stream table equation of state was used when process mix with stream and pure water) because it used only water. This flow sheet consisted of 11 blocks and s20 streams. The pre-reformer consisted of a reforming and water gas shift reaction while the internal reformer had only a reforming reaction. The feed (stream 1) flowing to the pre-reformer reacted with mixed gas recycled from the exhaust gas (stream 10). In the pre-reformer, there were two equilibrium reactions—reforming and water gas shift. Next, the outlet passed through the internal reformer, which involved the equilibrium reforming reaction. The water, having reacted with methane, was split from stream 4. The USER2 block is the SOFC stack coded in FORTRAN. There were two inlet streams—fuel and air—the fuel stream (stream 3) consisting of methane, carbon monoxide, carbon dioxide, hydrogen and water reacted with oxygen in air to produce the power or the electricity and the high temperature outlet stream. The splitter separated the water used in the internal reformer from the reactions in the cells. The depleted fuel (stream 5) was separated for recycling and flowed into the combustion to mix with the excess air. A small amount of combustion took place here that helped to make up the exhaust, which left the module and passed into another heat exchanger to make use of the valuable heat. Before going to the Rankine cycle (the bottom cycle in this process), the stream was used to preheat air feed in the pre-heater. The exhaust gas transferred heat with the cool stream in the heat exchanger to generate the steam rotating the turbine. Electrical energy was generated when the generator windings rotated in a strong magnetic field. After the steam left the turbine, it was cooled to its liquid state in the condenser. The pump pressurized the liquid prior to it going back to the boiler or the heat exchanger. Since the exhaust was still at a high temperature, it was used to preheat air before it flowed into cells. The first process required constant temperature and the second required constant current. For the first model, the temperature outlet of exhaust gas from cells was equal but not in the second model. The temperatures from the anode and cathode were different as the temperature on the anode side was higher than on the cathode side because of the electrochemical reaction and the extreme endothermic reaction. For this reason, the optimization was separate in each case, with each process having two objectives (maximizing the system efficiency and minimizing the environmental impact score) and thus this problem is called multi-objective optimization. By performing a multi-objective optimization using the GA technique, the set of operating conditions yielded an end result. System or total efficiency was calculated by dividing the useful energy by the higher heating value, while the environmental objective ensured that this process is environmentally friendly. To determine the Pareto optimal solution, the min-max method was developed using MATLAB. From the results, the process with fixed current density gave the higher optimal efficiency and lower environmental impact score. Although the mole fraction of CO_2 was the same, more power was generated than with the fixed temperature option. The fixed current density model is suited for a process that releases a certain current but another model will not disturb the process by changing the temperature.

RESULTS AND DISCUSSION

The polarization curve was generated to compare with the experimental work of Singhal (2000) as shown in (Figure 4).

At fixed air utilization (U_a) and fuel utilization (U_f) values of 0.25 and 0.86, the ratios of the flow rate of fuel and air changed to 5.6 $\times 10^{-3}$ and 0.35 $kg.s^{-1}$ (Campanari, 2001). Each

temperature produced the same trend. The cell voltage decreased in a nominally linear fashion, as a function of mean current density. The curve was in the range 1000–6000 A.m^{-2}; the so-called ohmic region. Figure 4 also shows that the values of the current study gives very good agreement with the experiment of Singhal (2000). Nevertheless, the model cannot be used to perform calculations for the whole SOFC system as it cannot investigate the cell voltage or temperature along the cells and its results should be considered as indicative average values. The base case for the SOFC is shown in Table 1.

The polarization curve from the fixed current model is shown in Figure 5. Because of the fixed current density, the output temperature varied. At the same U_a and U_f values of 0.25 and 0.86, respectively, this model produced a higher temperature at the same current density.

Table 1 Base case design and performance of the solid oxide fuel cell.

Parameter	Value
Temperature	1123 K
Pressure	1 atmosphere
Area	119 m^2
Air utilization	0.25

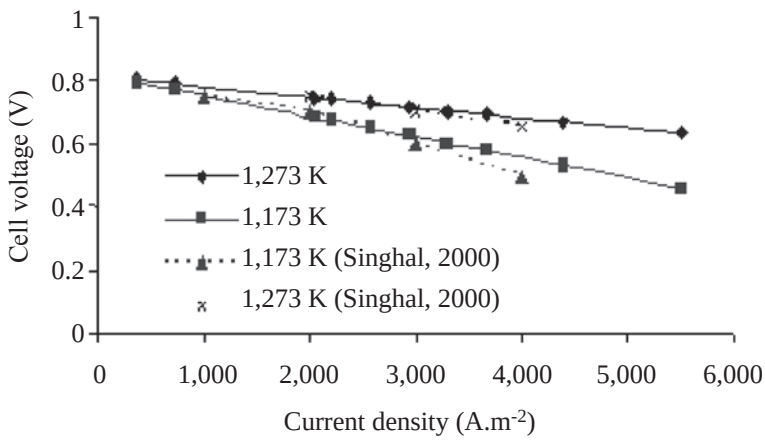

Figure 4 Fixed temperature polarization curve compared with Singhal (2000).

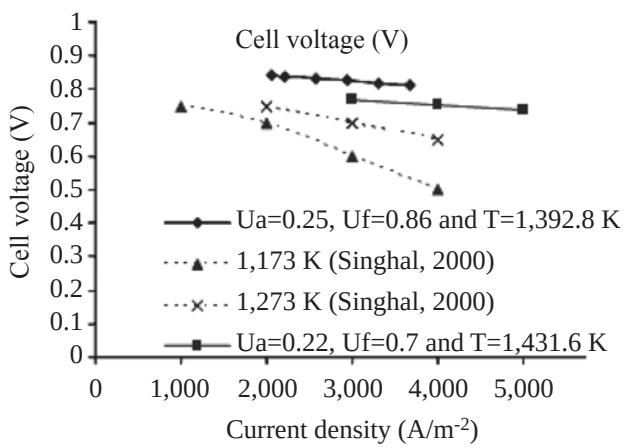

Figure 5 Fixed current polarization curve compared with (Singhal, 2000), where Ua is air utilization, U_f is fuel utilization and T is the temperature measured in Kelvin.

Performance of solid oxide fuel cell with Rankine cycle

The power generation system consists of not only the SOFC system but also the heat recovery unit. A simple Rankine cycle was used in the bottom cycle because it offers simplicity although it appeared to give low efficiency of power generation. The SOFC effluent was used to preheat the air feed. Furthermore, the hot fuel gas was used as a heating medium for the boiler in the Rankine cycle. Although there were two power generators, the main source of power was still the SOFC. For example, while the flow rates of fuel and air were 5.6×10^{-3} and 0.35 $kg.s^{-1}$, respectively, at 1173 K, the turbine in the Rankine cycle produced 3.74 kW and the pump consumed 0.07 kW Although the total power was 171 kW, the efficiency percentage was increased by only 0.02% of the existing SOFC power.

Optimization results

Optimization used the genetic algorithm with the CPSS method (Wasanapradit, 2000). A probability value was assigned to each individual according to its similarity to the fittest chromosome in that generation. Each individual will then be selected according to the assigned survival probability. If the total number of all selected individuals does not reach the required sub-population size after the first survival selection loop, the process of survival selection from the unselected individual list will be repeated until the required number is met. This procedure provides an opportunity for all chromosomes in the next generation. The parameters in the CPSS step used $\alpha = 0.3$ and $s = 0.3$. In addition, four main independent parameters were studied—the flow rates of the fuel feed, air feed, coolant and water in the Rankine cycle. The objectives to be optimized, and the decision variables are shown in Table 2.

Thus, the next simulation added the two conditions of the fuel to air ratio = 5.6×10^{-3}:0.35 and ratio of water to coolant in the Rankine cycle = 1:10 following the base-case conditions. Figure 6 shows the Pareto charts composed of the two objectives of efficiency and environmental impact score. The trend of the fuel and air flow rates was the same as that of the water and coolant in the Rankine cycle. Each generation produced a different objective function value. If the value in the new generation was better, the curve changed with the trend. On the other hand, if the results remained the same as in the previous generation, the curve did not fluctuate.

A hybrid approach was presented in this study to optimize the multi-objective, which used a combination of a genetic algorithm with the min-max method to obtain the optimal set of solutions. This is quite different from Figure 7 which shows the Pareto chart of the dependent parameters using the fixed temperature model where the trend is clearer in the suitable range. The result based on 500 generations provided a curve that decreases rapidly in the range 50 to 70% efficiency with a $2.0\text{-}2.8 \times 10^{-4}$ environmental impact score. This corresponds to several possible operating conditions from which the most appropriate has to be judged by the user. The approach of the min-max search technique (combination of random and sequential search) was used to generate the Pareto optimal solution. The results show how the GA is able to provide a solution with a lower deviation

Table 2 Objectives and decision variables.

Objective	Decision variable
Minimize environmental impact score	Fuel flow
Maximize percentage efficiency	Air flow
	Circulating water flow in Rankine cycle
	Coolant flow in Rankine cycle

from the ideal vector at 100% efficiency and a zero environmental impact score. Using the min-max method, the single optimum occurred at the 56th optimum generation with optimum efficiency of 74.69% and an optimum environmental impact score of 2.10×10^{-4} kg.s^{-1}.kW with power generation of 5.04×10^{4} W. Furthermore, the effluent contained a CO_2 concentration of 2.8% mole fraction.

The optimum fuel, air, water and coolant flow rates were 1.2×10^{-3}, 7.58×10^{-3}, 1.1×10^{-1} and 1.09×10^{-1} kg.s^{-1}, respectively.

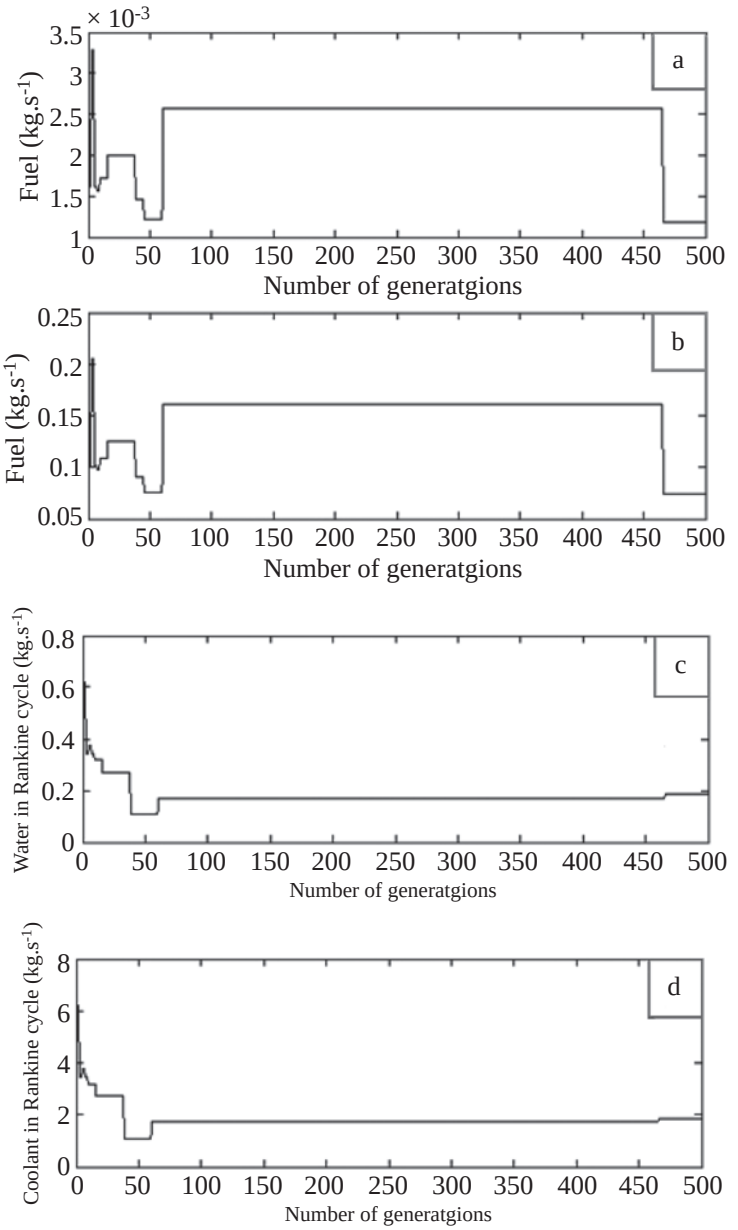

Figure 6 Four dependent parameters over multiple generations: (a) Fuel; (b) Air; (c) Water in Rankine cycle; and (d) Coolant in Rankine cycle.

Figure 8 shows the Pareto chart of the fixed current density model with 422 generations.

From Figure 8, the optimal solution is at 75.52% efficiency with a 0.16 $g.s^{-1}.kW$ environmental impact score. The amount of power generated was 221.28 kW and in the stack there was a CO_2 0.03 mole fraction. Moreover, the parameters of fuel, air, water and coolant flow rate at the optimum were 0.01, 0.33, 0.63 and 5.03 $kg.s^{-1}$, respectively. Both Figures 7 and 8 show the same trend but provide different environmental impact scores. Based on these

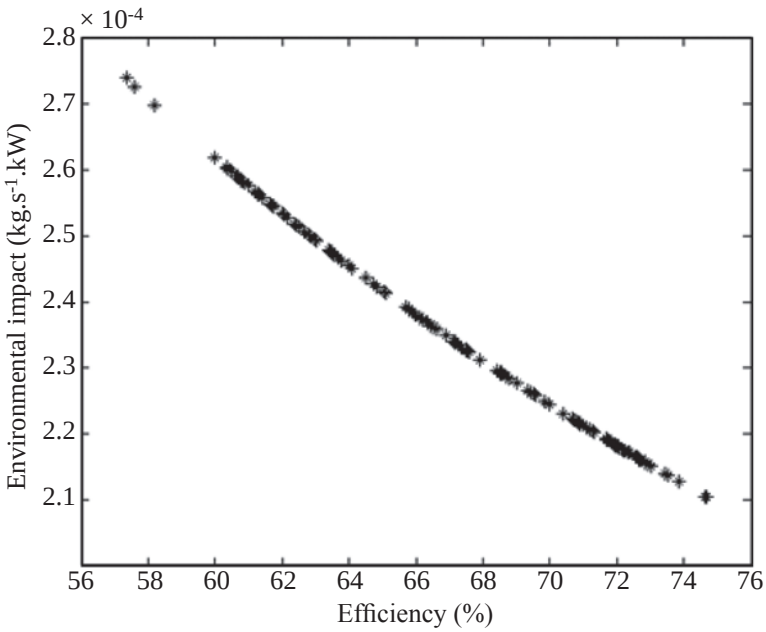

Figure 7 Pareto chart of the dependent parameters using the fixed temperature model.

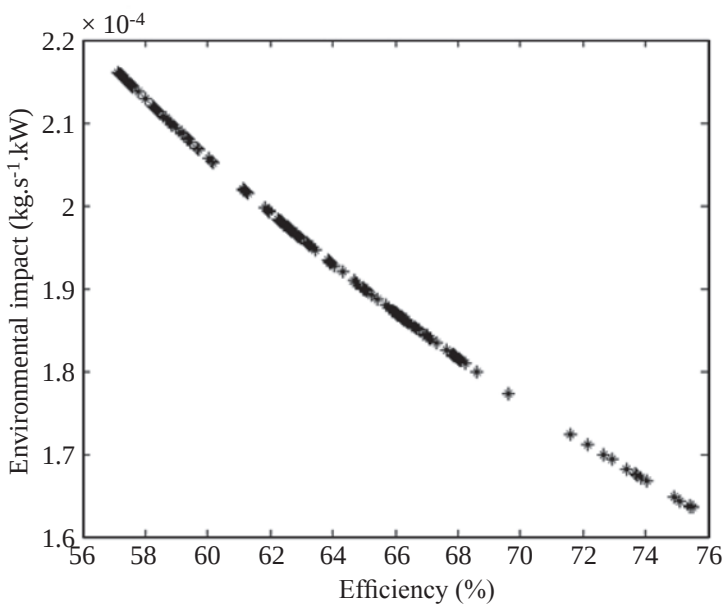

Figure 8 Pareto chart of fixed current density model after 422 generations.

results, either a fixed outlet temperature or fixed current density produces an efficiency of about 75% under different conditions. It is impossible to control both the current density and temperature. Thus, this study focused on not only the effect of the parameters but also on the effect of different models.

CONCLUSION

Tubular solid oxide fuel cell technology may be used in power generation because of its efficiency and environmentally friendly characteristics. Determining the optimal operational conditions will result in better performance under the best suitable conditions using the studied parameters of the flow rates of fuel, air, water and coolant. This work predicted the optimal operating conditions by maximizing system efficiency and minimizing the environmental impact score using a genetic algorithm as the optimization tool for the power generation process. The process consisted of a tubular solid oxide fuel cell operating with the Rankine cycle as the cogeneration system. The cell was developed separately from a common ASPEN plus block and the SOFC block was structured so that it could be easily extended to a whole stack of fuel cells. The whole process consisted of two parts—a tubular solid oxide fuel cell and a bottom cycle. For the bottom cycle, the Rankine cycle was embedded because it was simple and produced only water as emissions. Two different blocks were proposed, with the first using fixed air utilization and outlet temperature and the second using a fixed current density. Thus, two flow sheets were developed with each suiting different purposes.

ACKNOWLEDGEMENTS

The authors would like to express their thanks to Professor Peter Douglas, the University of Waterloo, as well as to the ChEPS Program, King Mongkut's University of Technology of Thonburi and the Centre for Advanced Studies in Industrial Technology, Department of Chemical Engineering, Faculty of Engineering Kasetsart University. for their great support in this research.

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