Operation Prediction of a Bioethanol Solar Reforming System Using a Neural Network*

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Abstract

The bioethanol reforming system (FBSR) using sunlight as a heat source is a fuel production system for fuel cells with little environmental impact. However, because solar radiation and outside air temperature are unstable, it is difficult to predict operation of the system with accuracy. Therefore, an operation prediction program of the FBSR using a layered neural network (NN) with the error-correction learning method has been developed. We developed a method of analyzing the operation of a natural energy system with sufficient accuracy. The weather pattern (the amount of global solar radiation and the outside air temperature) and energy-demand pattern for the past one year are inputted into the NN. Moreover, training signals are calculated by a genetic algorithm (GA). The training signals are given to the NN, and the operation pattern of the FBSR is made to learn. Operation of the FBSR on arbitrary days can be predicted by inputting the weather pattern and the energy-demand pattern into this learning NN. In this paper, the operation prediction program of the FBSR is developed, and details of the analytic accuracy are clarified. As a result of analyzing using the developed algorithm, when $\pm 20\%$ or less of power load fluctuation occurred, the operation plan was analyzable in 14% or less of error span. On the other hand, in operation prediction when $\pm 50\%$ or less of fluctuation is added to the outside temperature and global solar radiation, there was 16% or less analysis error.

Key words: Neural Network, Operation Prediction, Genetic Algorithm, Bioethanol, Solar Reforming, Fuel Cell

1. Introduction

Hydrogen supplied to a fuel cell is produced from fossil fuel, fuel alcohol, water electrolysis, etc. The environmental impact of the fuel cell changes with these hydrogen production methods. When distributing small-scale fuel cells to an urban area, installation of steam reforming of natural gas is influential ^{1), 2)}. Hydrogen production methods not dependent on fossil fuel have been investigated ^{3), 4)}. We are investigating the technique of bioethanol steam reforming using daylight as a heat source ⁵⁾. In the proposed system, hydrogen is produced by bioethanol steam reforming, and a proton-exchange-membrane fuel cell (PEM-FC) is operated. The heat of a Condensing Solar Collector is used for evaporation and steam reforming of the bioethanol fuel. In the utilization of bioethanol, CO₂ is hardly discharged. As renewable energy is used as the heat source, the proposed system is very clean equipment. However, the amounts of hydrogen production of this system differ according to the weather, time, season, installation location, etc. There are many examples

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Fig. 1 Fuel cell system with bioethanol solar reforming system (FBSR)

of the relation of meteorological data to the energy demand of buildings ^{6), 7)}. In this paper, when the weather pattern and the energy-demand pattern are inputted, a program that outputs the operation of the system is developed. We have been developing an analysis program of the dynamic operation planning of an energy system using a genetic algorithm (referred to as GA) ⁸⁾. However, a GA cannot predict the operation of an energy system. Moreover, the analysis time becomes very long with the increase in design variables. The optimal solution analyzed with a GA is used as the training signal of the neural network (referred to as NN) ⁹⁾. If the NN is made to learn based on a training signal, an operation result similar to the optimal solution can be predicted in a short time under arbitrary conditions (weather condition and energy-demand pattern). There have been many cases of operation planning of energy systems using a NN until now ^{10), 11)}. However, operation prediction of a dynamic system containing green energy has not been achieved. If this prediction method is realized, the optimum configuration for the area of introduction of the bioethanol solar reforming system can be proposed. The cost of equipment can be reduced because equipment capacity is optimized. Moreover, if the dynamic optimum operation of the system is calculable at high speed, installation in the controller will be possible. As a result, it is expected that the results of this study will contribute to the spread of distributed installation of fuel cells.

2. System configuration

2.1 Fuel cell system with bioethanol solar reforming system (FBSR)

Figure 1 is a block diagram of the fuel cell system with the bioethanol solar reforming system (referred to as FBSR) ⁵⁾. In the FBSR, two paraboloid rotating mirrors (described as Condensing Solar Collectors) that have a solar tracking system are used. The high-density solar energy in Condensing Solar Collector A is used for vaporization of the bioethanol fuel. The solar energy in Condensing Solar Collector B is used as the heat source to reform the fuel steam. The type and the condensing ratio of the Condensing Solar Collectors A and B differ. We are also evaluating the basic property of a condensing solar collector (Sun and Ice BmbH, Germany, <http://www.sun-and-ice.de>) which will be reported in another paper. When setting the condensing ratio from 1:120 to 1:150 and examining in Tomakomai at a time of clear sky in summertime, the condensing temperature exceeds 673K. When solar energy cannot be used, it generates electricity using the reformed gas stored in the cylinder, or commercial power is supplied. In order to reduce CO, a shifter and CO oxidation equipment are installed. As reformed gas contains a lot of steam, when compressing and storing reformed gas, moisture is removed by the cooler. Reformed gas is supplied to the fuel cell and the power is converted into regular voltage and a regular frequency with a DC-DC converter and an inverter. This power is supplied to an individual

house or a power grid through an interconnection device. The exhaust heat of the cooler, the fuel cell, and the CO oxidization equipment shown respectively in Fig. 1 is supplied to the heat storage tank, and this heat is supplied to the demand side.

2.2 Installation method of FBSR

Introducing the FBSR into a micro-grid is considered. Expected benefits from the micro-grid are backup power supply in case of emergency, reduction of environmental impact, and peak cut off for the power plant¹²⁾. Moreover, effective use of exhaust heat is possible and total efficiency is improved compared with the conventional power generation system. However, in the case study of this paper, the example of introducing FBSR into one house is investigated. This case is the simplest system.

2.3 Control of reformed fuel

The S/C (mole ratio of steam to ethanol) of the steady-state value of the reformed fuel supplied to the vaporizer equipment is 3.0. Moreover, the SV value (space velocity) in the catalyst layer in the solar reformer unit is 3000 hour⁻¹, the conversion ratio of the reformed gas is 95%, the methanization rate is 5%, and the CO generation percentage is 10%¹³⁾. When there is little solar radiation, the SV value is controlled to maintain the reaction temperature of the reforming unit at 673K or more.

2.4 Storage of reformed gas

The water content in the reformed gas is removed using the dryer. The pressure of this gas is P_0 and the quantity of flow is $U_{0,t}$. This gas is pressurized ($P_{cp} = 10\text{MPa}$) and stored with a compressor. The work of compressor $W_{p,t}$ is supposed to be the work of compression of the ideal gas, and is calculated using Eq. (1). φ_{cp} is the overall compressor efficiency. In the case study, φ_{cp} is set at 50% assuming a real machine. The power consumed with the compressor is supplied from the fuel cell.

$$W_{p,t} = P_0 U_{0,t} \ln(P_{cp}/P_0) / \varphi_{cp} \quad (1)$$

3. Energy and mass balance

3.1 Energy balance

Equations (2) and (3) express the balance of the power and heat, respectively. The left-hand side of each equation expresses inputs, and the right-hand side expresses outputs. ϕ_T and ϕ_{CT} in Eq. (2) are the efficiency of the inverter and the DC-DC converter, respectively. Moreover, $\dot{E}_{AUX}$ expresses the demand of auxiliary machinery. $\dot{H}_{Loss}$ on the right-hand side of Eq. (3) is the heat loss of the system.

Power balance

$$\phi_T \cdot \phi_{CT} \cdot \dot{E}_{CS} + \dot{E}_{CC} = \dot{E}_{SYS} + \dot{E}_{AUX} \quad (2)$$

Heat balance

$$\dot{H}_{CL} + \dot{H}_{CS} + \dot{H}_{OU} + \dot{H}_{ST} + \dot{H}_{BL} = \dot{H}_{SYS} + \dot{H}_{Loss} \quad (3)$$

3.2 Mass balance

Equation (4) expresses the mass balance of hydrogen, and Eq. (5) expresses the reaction formula of the steam reforming of ethanol. Equation (6) expresses the relation between the quantity of flow of bioethanol ($\dot{Q}_{BE}$) calculated using the mass balance, and the hydrogen quantity of flow ($\dot{Q}_{SR}$) in the solar reforming unit outlet. ϕ_C in the equation expresses the conversion ratio.

$$\text{Hydrogen balance} \quad \dot{Q}_{SR} + \dot{Q}_{HC} + \dot{Q}_{EX} = \dot{Q}_{OU} + \dot{Q}_{OU} - \dot{Q}_{SU} \quad (4)$$

$$\text{Steam reforming of bioethanol} \quad C_2H_5OH + 3H_2O \rightarrow 2CO_2 + 6H_2 - 173\text{kJ/mol} \quad (5)$$

$$\dot{Q}_{SR} = 0.2746 \cdot \phi_C \cdot \dot{Q}_{BE} \quad (6)$$

4. Operation prediction program of the SRF

4.1 Operation prediction algorithm

Changing the equipment will not be easy if an actual system is built. Therefore, optimization considering annual operation is required. Figure 2 shows the preparation procedure of the operation prediction algorithm of the SRF developed in this paper. In the operation prediction using the NN, as shown in Fig. 2, it is necessary to perform the learning process first. The training signal used for the learning calculation is previously calculated by the GA. The training signal is the optimal solution of the dynamic operation plan on a representative day. Moreover, the input data given to the NN are the past weather pattern (the global solar radiation and the outside air temperature at each time on January 1, 2006 to December 31) and the past energy-demand pattern (average value of every month for every time of power and heat demand). In the learning calculation by the NN, as described in Section 4.2 and Section 4.3, the weights of the network of each neuron are determined. If the learning calculation of the NN finishes, the weather pattern and energy-demand pattern of arbitrary days is given to the NN. As a result, the collecting areas of Solar Collectors A and B, the cylinder capacity of the reformed gas, and the capacity of the heat storage tank are obtained.

4.2 Structure of the neural network

The structure of the layered neural network introduced in this paper is shown in Fig. 3. This neural network consists of three layers, the input, the medium, and the output. All the neurons between each layer of the NN are connected with networks. Each neuron is outputted to output layer $S_{o,k,j}$ according to the magnitude of the input. Input-output

Fig. 2 Procedure of the SRF prediction algorithm

Fig. 3 Layered neural network of the proposed system

Fig. 4 Input and output of the neuron

between the neurons of $n-1$ layer and n layer is shown in Fig. 4. Input x_j^n of neuron j in n layer is calculable using output out_k^{n-1} and weight $w_{j,k}^{n,n-1}$ of neuron k of $n-1$ layer, as shown in Eq. (7):

where $j=1, \dots, L_n$ and $k=1, \dots, L_{n-1}$.

$$x_j^n = \sum_{k=1}^{L_{n-1}} w_{j,k}^{n,n-1} \cdot out_k^{n-1} \quad (7)$$

Output out_j^n of neuron j in n layer is given with the sigmoid function of input x_j^n , as shown in Eq. (8).

$$out_j^n = \frac{1}{1 + \exp(-x_j^n)} \quad (8)$$

4.3 Learning calculation

(1) The learning method

All weight $w_{j,k}^{n,n-1}$ in the NN shown in Fig. 3 using the error-correction learning method is determined. So, the past weather pattern and the energy-demand pattern in a building are given to the NN. Training signals are solutions of the operation plan on the representative day previously calculated by the GA. When $w_{j,k}^{n,n-1}$ is decided by learning of the NN, the error of the training signal and the data of the output layer can be evaluated from Eq. (9). This error is expressed as Err_N , and the NN is made to learn, changing weight $w_{j,k}^{n,n-1}$ so that Err_N may approach zero.

$$Err_N = \frac{1}{2} \cdot \sum_{j=1}^{L_n} (y_j - out_j^N)^2 \quad (9)$$

(2) Modification of weights

Corrected weight $w_{j,k}^{n,n-1}$ is expressed with Eq. (10) using the weight before modification $\bar{w}_{j,k}^{n,n-1}$ and amount of modifications $\Delta w_{j,k}^{n,n-1}$. Amount of modifications $\Delta w_{j,k}^{n,n-1}$ in Eq. (10) is expressed with Eq. (11). The term of the partial differential of the right-hand side of Eq. (11) is calculable by Eqs. (12) and (13) ¹⁴⁾.

$$w_{j,k}^{n,n-1} = \bar{w}_{j,k}^{n,n-1} + \Delta w_{j,k}^{n,n-1} \quad (10)$$

$$\Delta w_{j,k}^{n,n-1} = -\eta \frac{\partial Err_N}{\partial w_{j,k}^{n,n-1}} = -\eta \frac{\partial Err_N}{\partial x_j^n} out_j^{n-1} \quad (11)$$

At the case of $n = N$

$$\frac{\partial Err_N}{\partial x_j^n} = -(y_j - x_j^N) \cdot out_j^N \cdot (1 - out_j^N) \quad (12)$$

At the case of $n < N$

$$\frac{\partial Err_N}{\partial x_j^n} = \left\{ \sum_{l=1}^{L_n} \frac{\partial Err_N}{\partial x_j^{n+1}} \cdot w_{l,j}^{n+1,n} \right\} \cdot out_j^n \cdot (1 - out_j^n) \quad (13)$$

(3) Analysis flow of the learning process

Figure 5 shows the analysis flow of the learning process of the NN. All weights $w_{j,k}^{n,n-1}$ are first determined at random, and learning rate η in Eq. (11) is given to the program. Next, input data x_j^n described in Section 4.1 and 4.2 and training signal y_j described at the bottom are inputted into the program, and input x_j^n and output out_j^n of each neuron are calculated. Equation (12) is calculated using out_j^n and y_j , and Eq. (13) is calculated further. These results are introduced into Eq. (11), and $\Delta w_{j,k}^{n,n-1}$ are calculated. When this value is given to Eq. (10), the weight of each neuron can be updated. The analysis error is calculated using Eq. (9), and calculation will finish if this value is smaller than the value set

Fig. 5 Analysis flow of the NN learning process

Fig. 6 Operation plan of a representative day

Fig. 8 Analysis flow of the training signal using GA

Fig. 7 Chromosome code

- Determination of the optimal solution
- Area of solar collector A
 - Area of solar collector B
 - Capacity of hydrogen cylinder
 - Capacity of heat storage tank

up previously. On the other hand, when the analysis error is larger than the value set up previously, as shown in Fig. 5, the process is returned and calculated repeatedly.

4.4 Preparation of the training signal using a GA

4.4.1 Dynamic operation plan of a representative day

A GA can investigate optimization of the nonlinear problem of many variables. However, determination of the solution parameter (the population of chromosomes, selection, mutation probability, crossover probability, generation number) concerning genetic manipulation requires many trials. Moreover, because a GA has the characteristic of random search, the analysis time will be long when the design variables increase in number. Therefore, when the operation plan of the FBSR is analyzed by a GA, a very long time to try will be required. On the other hand, with the NN, although based on the network structure of the neurons, the time to try is short compared with GA calculation. So, in this paper, the training signal of the NN is prepared using a GA and actual operation prediction is analyzed only by the NN.

4.4.2 Start time of system operation

Figure 6 shows the case of the power-demand pattern in a building and the operation pattern of the system. In this figure, solar radiation is obtained with a Condensing Solar Collector in period R_{dh} from 06:00 to 18:00. In this case, start time t_{st} of the system

operation is 06:00. In insufficient time zones, the system generates electricity using the reformed gas stored during the daytime. In period R of time t_{gs} to time t_{ge} shown in Fig. 6, energy is supplied from the fuel cell. Although t_{gs} and t_{ge} can be determined arbitrarily, in the case study in Section 5, it is set at 23:00 and 07:00. This time zone is set at midnight power in many domestic electric power companies.

4.4.3 Chromosome model and analysis flow

The collecting area of Solar Collector B of the FBSR is expressed with the chromosome code shown in Fig. 7. The chromosome code is 13-bit genetic code of 0 or 1. Figure 8 shows the analysis flow for obtaining training signals using the GA. Many chromosome codes are generated, and the adaptive values (objective function) described in the following section for all the chromosomes are calculated. Chromosome groups with a low adaptive value are exchanged for chromosome groups newly generated at random. Moreover, handling of the crossover and the mutation are added to chromosomes and diversity is maintained. These calculations are repeated by the number of generation numbers set up previously. In the last generation, it is decided that the chromosome with the highest adaptive value is the optimal solution. The collecting area of Solar Collector B is decided by decoding this chromosome code. Using this result, the cylinder capacity of the reformed gas, the capacity of the heat storage tank, and the collecting area of Solar Collector A are calculated. The maximum value of the quantity of reformed gas and exhaust heat to be stored at each time on a representative day is decided as the capacity of the reformed gas cylinder and the heat storage tank. The collecting area of Solar Collector A is calculated from the heat quantity required to reform bioethanol fuel by Solar Collector B.

4.4.4 Objective function and adaptive value

Equation (14) expresses the sum total of the difference in the power of the system and demand on a representative day. When the cylinder capacity of the reformed gas and the capacity of the heat storage tank are expressed as V_{H_2} and V_{hw} , respectively, objective function f_o of the system is given in Eq. (15). $w_{o,1}$, $w_{o,2}$, and $w_{o,3}$ in Eq. (15) express the weight of each term. In this paper, it is decided that the adaptive value in the GA is a high solution, so that the value of f_o is small. Moreover, the reformed gas cylinder and the heat storage tank are designed to be as small as possible. In this objective function, the supply-and-demand balance error of power is minimized. Furthermore, the reforming gas cylinder and the heat storage tank are made small, and the whole system is miniaturized.

$$Err_{day} = \sum_{t_{gs}}^{t_{ge}} |\dot{E}_N - \dot{E}_{SYS}| \quad (14)$$

$$f_o = w_{o,1} \cdot Err_{day} + w_{o,2} \cdot V_{H_2} + w_{o,3} \cdot V_{hw} \quad (15)$$

5. Case study

5.1 Analysis system

Operation of the system when the FBSR shown in Fig. 1 is introduced into an individual house is predicted. The energy demanded of the individual house used as input data introduces the data of the reference¹⁵⁾. Moreover, the database of the Japan Meteorological Agency is used concerning outside air temperature and global solar radiation. The reference⁵⁾ has described the calculation method of the amount of direct solar radiation obtained by the Condensing Solar Collector. Operation of the system is taken as the pattern shown in Fig. 6 where, $t_{gs} = 08:00$ and $t_{ge} = 21:00$. The data inputted into the NN by learning calculation are the weather pattern in 2006 and the energy-demand pattern of a house¹⁶⁾. Operation prediction of the FBSR on arbitrary days is calculable by giving the learning NN the weather pattern and the energy-demand pattern.

Table 1 Conditions of the system components

Capacity of the PEM	1000 W
Ratio of number of moles of water to number of moles of carbon	3.0
Outlet temperature of vaporizer unit	673 K
Entrance temperature of reformed gas cooler	453 K
Outlet temperature of reformed gas cooler	313 K
Efficiency of compressor	50 %
Efficiency of DC-DC converter and inverter	95 %
Compression pressure of reformed gas	10 MPa
Rate of utilization of fuel at the side of anode	70 %

Table 2 Parameters of the GA

The number of chromosomes	5000
Proportion of the chromosome to select	40 %
Crossover probability	0.2
Mutation probability	0.2
The number of generations	100

Table 3 Parameters of the NN

Learning rate	0.1
Stabilization constant	0.1
The number of times of a iteration	50000

5.2 Characteristics of the system

The single-cell performance of the PEM-FC is shown in Fig. 9. This performance is obtained from the experiments in the references ^{17), 18)}. The maximum output point of the single cell is decided as 100% of a load factor in this paper. Figure 10 shows the relation between the load factor and the power density prepared from single-cell performance. The characteristics shown in Fig. 10 are divided into three areas, and approximate expressions are shown in this figure. When the production of electricity of the PEM-FC is decided, the generation efficiency, the power density, and the amount of exhaust heat will be decided from Figs. 9 and 10. The conditions of the system components used in analysis are shown in Table 1.

5.3 Analysis condition

The parameters introduced into the analysis of the GA and the NN are shown in Tables 2 and 3, respectively. These values were determined by applying a trial-and-error method for many analyses. When operation of the FBSR is analyzed by the NN using the conditions in Table 3, the computation time is 90 to 110 times faster compared with the GA.

The analytical object is an individual house in Sapporo with the weather pattern and the energy-demand pattern shown in Fig. 11. There is no cooling load in the summer season, and hot water supply, baths, and space heating load are included in the heat demand. Moreover, the load of electric lights and household appliances is included in the power demand, and there is no large difference in each month.

In the operation plan in this paper, the priority of design variables is in order of the collecting area of the solar collector, the cylinder capacity of the reformed gas, and the capacity of the heat storage tank. Then, weights $w_{o,1}$, $w_{o,2}$ and $w_{o,3}$, of the objective function shown in Eq. (15) is set at 0.7, 0.2, and 0.1, respectively.

6. Result of operation prediction

6.1 Preparation of training signal

Figure 12 shows the result of the operation plan of the FBSR by the GA that introduced the weather pattern in 2006. Figures 12 (a) and 12 (b) express the collecting area of Solar Collectors A and B, the cylinder capacity of the reformed gas (expressed with hydrogen quantity), and the capacity of the heat storage tank, respectively. The rate of energy supplied every month from the FBSR to the power- and heat-demand amount of a representative day is shown in Fig. 12 (c).

(1) Difference for every year

In order to examine the difference for every year, the collecting areas of the solar collector in January, November, and December in 2004 to 2006 were analyzed. Since January, November, and December have small solar radiation, their difference in the

Fig. 9 Cell stack power output

Fig. 10 Relation between load factor and power output of the cell stack

Fig. 11 Meteorological pattern and energy demand pattern in Sapporo

Fig. 12 Analysis results of the operation plan using GA

collecting area of the solar collector is larger than in other months. These results are shown in Fig. 12 (a). The difference of every month of these years was 12% at maximum.

(2) The cylinder capacity of the reformed gas and capacity of the heat storage tank

As shown in Fig. 12 (b), the change of the cylinder capacity of the reformed gas is less than 12%, which is small compared with the heat storage capacity. The reason is the objective function of the system described in the following section. On the other hand, because the heat-demand amount changes greatly with the season, the change in the heating storage capacity every month is large.

(3) Amount of energy supplied from the FBSR

As shown in Fig. 12 (c), the power supplied from the FBSR is 67% to 76% of the demand. However, the heat supplied from the FBSR is 3% to 47%, differing greatly according to the season. Supplying energy for the power demand from t_{gs} to t_{ge} is included in the objective function (Eqs. (14) and (15)) of the FBSR. Therefore, the power

supply rate from the FBSR is high compared to demand.

6.2 Operation prediction by the NN

(1) Highest analytic accuracy of the NN

Operation of the system is predicted by the learning NN using the same input data introduced by the learning process of the NN. These analysis results have the highest accuracy in the proposed NN. Figure 13 shows the analysis result in this case. Except for the amount of hydrogen storage, there is less than 1% error. The largest error in hydrogen storage is 1.7%. From this result, with the difference of input data and the data of the learning process, system operation can be predicted with an accuracy of less than several percent.

(2) Analytic accuracy of operation prediction

Figure 14 shows the analysis error when adding $\pm 5\%$, $\pm 10\%$, and $\pm 20\%$ of fluctuation at random to the power-demand pattern introduced into learning of the NN. Figure 15 shows the analysis error when adding $\pm 10\%$, $\pm 30\%$, and $\pm 50\%$ of fluctuation at random to the weather pattern (the outside air temperature and the global solar radiation) used by the learning process of the NN. However, when loads are added to input data at random, the pattern of the analysis error of the NN has diversity. But the maximum value with error converges on the constant range. When operation of the system is predicted from the input data with $\pm 20\%$ of load fluctuation added to the power load of the learning process, the analysis errors of the solar collecting area, the cylinder capacity of the reformed gas, and the heating storage capacity are 6%, 14%, and 11%, respectively. On the other hand, when operation of the system is predicted from the input data with $\pm 50\%$ of load fluctuation added to the outside air temperature and the global solar radiation of the learning process, the analysis errors of the solar collecting area, the cylinder capacity of the reformed gas, and the heating storage capacity are 16%, 13%, and 14%, respectively. In the operation prediction program of the FBSR developed in this paper, accurate analysis within the limits

Fig. 13 Calculation error of Neural network to GA

(a) Area of the solar collector A

(b) Capacity of the hydrogen storage

(c) Capacity of the heat storage

Fig. 14 Analysis result of the neural network in the case of with power change

(a) Area of the solar collector A

(b) Capacity of the hydrogen storage

(c) Capacity of the heat storage

Fig. 15 Analysis result of the neural network in the case of with outside temperature and solar radiation change

described above is possible.

7. Conclusions

The operation prediction program of a fuel cell system with a bioethanol solar reforming system using a neural network was developed. In this program, the operation plan of a building analyzed using a genetic algorithm is introduced as a training signal. When input data (weather pattern and energy-demand pattern) are given to the learning program, the operation method of the system on arbitrary days can be obtained. The operation method obtained in analysis is the collecting area of the solar collector, the cylinder capacity of the reformed gas, and the capacity of the heat storage tank. Operation prediction of individual houses was analyzed using the program developed. Moreover, the analytic accuracy of the operation prediction by the proposal NN program in case random fluctuation is added to the weather pattern and the energy-demand pattern is shown. When operation of the system is predicted from the input data with $\pm 20\%$ of load fluctuation added to the power load of the learning process, there were analysis errors of 14% or less. On the other hand, when operation of the system is predicted from the input data with $\pm 50\%$ of load fluctuation added to the outside air temperature and the global solar radiation of the learning process, there were analysis errors of 16% or less. Even if power load fluctuation ($\pm 20\%$ or less) or weather fluctuation ($\pm 50\%$ or less, outdoor air temperature and the amount of global solar radiation) occurs, the operation analysis error of the proposal algorithm is 16% at the maximum. The fluctuating range of the power, outside air temperature and amount of solar radiation was determined in consideration of the actual design. Especially prediction of outdoor air temperature and the amount of global solar radiation is difficult. But the analytic accuracy realized in this paper is available enough to a design and operation plan of the system.

Nomenclature

$\dot{E}$	power	W	$\dot{q}$	amount of global solar radiation	W/m ²
$\dot{E}_N$	power demand	W	R	operating period of the fuel cell	s
$\dot{E}_{SYS}$	production of electricity of the system	W	R_{dh}	period of the day light	s
$\dot{E}_{AUX}$	consumption power of auxiliary the machinery	W	$S_{m,j,i}$	the intermediate layer's neuron connected to j from neuron i	
ELF	load factor		$S_{o,k,j}$	the output layer's neuron connected to k from neuron j	
Err_{day}	difference of the power generation of the system and demand in a representative day	W	T	outside air temperature	K
Err_N	error of the output data and training signal of the NN		t	sampling time	s
f_o	objective function		t_{ge}	operation finish time of a fuel cell	
$\dot{H}$	heat	W	t_{gs}	start-up time of a fuel cell	
$\dot{H}_{Loss}$	heat loss	W	t_{st}	sampling start time	o'clock
i, j, k	the number of a neuron		$U_{0,t}$	reformed gas quantity of flow at the reforming unit outlet	m ³ /s
L_n	the number of neurons of n layer		V_{H_2}	the amount of hydrogen storage	g
N, n	layer number		V_{hw}	exhaust heat quantity to be stored	J
out_y^z	the output of the neuron y of layer z		W_p	Work of the compressor	W
P_{cp}	compression pressure of reformed gas	Pa	$w_{j,i}^{n,m}$	weight of the neuron i of layer m , and the network of neuron j of layer n	
P_0	reformed gas pressure at the reforming unit outlet	Pa	$\bar{w}$	weight before modification	
Q	quantity of flow	g/s	Δw	amount of modifications of weight	
Q_{OU}	hydrogen quantity lost in CO oxidation unit	g/s	w_o	weight of the component of the objective function	
			x_y^z	input to the neuron y of layer z	
			y_j	training signal	

Greek Symbols			CC	commercial power
ϕ_c	conversion ratio	%	CL	reformed gas cooler
ϕ_{CT}	inverter efficiency	%	CS	cell stack
ϕ_T	DC-DC converter efficiency	%	OU	CO oxidation unit
ϕ_{cp}	overall compressor efficiency	%	SR	solar reforming unit
η	learning rate in the NN		ST	heat storage tank
Subscripts			SU	shift unit
BE	bioethanol		SYS	system
BL	boiler			

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