2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)
Melbourne, Australia, Nov 28 - Dec 1, 2016

An ANN-based Design for Weather Derivatives in Consideration of Meteorological Uncertainties

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***Abstract*—In this paper, an intelligent design method of weather derivatives is proposed to deal with meteorological uncertainties. This paper aims at equalizing the payoffs in the color option. The proposed method makes use of a hybrid intelligent system that consists of DA (Deterministic Annealing) clustering as a prefiltering technique, MLP (Multi-Layer Perceptron) of ANN (Artificial Neural Network) for a predictor and EPSO (Evolutionary Particle Swarm Optimization) of evolutionary computation for optimizing parameters of the contract. The objective function is to minimize the difference of received payoffs between two companies. The effectiveness of the proposed method is demonstrated in real data simulation.**

Keywords*— weather derivatives; deterministic annealing clustering; forecasting; artificial neural network; evolutionary compitation; EPSO; Monte Carlo Simulation

I. INTRODUCTION

This paper presents a hybrid intelligent system for designing a color option of weather derivatives. In recent years, risk hedges are one of important topics in energy companies. The price of a certain commodity often varies like the currency exchange rate. To carry out risk hedges, derivatives play a key role to reduce risks. General speaking, they contribute to the stabilization financial conditions and management. Apart from financial derivatives, weather derivatives correspond to a tool to protect companies against unexpected losses by the changes of weather conditions [1, 2]. Since WRMA [3] (Weather Risk Management Association) was founded in 1999, the total original principal of weather derivatives via OTC (Over The Counter) is inclined to increase [4]. As a result, the market size has been expanding in the world. Pricing of weather derivatives is one of important tasks. It aims at setting up the contract with the equivalence of payoffs for an uncertain weather index in the probabilistic process. The conventional methods may be classified into the followings:

a) the Black-Sholes equation and the variants [5],[9],[10]
b) MCS (Monte Carlo Simulation) with the probabilistic distribution of predicted weather index[6- 8]
c) Estimation of pay-off function in color options [11]

Method a) makes assumption that the weather index follows the Brownian motion that is one of the random processes. However, it is pointed out that the weather indices have a trend or the seasonality. In other words, the method deals with ideal conditions in financial engineering that do not reflect the realistic ones in weather derivatives. Method b) focuses on the predicted temperature to evaluate pricing through MCS. The mainstream of Method b) is the statistical methods. Method c) handles how to construct the payoff function between two compnies in color options to equalize the payoff.

In this paper, a method is proposed to handle pricing of weather derivatives with ANN(Artificial Neural Network) in conjuction with Method c). It has an advantage to approximate any nonlinear functions in comparison with the statistical methods. As an ANN model, MLP(Multi-layer Preceptron) is used to forecast daily average temperature. A prefiltering technique of DA (Deterministic Annealing) clustering [13,14] is employed to improve the performance of MLP that is constructed at each cluster. The use of the prefiltering technique makes the learning process of MLP easier due to data similarity [14]. Since this paper aims at designing the collar option in summer, three clusters such as average, hot and cool summer are considered. This paper focuses on weather derivatives for average summer as the first stage of research. Next, the frequency distribution of daily average temperature is created by generating probabilistic input variables for the predicted model. The parameters of the color option are estimated to minimize the difference of payoffs between two companies for samples obtained from the frequency distribution. To obtain a globally optimal or its highly approximate solution, EPSO [16-18] of evolutionary computation is used to evaluate the parameters. The proposed method is successfully applied to real data in Tokyo, Japan.

II. WEATHER DERIVATIVE

This section explains the concept of weather derivatives. If the weather conditions are satisfied, the predetermined payoffs are given to the contractants regardless of the extent of damages they received. One of the features on weather derivatives is to make use of weather indices such as temperature, rainfalls, snowfalls, *etc*. to evaluate the payoffs. As the typical weather indices, CDD (Cooling Degree Day) and HDD (Heating Degree Day) are well-spread in weather derivatives. They may be written as

$$CDD = max(T_{ave} - T_{base}, 0) \qquad (1)$$

$$HDD = max(T_{base} - T_{ave}, 0) \qquad (2)$$

where
T_{ave} : average temperature
T_{base} : reference temperature such as 65°F
$max(\cdot,*)$: larger value in $\cdot$ and $*$

CDD is used to measure how the day is hot in summer. If it exceeds the reference temperature, air conditioning facilities are turned on to cool the buildings or rooms. On the other hand, HDD indicates an opposite case to CDD. Namely, it reflects the measure of energy consumption in winter by evaluating the difference between daily average temperature and 65°F. Also, as another index, CAT (Cumulative Average Temperature) has been used in Europe. It may be written as

$$CAT = \sum_{i=1}^{N} T_{ave}(i) \tag{3}$$

where

$T_{ave}(i)$: average temperature on day i
N: duration to be evaluated

It has advantage to deal with the risk hedge for a month or year in which the cumulative of the average temperature is used as the index. Although, CDD and HDD focus on only daily average temperature, it is important to handle risk handle for a certain period. To extend the indices of CDD and HDD into general forms, Cumulative CDD and HDD may be defined as

$$Cumulative\ CDD = \sum_{i=1}^{N} CDD_i \tag{4}$$

$$Cumulative\ HDD = \sum_{i=1}^{N} HDD_i \tag{5}$$

where

$CDD_i(HDD_i)$: $CDD(HDD)$ on day i

Also, the derivatives may be classified into the following:

a) call option
b) put option
c) color option
d) swap

Item a) above is a scheme that after paying fees called *premium*, payoffs are given once the temperature conditions are stratified. The conditions mean that temperature exceeds a certain predetermined value. The payoffs are determined by the contract model. Item b) is opposite to case of Item a) in a sense that payoffs are provided if temperature drops to a lower value as shown in Fig. 1. Item c) is another combination of Items a) and b) that sets up a dead zone. Item d) is a combination of Items a) and b) in which two companies with conflicting risks hedge a risk without the dead zone. It has a feature that the risk is complementarily hedged in case of temperature rising or dropping [1], [2].

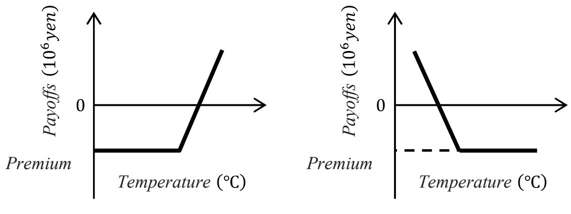

Fig. 1. Concept of each option.

III. DA Clustering

This section describes Deterministic Annealing (DA) Clustering. It is similar to Simulated Annealing (SA) in a sense that temperature parameter is used to control the algorithm repeatedly. Now, let us review SA developed by Kirkpatrick, *et al* . [12]. It makes use of the Metropolis algorithm that employs a criterion if the generated state is adopted or not in Monte Carlo Simulation. It stems from statistical physics and aims at solving nonlinear optimization problems. It employs analogy of the annealing process of the heat bath of metal and evaluates an optimal solution by cooling temperature parameter gradually. If temperature is high, the state is allowed to expand into the search range. As temperature becomes low, the range is shrinking converges to an optimal solution.

Rose, *et al.* developed DA clustering [13] that is similar to SA. DA is based on free energy that is one of states in thermal dynamics. It focuses on changing the cost functions rather than the states from a simple form to the original nonlinear one step by step. In other words, the algorithm parameter corresponding to the inverse of temperature plays a key role to change the cost function gradually. Next, suppose DA clustering in which DA is applied to clustering given data x is classified into *K* clusters. It is one of global clustering methods that are not affected by the initial conditions. The cost function may be written as

$$d = \sum_{\boldsymbol{x}} \sum_{i=1}^{K} P(C_i|\boldsymbol{x}) \left\| \boldsymbol{x} - \boldsymbol{y}_i \right\|^2 \tag{6}$$

where
d: cost function
$P(C_i|\boldsymbol{x})$: attribution in probabilistic that vector $\boldsymbol{x}$ belongs to cluster i
$\|\cdot\|$: Euclidean norm of vector $\cdot$
$\boldsymbol{x}$: data to be clustered
K: number of clusters
$\boldsymbol{y}_i$: center of cluster i

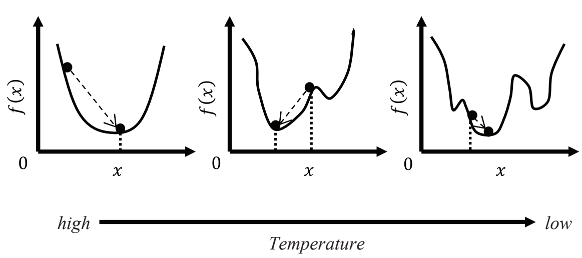

Fig. 2. Concept of DA.

The main difference between DA clustering and k-means of the conventional method is that the former has probabilistic attribution of [0, 1] and the latter has deterministic ones, *i.e.*, 0 or 1. According to the principal of maximum entropy, the attribute of DA may be written as

$$P(C_i|\boldsymbol{x}) = \frac{exp\left(-\beta||\boldsymbol{x}-\boldsymbol{y}_i||^2\right)}{\sum_{j=1}^{K} exp\left(-\beta\left||\boldsymbol{x}-\boldsymbol{y}_j|\right|^2\right)} \tag{7}$$

where, β: parameter such $\beta = \frac{1}{T}$ $(T: temperature)$

The principal of maximum entropy is a method that constructs a probabilistic model to maintain uniform weights at each attribute while minimizing (5). In an equilibrium of free energy, certain y_i of cluster i may be written as

$$\boldsymbol{y}_i = \frac{\sum_x \boldsymbol{x} P(C_i|\boldsymbol{x})}{\sum_x P(C_i|\boldsymbol{x})} \tag{8}$$

Therefore, it turns out that changing the cost function with parameter β leads to a deterministic optimal solution in (6). The algorithm of DA may be summarized as follows:

Step 1: Set initial conditions (initial temperature, cooling schedule, the termination conditions, *etc*.).
Step 2: Prepare the initial conditions of clusters.
Step 3: Calculate the attribute at each cluster with (7).
Step 4: Update the clusters with (8).
Step 5: Evaluate the attribute at each updated cluster with (7).
Step 6: Calculate the cost function in (6).
Step 7: Stop if the following conditions are satisfied:

$$\left|\frac{d^{(l+1)} - d^{(l)}}{d^{(l)}}\right| \leq \varepsilon \tag{9}$$

where
l: iteration number
ε: termination conditions
Otherwise, return to Step 8.
Step 8: Stop if $\beta \geq \beta_{max}$ (β_{max}: upper bound of β). Otherwise, update β to return to Step 4.

It should be noted in Step 2 that a center at each cluster is selected from data $\boldsymbol{x}$. Steps 4-7 are repeated until ε becomes a sufficiently small value.

IV. EPSO

In this section, EPSO of swarm intelligence is outlined [16,17]. Miranda and Fonseca developed the method that applied ES (Evolutionary Strategy) to PSO (Particle Swarm Optimization) [18]. ES is one of evolutionary computation techniques that solve nonlinear optimization problems by adding the Gaussian noise to the current solution to generate new states. PSO comes from an analogy in which a group of birds on fishes are in search of food. The solution candidates may be regarded as a group of particles that try to find out better solutions while sharing information on better solutions and interacting with each other. Although PSO efficiently evaluates better solutions due to multi-point search, it has a drawback to get stuck in a local minimum easily if the algorithm parameters are inappropriate. To overcome the problem, EPSO was developed to tune up the parameters at each iteration to escape from a local minimum. It has a strategy to carry out mutations for the parameters in the moving rule. The use of mutations prevents the solution candidates from getting stuck in a local minimum. Also, the mutations are given to best solution *i.e., gbest* in PSO to make solution candidates more diverse and obtain much better solutions. The moving rule of EPSO may be written as

$$S_i^{t+1} = S_i^t + V_i^{t+1} \tag{10}$$

$$V_i^{t+1} = w_{i0}^* V_i^t + w_{i1}^*(pbest_i - S_i^t) + w_{i2}^*(gbest^* - S_i^t) \tag{11}$$

$$w_{ik}^* = w_{ik} + \tau N(0,1) \tag{12}$$

$$gbest^* = gbest + \tau' N(0,1) \tag{13}$$

where
S_i^t: location of particle i at iteration t
V_i^t: velocity of particle i at iteration t
$pbest_i$: best solution of particle i until now
$gbest$: best solution of a group of agents until now
w_{ik} $(k = 0,1,2)$: weights ($\cdot^*$: mutated parameter $\cdot$)
τ, τ': learning rates
$N(0,1)$: Gaussian random numbers with mean 0 and variance 1

It should be noted that ES is repeatedly used to copy solution candidates, apply the mutation operation to them and select the best solution from the mutated solution candidates. The algorithm of EPSO may be summarized as follows:

Step 1: Set the initial conditions.
Step 2: Replicate each particle.
Step 3: Evaluate new the solutions with the moving rule.
Step 4: Calculate the cost function for each particle.
Step 5: Select if the termination conditions are satisfied. Otherwise, return to Step 2.

Step1 gives the initial conditions of weights and location for each particle, the replication rates, *etc*. Step 2 copies each particle to make solution candidates more diverse with (12). Step 3 makes use of mutated particles to evaluate new solutions. Step 4 determines survivals of solutions by calculating the cost function for all the solution candidates and selecting the best solution from them. Step 5 involves the process that updates new *pbest* and *gbest* if better solutions are evaluated until now. In Step 6, the termination conditions are set up to be certain maximum interaction counts.

V. Proposed Method

This paper proposes a new method for weather derivatives. The proposed method makes use of DA clustering, MLP of ANN and EPSO of evolutionary computation to model the weather derivatives as shown in Fig. 3. In 2001, the color option was carried out between Tokyo Electric Power Company (TEPCO) and Tokyo Gas Company (TGC). As mentioned before, the color option plays a role to alleviate unexpected losses in a complement way. The following risk structure was employed: TEPCO received high payoffs from TGC in case of high daily average temperature. On the other hand, TGC obtained them from TEPCO in case of low daily average temperature. Fig. 4 shows the concept of color option with parameters x_1-x_6. This contract had a feature that TEPCO paid ¥800,000 to TGC for 0.1℃ temperature rise if the daily average temperature exceeded 26.5℃. On the other hand, TGC gave ¥800.000 to TEPCO for 0.1℃ temperature fall if the daily average temperature dropped to 25.5℃. That was because the daily average temperature sets up a dead zone between 25.5℃ and 26.5℃. The two cases above had the payoff limitation of ¥12,000,000 to be received [20].

A. Tenperature Forecasting

Pricing of weather derivatives requires temperature forecasting. As the conventional methods, Dischel D1 model [6] or Cao-Wei model [7] were developed to model the stochastic process of temperature variations in weather. The stochastic models are based on the average recursive model that employs the average temperature for several years, temperature on the previous days, and the difference between temperature on the day and the previous day. The main difference between two models is that the Cao-Wei model has a function to consider the diremption from the annual trend in a since curve. However, it is well-known that ANN outperforms the statistical model due to good approximation for nonlinear systems.

In this paper, a preconditioned ANN model is proposed to deal with temperature forecasting. As the preconditioner, DA clustering is employed to carry out clustering of input data into some clusters such as average, hot and cool summer. As the first stage of research, this paper deals with average summer data. As ANN, MLP is used to predict one-day ahead daily average temperature. As the input variables of MLP, the maximum and minimum temperature, average humidity and minimum humidity are used. After the frequency distribution of each input variable is created, MCS (Monte Carlo Simulation) is carried out by generating random numbers based on the frequency distribution.

B. Estimation of Optimal Parameters

EPSO of evolutionary computation is used to estimate parameters x_1-x_6 in Fig. 4. As mentioned before, EPSO is one of high performance evolutionary computation. It is important to maintain the equivalence of payoffs to be received in the contract model of weather derivatives. In this paper, the frequency distribution of predicted daily average temperature is used to generate a set of samples. The optimal parameters are determined by minimizing the cost function of the equivalence of payoffs for a set of samples. As the model of weather derivative, the color option between TEPCO and TGC is employed. In the model, the parameters are optimized by EPSO. The proposed method may be summarized as follows:

Step 1: Set the initial conditions for given data.
Step 2: Divide given data into three clusters of average, hot and cool summer with DA clustering for 40 years data.
Step 3: Construct MLP for average summer.
Step 4: Create the frequency distribution of predicted daily average data by Monte Carlo Simulation for MLP obtained data Step 3.
Step 5: Evaluate the optimal parameters by EPSO for a set of samples selected from the frequency distribution at Step 4.

The cost function to be minimized may be written as

$$f = \left| \sum_{i=1}^{N} Eprice(t_i) - \sum_{i=1}^{N} Gprice(t_i) \right| \rightarrow min \tag{14}$$

$$Eprice(t) = min(x_3 \times (x_1 - t), x_5) \;\; (t \leq x_1) \tag{15}$$

$$Eprice(t) = max(x_4 \times (t - x_2), x_6) \;\; (t \geq x_2) \tag{16}$$

$$Eprice(t) = 0 \quad (otherwise\,) \tag{17}$$

$$Gprice(t) = max(-x_3 \times (x_1 - t), -x_5) \;\; (t \leq x_1) \tag{18}$$

$$Gprice(t) = min(-x_4 \times (t - x_2), -x_6) \;\; (t \geq x_2) \tag{19}$$

$$Gprice(t) = 0 \quad (otherwise) \tag{20}$$

where
f: cost function
$Eprice(\cdot)$: payoffs that TEPCO should receive
$Gprice(\cdot)$: payoffs that TGC should receive
t_i: the i-th daily average temperature selected from the frequency distribution
N: No. of samples

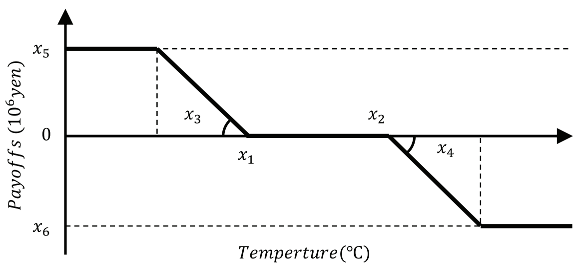

Fig. 4. Concept of collor option.

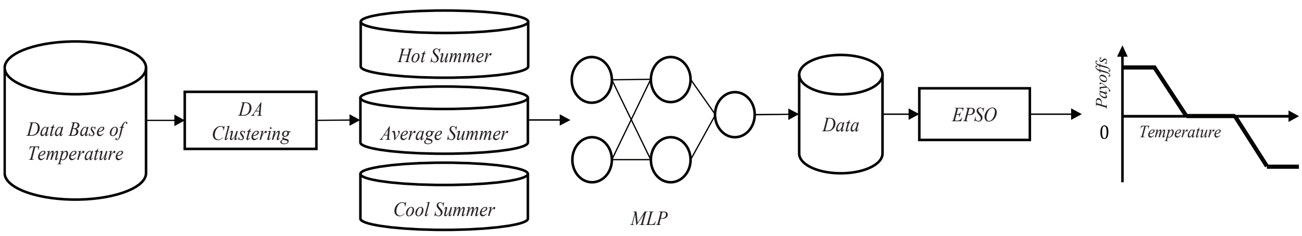

Fig. 3. Concept of proposed method.

$x_1 - x_6$: parameters

VI. Simulation

A. Simulation Conditions

(1) The proposed method was applied to real data in Tokyo [20]. As learning data, a set of the daily average temperature curves from August 1 to September 30 for 40 years (1961-2000) were employed while test data of 2001 was employed. The use of DA clustering gave three clusters such average, hot and cool summer, where the used parameters were shown in Table 1. The proposed method was examined for test data in 2001.

(2) MLP was used to evaluate the frequency distribution of the predicted temperature with input variables obtained by MCS. The following two cases were investigated:

Case 1: No. of sample data is 1,000
Case 2: No. of sample data is 30,000

(3) To determine the parameters of the contract model, the cost function was set up to (14), which means the equalization of received payoffs for two companies in the color option. The algorithm of EPSO stops if the cost function to be optimized is equal to or less than 0.01.

(4) To demonstrate the effectiveness of the proposed method, PSO was used as a comparative method. A thousand of samples were prepared to examine the influence of initial conditions on the final solution in Case 2. Table 2 gave the parameters of PSO and EPSO.

B. Simulation Results

Table 3 shows the results of DA clustering for 40-years data, where three clusters such as cool, hot and average summer are given. It can be seen that the number of cool, hot and average summer data are 10, 13 and 17, respectively. Fig. 5 (a) shows the frequency distribution of daily average temperature in case

TABLE I. Parameters of DA Clustering

Parameters	Values
No. of Clusters	3
β_{max}	3000
β_{min}	1.0
$\Delta\beta$	10.0
Convergence Criterion ε	0.001

TABLE II. Parameters of Each Optimization Method

Parameters	Methods	
	PSO	***EPSO***
No. of Agents	30	30
No. of Iterations	400	400
w_1, w_2, w_3	0.7, 0.7, 0.7	
w_{min}, w_{max}		0.01, 1.0
τ, τ'		0.07, 0.001
Replication Rate		2

TABLE III. Results of DA Clustering

Cluster No.	Types	No. of Data
1	Cool	10
2	Hot	13
3	Average	17

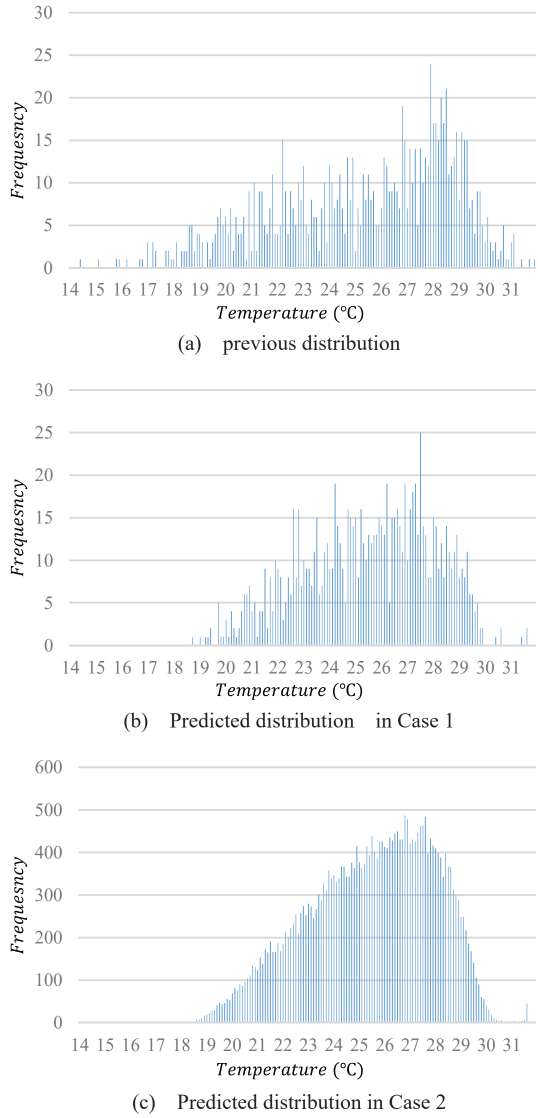

Fig. 5. Frecuency distribution of average temperature.

TABLE IV. Estimated Parameters

Methods	x_1	x_2	x_3	x_4	x_5	x_6
Original	25.5	26.5	8.0	-8.0	12.0	-12.0
PSO	25.0	26.4	7.0	-8.7	10.7	-12.6
EPSO	25.1	26.0	9.0	-7.9	11.5	-13.0

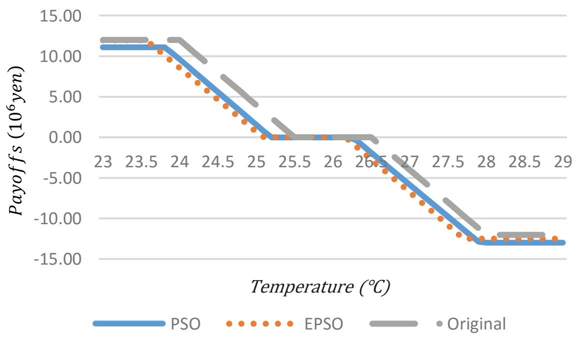

Fig. 6. Comparison of contract models.

TABLE V. COMPARISON OF TOTAL PAYOFFS

Original	PSO	EPSO
¥169,600,000(1.000)	¥71,910,000(0.423)	¥63,770,000(0.376)

Note) Values in parenthesis idicate the normalized data by the original.

of historical data. Fig. 5 (b) gives the frequency distribution obtained by ANN in Case 1 with 1,000 data while Fig. 5 (c) provides Case 2 with 30,000 data. It can be observed that the frequency distribution becomes smoother in Case 2 in comparison with Case 1. Table 4 shows the estimated parameters for the original contract, and the proposed method with PSO and EPSO. The number of sampling data was set up to be 30,000 in Case 2. The final solution was selected from the solution with the minimum cost function of (14). Although there is a small difference between the original and the proposed models, say, in case of x_1 and x_2, the final cost function of the proposed method is quite different from that of the original method due to the high nonlinearity. In fact, the small amount of 0.01 ℃ brings about the large payoffs. Table 6 provides a comparison of the three contract models, where the original and the proposed models with PSO and EPSO are given. It can be observed that the proposed method estimated the parameters in a lower value in comparison with the original model. Although TEPCO received ¥169,600,000 from TGC in the original model, the proposed method evaluated lower payoffs that corresponded to 62.4 % reduction (see Table 5).

VII. Conclusion

This paper has proposed an efficient ANN-based method for designing weather derivatives with meteorological uncertainties. The proposed method made use of preconditioned MLP of ANN for predicting the frequency distribution of daily average temperature. As the precondition technique, DA clustering of global clustering was used to divide a set of summer data into three clusters. The use of the precondition technique contributed to the improvement of ANN model accuracy due to the data similarity in each cluster. This paper focused on average summer as the first stage of research. EPSO of evolutionary computation was employed to evaluate the parameters of the collar option between TEPCO and TGC in 2001 by realizing the equivalence of the payoffs for a set of samples obtained through Monte Carlo Simulation. The proposed method was applied to real data of the collar option to real data of the collar option. The simulation results have shown that the proposed method evaluated more reasonable payoffs in comparison with the conventional method since 2001 was involved in average summer. It can be seen that the proposed method contributed to 62.4 % reduction of the payoffs TGC should pay to TEPCO. The proposed method allows weather derivative planners to construct more reasonable contract models by preconditioned ANN, Monte Carlo Simulation and EPSO.

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