Gaussian Process-based Predictor of Electric Power Damage Caused by Typhoons in Japan Using Artificial Bee Colony Algorithm

Tomohiro Hachino, Hitoshi Takata, Seiji Fukushima, and Yasutaka Igarashi

***Abstract*—**Electric power systems in Japan have suffered from natural disasters caused by typhoons repeatedly. The electric power supply is sometimes cut off in wide areas for a long time by typhoons, which brings an undesirable effect on society. To speedily restore the electric power supply, it is necessary to predict the amount of electric power damage accurately for an approaching typhoon. This paper presents a method of predicting the amount of electric power damage caused by typhoons for the Amami archipelago in Japan using Gaussian process (GP) model. The relation between the typhoon weather information and the electric power damage is represented by the GP prior model and this model is trained by the separable least-squares (LS) approach combining the linear LS method with artificial bee colony algorithm. The predicted amount of damage is given by the predictive mean of the GP and its confidence measure is evaluated by the predictive variance of the GP. Simulation results based on actual data of typhoons that hit or came close to the Amami archipelago are shown to illustrate the effectiveness of the proposed predictor.

***Keywords*—**Artificial bee colony algorithm, damage caused by typhoon, electric power system, Gaussian process model, prediction.

I. Introduction

ELECTRIC power systems in Japan have suffered from natural disasters such as typhoons, rainstorms and earthquakes. Typhoons are defined as intense tropical cyclones that have an extremely high wind speed when they are generated in eastern Asia [1]. The risk management of damage caused by typhoons has been studied for water floods [2], [3]. Damage to electric power facilities caused by typhoons is one of the most common meteorological disasters in Japan [4]–[6]. Once electric power supply is cut off by typhoons, the social life is paralyzed. To ensure the speedy restoration of electric power supply, one has to predict the amount of damage accurately for an approaching typhoon so that the staffs and materials necessary for restoration are appropriately arranged. Since there are many islands in Japan, it is urgent to develop an accurate prediction method for electric power damage. For island areas such as the Amami archipelago in Japan, the staff and materials necessary for restoration must be appropriately prepared and sent there according to the predicted amounts of damage before the arrival of the typhoon.

So far, a rough predictions based on experience have been made in the field using the past typhoon weather information and electric power damage. On the other hand, we have developed two-stage predictors that consist of neural networks and linear or second-order regression from the viewpoint of nonlinear prediction [7]–[9]. However, these prediction methods need to use a large number of parameters to describe the nonlinearity between the typhoon weather information and the electric power damage. This is presently one of the drawbacks of these predictors, because we can use only limited amounts of training input (typhoon weather information) and output (electric power damage) data. Moreover, confidence measures for the predicted amount of damage cannot be obtained for the two-stage predictors.

To overcome these problems, in this paper, we proposes a novel prediction method using the Gaussian process (GP) model trained by artificial bee colony (ABC) algorithm. The GP model is a non-parametric model and fits naturally into the Bayesian framework [10]–[12]. This model has recently attracted much attention for system identification [13]–[15], time series forecasting [16], [17], and predictive control [18]. The proposed GP-based predictor includes far fewer parameters to describe the nonlinearity than the two-stage predictors. The predicted amount of damage is given by the predictive mean of the GP and its confidence measure is evaluated by the predictive variance of the GP.

The parameters included in the GP model and the adjusting parameters for quantification of the typhoon track have to be properly trained based on the training input and output data. Generally this training becomes nonlinear optimization problem. In this paper, the separable least-squares (LS) approach combining the linear LS method with ABC algorithm is presented for this training. ABC algorithm is an optimization algorithm inspired by an intelligent behavior of honeybee swarms and has high potential for both global and local

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optimizations [19]. Many applications of ABC algorithm have been also reported for vehicle routing problem [20] and field excitation control problem of power system [21]. ABC algorithm finds the best solution through search by the three types of bees; the employed bees, the onlooker bees, and the scout bees. This algorithm consists of only the basic arithmetic operations and does not require complicated coding and genetic operations such as crossovers and mutations of genetic algorithm. Moreover, the performance of ABC algorithm is better than or similar to those of other population-based algorithms in spite of a few setting parameters [19], [22], [23]. These advantages suggest that the use of ABC algorithm increases efficiency when the GP-based predictor is trained.

This paper is organized as follows. In Sect. II, the problem is formulated. In Sect. III, the quantification technique for the typhoon track is given. In Sect. IV, the GP prior model for prediction is derived. In Sect. V, the training algorithm of the GP prior model is presented using the separable LS approach. In Sect. VI, the estimation method of the typhoon weather data used for prediction is described. In Sect. VII, the prediction of the electric power damage is carried out from the GP posterior distribution. In Sect. VIII, the performance of the proposed prediction method is demonstrated through numerical simulation using actual data of damage for the Amami archipelago in Japan. Finally some conclusions are remarked in Sect. IX.

II. Statement of the Problem

The objective area for prediction is taken to be the Amami archipelago in Japan. This archipelago is located at about latitude 27.83°N and longitude 128.08°E.

The input of the predictor is the typhoon weather information:

$$\boldsymbol{x} = [x_1, x_2]^{\mathrm{T}} \tag{1}$$

where x_1 is the typhoon track and x_2 [m/s] is the maximum instantaneous wind speed. The output from the predictor is the amount of electric power damage y, such as the power failure circuit. It is possible to choose other weather information as the input, but it increases the scale of the predictor. Therefore, we choose only the typhoon track and the maximum instantaneous wind speed that affect the amount of electric power damage greatly.

It is assumed that we collect the typhoon weather data released from the Meteorological Agency:

$$\begin{aligned} \boldsymbol{X} &= [\boldsymbol{x}(1), \boldsymbol{x}(2), \cdots, \boldsymbol{x}(N)]^{\mathrm{T}} \\ \boldsymbol{x}(j) &= [x_1(j), x_2(j)]^{\mathrm{T}} \end{aligned} \tag{2}$$

and the corresponding actual data of the amount of electric power damage:

$$\boldsymbol{y} = [y(1), y(2), \cdots, y(N)]^{\mathrm{T}} \tag{3}$$

where N is the number of the typhoons that hit or came close to the Amami archipelago in the past.

The purpose of this paper is to construct a prediction system that can predict the amount of electric power damage with its confidence measure from the weather data of a new approaching typhoon.

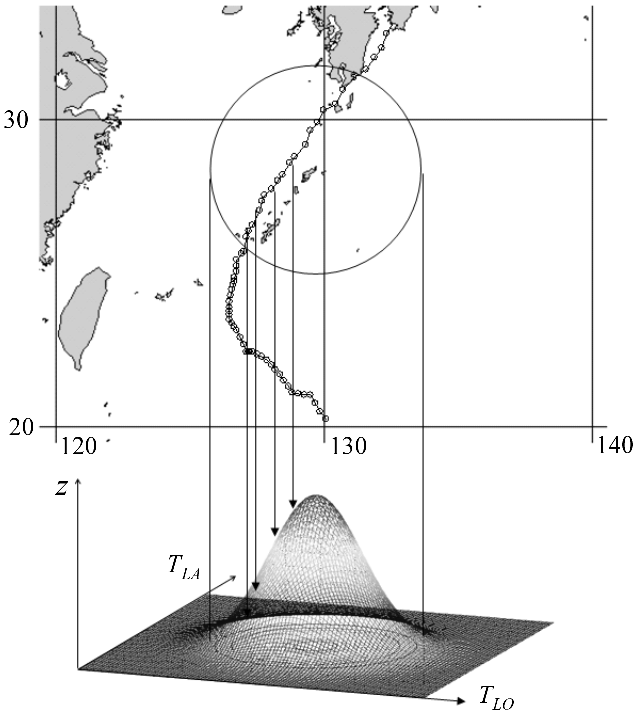

Fig. 1 Quantification of the typhoon track

III. Quantification of Typhoon Track

The typhoon track strongly correlates with the amount of electric power damage. In order to input the typhoon track into the predictor, we have to quantify it as a numerical value. In general, in the Northern Hemisphere, the wind force in the east side of the typhoon is stronger than that in the west side of the typhoon. This wind characteristic suggests that the typhoon via the west side of the Amami archipelago probably causes more damage than the typhoon via the east side of the Amami archipelago. Moreover, since the typhoon is likely to stay around the Amami archipelago for a long time, the electric power system may frequently suffer from major damage. Therefore, we have to consider the wind characteristic and the stagnancy of the typhoon when the typhoon track is quantified. First, the centers of the typhoon are plotted every hour in the range from latitude 26°N to 31°N. Then, a Gaussian function is arranged on the Amami archipelago as shown in Fig. 1. The numerical value of the typhoon track is calculated by summing the altitude values of the arranged function corresponding to the plotted centers as follows:

$$\begin{aligned} x_1 &= \sum_{j=1}^{n} z_j \\ z_j &= \exp\left\{ -\frac{(T_{LAj} - C_{LA})^2 + (T_{LOj} - C_{LO} + \alpha)^2}{\beta^2} \right\} \end{aligned} \tag{4}$$

where T_{LAj} is the latitude of the typhoon center, T_{LOj} is the longitude of the typhoon center, C_{LA} is the latitude of the Amami archipelago, C_{LO} is the longitude of the Amami archipelago, $\alpha > 0$ is the bias for the typhoon center, β is the width of the Gaussian function, and n is the number of the plotted centers of the typhoon. Note that the value of the typhoon track becomes large in the case that the typhoon stays around the Amami archipelago for a long time. The bias α is introduced to take the wind characteristic of the typhoon into consideration. A way of determining the adjusting parameter vector $\boldsymbol{\theta}_p = [\alpha, \beta]^{\mathrm{T}}$ suboptimally will be discussed in Sect. V.

IV. GP Prior Model for Prediction

Assume that the relation between the typhoon weather information $\boldsymbol{x}$ and the amount of electric power damage y is described as

$$y = f(\boldsymbol{x}) + \varepsilon \tag{5}$$

where $f(\cdot)$ is a function which is assumed to be stationary and smooth. ε is assumed to be a zero-mean Gaussian noise with variance σ_n^2. The assumption of smoothness means that the amounts of electric power damage have a high correlation and becomes similar values for the typhoon weather data that are close to each other. The determination of the standard deviation σ_n will be discussed in Sect. V.

Let the function value vector corresponding to the typhoon weather data given by (2) be

$$\boldsymbol{f} = [f(\boldsymbol{x}(1)), f(\boldsymbol{x}(2)), \cdots, f(\boldsymbol{x}(N))]^{\mathrm{T}} \tag{6}$$

Then this function value vector $\boldsymbol{f}$ is represented by GP regression. The GP is a Gaussian random function and is completely described by its mean function and covariance function. We can regard it as a collection of random variables with a joint multivariable Gaussian distribution. Therefore, the function value vector $\boldsymbol{f}$ can be represented by the GP as

$$\boldsymbol{f} \sim \mathcal{N}(\boldsymbol{m}(\boldsymbol{X}), \boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X})) \tag{7}$$

where $\boldsymbol{m}(\boldsymbol{X})$ is the N-dimensional mean function vector and $\boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X})$ is the N-dimensional covariance matrix evaluated at all pairs of the training input data. Equation (7) means that $\boldsymbol{f}$ has a Gaussian distribution with the mean function vector $\boldsymbol{m}(\boldsymbol{X})$ and the covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X})$.

In this paper, the mean function $m(\boldsymbol{x})$ is expressed by the first-order polynomial, i.e., a linear combination of the input variable:

$$m(\boldsymbol{x}) = \bar{\boldsymbol{x}}\boldsymbol{\theta}_m \tag{8}$$

where $\bar{\boldsymbol{x}} = [\boldsymbol{x}^{\mathrm{T}}, 1]$ and $\boldsymbol{\theta}_m = [\theta_{m1}, \theta_{m2}, \theta_{m3}]^{\mathrm{T}}$ is the unknown weighting parameter vector for the mean function. Thus, the mean function vector $\boldsymbol{m}(\boldsymbol{X})$ is described as follows:

$$\begin{aligned} \boldsymbol{m}(\boldsymbol{X}) &= [m(\boldsymbol{x}(1)), m(\boldsymbol{x}(2)), \cdots, m(\boldsymbol{x}(N))]^{\mathrm{T}} \\ &= \bar{\boldsymbol{X}}\boldsymbol{\theta}_m \end{aligned} \tag{9}$$

where $\bar{\boldsymbol{X}} = [\boldsymbol{X}, \boldsymbol{e}]$ and $\boldsymbol{e} = [1, 1, \cdots, 1]^{\mathrm{T}}$ is the N-dimensional vector of ones.

The covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X})$ is constructed as

$$\boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X}) = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} & \cdots & \Sigma_{1N} \\ \Sigma_{21} & \Sigma_{22} & \cdots & \Sigma_{2N} \\ \vdots & \vdots & & \vdots \\ \Sigma_{N1} & \Sigma_{N2} & \cdots & \Sigma_{NN} \end{bmatrix} \tag{10}$$

where the element $\Sigma_{pq} = cov(f(\boldsymbol{x}(p), f(\boldsymbol{x}(q))) = s(\boldsymbol{x}(p), \boldsymbol{x}(q))$ is a function of $\boldsymbol{x}(p)$ and $\boldsymbol{x}(q)$. The following Gaussian kernel is utilized as the covariance function $s(\boldsymbol{x}(p), \boldsymbol{x}(q))$:

$$s(\boldsymbol{x}(p), \boldsymbol{x}(q)) = \sigma_y^2 \exp\left(-\frac{\| \boldsymbol{x}(p) - \boldsymbol{x}(q) \|^2}{2\ell^2}\right) \tag{11}$$

where $\| \cdot \|$ denotes the Euclidean norm. Equation (11) means that the covariance of the function values depends only on the distance between the inputs $\boldsymbol{x}(p)$ and $\boldsymbol{x}(q)$. A high correlation between the function values occurs for inputs that are close to each other. The overall variance of the random function can be controlled by varying σ_y, and the characteristics length scale of the process can be changed by varying ℓ.

As the amount of electric power damage $\boldsymbol{y}$ is a noisy observation, we can derive the following GP prior regression from (7):

$$\boldsymbol{y} \sim \mathcal{N}(\boldsymbol{m}(\boldsymbol{X}), \boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X})) \tag{12}$$

where

$$\begin{aligned} \boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X}) &= \boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{X}) + \sigma_n^2 \boldsymbol{I}_N \\ \boldsymbol{I}_N &: N \times N \text{ identity matrix} \end{aligned} \tag{13}$$

and $\boldsymbol{\theta}_c = [\sigma_y, \ell, \sigma_n]^{\mathrm{T}}$ is called the *hyperparameter* vector. In the following, $\boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X})$ is written as $\boldsymbol{K}$ for simplicity.

V. Training by ABC algorithm

A. Separable LS Approach

The accuracy of the prediction greatly depends on the unknown parameter vectors, i.e., the weighting parameter vector $\boldsymbol{\theta}_m$ of the mean function, the hyperparameter vector $\boldsymbol{\theta}_c$ of the covariance function, and the adjusting parameter vector $\boldsymbol{\theta}_p$ of the quantification of the typhoon track. Therefore, the parameter vector $\boldsymbol{\theta} = [\boldsymbol{\theta}_m^{\mathrm{T}}, \boldsymbol{\theta}_c^{\mathrm{T}}, \boldsymbol{\theta}_p^{\mathrm{T}}]^{\mathrm{T}}$ has to be determined suboptimally. This training is carried out by minimizing the negative log marginal likelihood of the typhoon weather data and the actual amount of electric power damage:

$$\begin{aligned} J &= -\log p(\boldsymbol{y}|\boldsymbol{X}, \boldsymbol{\theta}) \\ &= \frac{1}{2}\log|\boldsymbol{K}| + \frac{1}{2}(\boldsymbol{y} - \boldsymbol{m}(\boldsymbol{X}))^{\mathrm{T}}\boldsymbol{K}^{-1} \\ &\quad \times (\boldsymbol{y} - \boldsymbol{m}(\boldsymbol{X})) + \frac{N}{2}\log(2\pi) \\ &= \frac{1}{2}\log|\boldsymbol{K}| + \frac{1}{2}(\boldsymbol{y} - \bar{\boldsymbol{X}}\boldsymbol{\theta}_m)^{\mathrm{T}}\boldsymbol{K}^{-1}(\boldsymbol{y} - \bar{\boldsymbol{X}}\boldsymbol{\theta}_m) \\ &\quad + \frac{N}{2}\log(2\pi) \end{aligned} \tag{14}$$

As the cost function J generally has multiple local minima, this training becomes a nonlinear optimization problem. However, we can separate the linear optimization part and the nonlinear optimization part for this problem. Note that if the candidates for the hyperparameter vector $\boldsymbol{\theta}_c$ and adjusting parameter vector $\boldsymbol{\theta}_p$ are given, the weighting parameter vector $\boldsymbol{\theta}_m$ can be estimated by the linear LS method putting $\partial J/\partial\boldsymbol{\theta}_m = \mathbf{0}$:

$$\boldsymbol{\theta}_m = (\bar{\boldsymbol{X}}^{\mathrm{T}}\boldsymbol{K}^{-1}\bar{\boldsymbol{X}})^{-1}\bar{\boldsymbol{X}}^{\mathrm{T}}\boldsymbol{K}^{-1}\boldsymbol{y} \tag{15}$$

However, even if $\boldsymbol{\theta}_m$ is known, the optimization with respect to $\boldsymbol{\theta}_c$ and $\boldsymbol{\theta}_p$ is a complicated nonlinear problem and might suffer from the local minima problem. Therefore, in this paper, we combine the linear LS method with ABC algorithm to determine the unknown parameter vector $\boldsymbol{\theta}$. Only $\boldsymbol{\Omega} = [\boldsymbol{\theta}_c^{\mathrm{T}}, \boldsymbol{\theta}_p^{\mathrm{T}}]^{\mathrm{T}} = [\sigma_y, \ell, \sigma_n, \alpha, \beta]^{\mathrm{T}}$ is represented with the positions of the food sources and is searched for by ABC algorithm.

B. Outline of ABC Algorithm

ABC algorithm is an optimization algorithm inspired by the behavior of real honeybees [19]. In this algorithm, the colony of artificial bees consists of the three groups of bees; the employed bees, the onlooker bees, and the scout bees. The roles of these groups are as follows:

1) Employed bees

The employed bees determine a food source within the neighborhood of the food source in their memory. The size of the employed bees is half of the colony size. Every employed bee works on only one food source. Therefore, the number of the employed bees is equal to the number of the food sources. The employed bees evaluate the profitability of the food sources such as the nectar amount, and share their information with the onlooker bees in the hive. A employed bee that has worked on abandoned food source is differentiated into a scout bee.

2) Onlooker bees

The onlooker bees waiting in the hive select one food source through the information obtained from the employed bees' dances and search in the neighborhood of the selected food source. This selection is implemented by the "roulette-wheel" slots weighted in proportion to the profitability of the food source. Therefore the onlooker bees are likely to search around more profitable food sources. The size of the onlooker bees is also half of the colony size.

3) Scout bees

The scout bee differentiated from the employed bee searches a new food source randomly.

In the optimization problem, the positions of the food sources correspond to the candidates of the solution and the profitability of the food source shows the fitness value that represents the goodness of the solution. The suboptimal solution is obtained by repeating search by the employed, onlooker, and scout bees.

C. Training of GP Prior Model

The proposed training algorithm by the separable LS approach is as follows:

step 1: Initialization

(1-1) Generate an initial population of N_s bees with random positions of the food sources $\boldsymbol{\Omega}_{[i]}$ $(i = 1, 2, \cdots, N_s)$ from (16):

$$\Omega_{ij} = \Omega_{min,j} + rand[0,1]\cdot(\Omega_{max,j} - \Omega_{min,j}) \quad (j = 1, 2, \cdots, 5) \tag{16}$$

where N_s denotes the size of the employed bees or onlooker bees and Ω_{ij} is the jth element of the vector $\boldsymbol{\Omega}_{[i]}$. $\Omega_{min,j}$ and $\Omega_{max,j}$ are the minimum and maximum values for Ω_{ij}, respectively. $rand[0,1]$ is uniformly distributed random number with amplitude in the range $[0, 1]$.

(1-2) Set the iteration counter l to 1.

(1-3) Set the counter for abandonment $trial_i$ to 0. The counter $trial_i$ shows the number of times that the solution $\boldsymbol{\Omega}_{[i]}$ is not improved by the employed and onlooker bees.

step 2: Quantification of the typhoon track

Quantify the typhoon track to the numerical value using $\boldsymbol{\theta}_{p[i]}$ $(i = 1, 2, \cdots, N_s)$ by the quantification technique given in Sect. III.

step 3: Construction of the covariance matrix

Construct N_s candidates of the covariance matrix $\boldsymbol{K}_{[i]}$ using $\boldsymbol{\theta}_{c[i]}$ $(i = 1, 2, \cdots, N_s)$.

step 4: Estimation of $\boldsymbol{\theta}_m$

Estimate N_s candidates for $\boldsymbol{\theta}_{m[i]}$ $(i = 1, 2, \cdots, N_s)$ from (15).

step 5: Fitness value calculation

Calculate the negative log marginal likelihood of the typhoon weather data and the actual electric power damage:

$$\begin{aligned} J_i(\boldsymbol{\Omega}_{[i]}) \;=\; & \frac{1}{2}\log|\boldsymbol{K}_{[i]}| + \frac{1}{2}(\boldsymbol{y} - \bar{\boldsymbol{X}}_{[i]}\boldsymbol{\theta}_{m[i]})^{\mathrm{T}}\boldsymbol{K}_{[i]}^{-1} \\ & \times(\boldsymbol{y} - \bar{\boldsymbol{X}}_{[i]}\boldsymbol{\theta}_{m[i]}) + \frac{N}{2}\log(2\pi) \end{aligned} \tag{17}$$

and the fitness value $F_i(\boldsymbol{\Omega}_{[i]}) = 1/J_i(\boldsymbol{\Omega}_{[i]})$.

step 6: Search by the employed bees

(6-1) Determine the new positions of the food sources $\boldsymbol{V}_{[i]} = [\boldsymbol{\vartheta}_{c[i]}^{\mathrm{T}}, \boldsymbol{\vartheta}_{p[i]}^{\mathrm{T}}]^{\mathrm{T}}$ around $\boldsymbol{\Omega}_{[i]}$ for the employed bees from (18):

$$V_{ij} = \Omega_{ij} + rand[-1,1]\cdot(\Omega_{ij} - \Omega_{kj}) \quad (j = 1, 2, \cdots, 5) \tag{18}$$

where V_{ij} is the jth element of the vector $\boldsymbol{V}_{[i]}$ and k is a random integer selected from $\{1, 2, \cdots, N_s\}$, where $k \neq i$.

(6-2) Quantify the typhoon track to the numerical value using $\boldsymbol{\vartheta}_{p[i]}$ $(i = 1, 2, \cdots, N_s)$ by the quantification technique given in Sect. III.

(6-3) Construct N_s candidates of the covariance matrix $\boldsymbol{\mathcal{K}}_{[i]}$ using $\boldsymbol{\vartheta}_{c[i]}$ $(i = 1, 2, \cdots, N_s)$.

(6-4) Estimate N_s candidates for $\boldsymbol{\vartheta}_{m[i]}$ $(i = 1, 2, \cdots, N_s)$ from (15).

(6-5) Calculate the objective function value:

$$\begin{aligned} J_i(\boldsymbol{V}_{[i]}) \;=\; & \frac{1}{2}\log|\boldsymbol{\mathcal{K}}_{[i]}| + \frac{1}{2}(\boldsymbol{y} - \bar{\boldsymbol{\mathcal{X}}}_{[i]}\boldsymbol{\vartheta}_{m[i]})^{\mathrm{T}}\boldsymbol{\mathcal{K}}_{[i]}^{-1} \\ & \times(\boldsymbol{y} - \bar{\boldsymbol{\mathcal{X}}}_{[i]}\boldsymbol{\vartheta}_{m[i]}) + \frac{N}{2}\log(2\pi) \end{aligned} \tag{19}$$

and the fitness value $F_i(\boldsymbol{V}_{[i]}) = 1/J_i(\boldsymbol{V}_{[i]})$.
(6-6) If $F_i(\boldsymbol{\Omega}_{[i]}) < F_i(\boldsymbol{V}_{[i]})$, update $\boldsymbol{\Omega}_{[i]}$, $\boldsymbol{\theta}_{m[i]}$ and $F_i(\boldsymbol{\Omega}_{[i]})$ by $\boldsymbol{V}_{[i]}$, $\boldsymbol{\vartheta}_{m[i]}$ and $F_i(\boldsymbol{V}_{[i]})$, respectively, and set $trial_i = 0$. Otherwise set $trial_i = trial_i + 1$. This procedure is called "greedy selection".

The search by the employed bees is depicted in Fig. 2.

step 7: Search by the onlooker bees
(7-1) Choose one position of the food source for each onlooker bee from $\boldsymbol{\Omega}_{[i]}$ $(i = 1, 2, \cdots, N_s)$ through "roulette-wheel" slots weighted in proportion to the fitness value of the employed bee. Namely each onlooker bee selects one position of the food source with probability of $F_i(\boldsymbol{\Omega}_{[i]})/\sum_{p=1}^{N_s} F_p(\boldsymbol{\Omega}_{[p]})$.
(7-2) Calculate the new positions of the food sources $\boldsymbol{V}_{[i]}$ corresponding to the selected positions $\boldsymbol{\Omega}_i$ from (18).
(7-3) Quantify the typhoon track to the numerical value using $\boldsymbol{\vartheta}_{p[i]}$ $(i = 1, 2, \cdots, N_s)$ by the quantification technique given in Sect. III.
(7-4) Construct N_s candidates of the covariance matrix $\boldsymbol{\mathcal{K}}_{[i]}$ using $\boldsymbol{\vartheta}_{c[i]}$ $(i = 1, 2, \cdots, N_s)$.
(7-5) Estimate N_s candidates for $\boldsymbol{\vartheta}_{m[i]}$ $(i = 1, 2, \cdots, N_s)$ from (15).
(7-6) Calculate the fitness value $F_i(\boldsymbol{V}_{[i]}) = 1/J_i(\boldsymbol{V}_{[i]})$ from (19).
(7-7) Carry out the greedy selection with the same way of *step 6 (6-6)*.

The search by the onlooker bees is depicted in Fig. 3.

step 8: Search by the scout bees

If the counter for abandonment $trial_i$ is greater or equal to the prespecified number *limit*, carry out the following procedure.
(8-1) Differentiate the corresponding employed bee into the scout bee and generate the new position of the food source $\boldsymbol{\Omega}_{[i]}$ for the scout bee randomly from (16).
(8-2) Quantify the typhoon track to the numerical value using the corresponding $\boldsymbol{\theta}_{p[i]}$ by the quantification technique given in Sect. III.
(8-3) Construct the covariance matrix $\boldsymbol{K}_{[i]}$ using the corresponding $\boldsymbol{\theta}_{c[i]}$.
(8-4) Estimate $\boldsymbol{\theta}_{m[i]}$ from (15).
(8-5) Calculate the fitness value $F_i(\boldsymbol{\Omega}_{[i]}) = 1/J_i(\boldsymbol{\Omega}_{[i]})$ from (17).

This step means that if the solution is not improved *limit* times through search by the employed and onlooker bees, the corresponding employed bee gives up to search around his food source and transforms himself to the scout bee to search around randomly selected food source. Since the number *limit* is usually set to be the product of the employed bee size and the dimension of the search space [19], this number is taken to be $limit = N_s \times 5$ in this paper.

The search by the scout bees is depicted in Fig. 4.

step 9: Repetition

Set the iteration counter to $l = l + 1$ and go to *step 6* until the prespecified iteration number l_{max}.

Finally, at the termination of this algorithm when $l = l_{max}$, the suboptimal $\hat{\boldsymbol{\Omega}} = [\hat{\boldsymbol{\theta}}_c^{\mathrm{T}}, \hat{\boldsymbol{\theta}}_p^{\mathrm{T}}]^{\mathrm{T}}$ and the corresponding $\hat{\boldsymbol{\theta}}_m$ are determined by the best position of the food source.

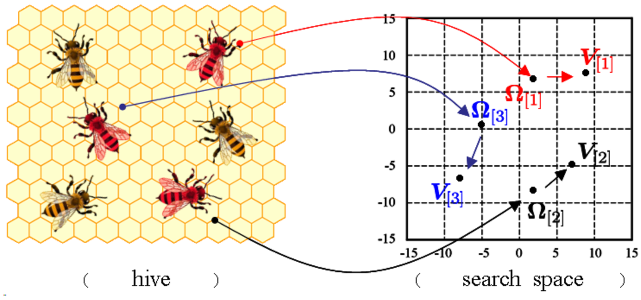

Fig. 2 Search by the employed bees

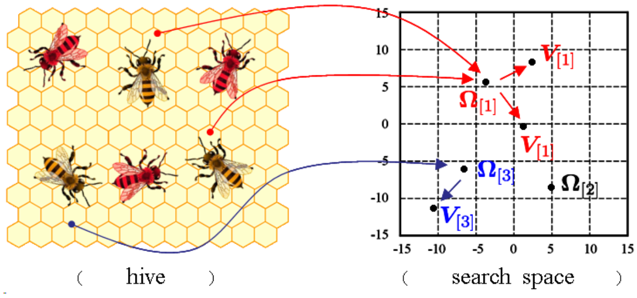

Fig. 3 Search by the onlooker bees

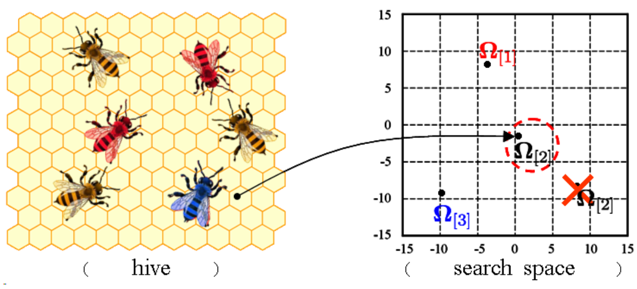

Fig. 4 Search by the scout bees

VI. Estimation of Typhoon Weather Data for Prediction

For island areas such as the Amami archipelago, the amount of electric power damage caused by typhoon is appropriately predicted and the staff and materials necessary for restoration are dispatched to the isolated islands just before ships and airplanes are canceled. In this paper, when the typhoon arrives at latitude 23°N, the prediction of the electric power damage is started. The reason why this timing is chosen to carry out the prediction is that it takes about 24 hours on average for typhoons to reach the Amami archipelago after they reach latitude 23°N and we can only just arrange the staff and materials necessary for restoration in the Amami archipelago in the meantime. In the following, the time when the typhoon arrives at latitude 23°N is referred to as the *implementation time*.

In order to carry out the prediction at the implementation time, the typhoon weather data $\boldsymbol{x}_* = [x_{1*}, x_{2*}]^{\mathrm{T}}$ at the time when it comes close to the Amami archipelago are necessary. The typhoon weather data are estimated using the predictive typhoon weather data announced by the Meteorological Agency.

First, assuming that the typhoon will pass through the centers of the probability circles in the track forecast announced by the Meteorological Agency, we estimate the numerical value x_{1*} of the typhoon track by the quantification technique mentioned in Sect. III. Since the centers of the probability circles in the track forecast are usually given every 12 hours by the Meteorological Agency, the centers every hour are plotted by interpolation after two centers of probability circles are linked by a straight line, then the numerical value x_{1*} of the typhoon track is evaluated by (4).

The maximum instantaneous wind speed x_{2*} is estimated from the following second-order polynomial:

$$\begin{aligned} x_{2*} &= a_0 + a_1 u_1 + a_2 u_2 + a_3 u_1 u_2 + a_4 u_1^2 + a_5 u_2^2 \\ &= \boldsymbol{z}^{\mathrm{T}} \boldsymbol{\vartheta} \end{aligned} \tag{20}$$

where $\boldsymbol{z} = [1, u_1, u_2, u_1 u_2, u_1^2, u_2^2]^{\mathrm{T}}$, $\boldsymbol{\vartheta} = [a_0, a_1, a_2, a_3, a_4, a_5]^{\mathrm{T}}$, u_1 is the maximum wind speed at the implementation time, and u_2 is the predictive closest distance between the typhoon center and the Amami archipelago. The unknown parameter vector $\boldsymbol{\vartheta}$ is estimated by the linear LS method based on the past data of the maximum instantaneous wind speed at the Amami archipelago, the maximum wind speed at the implementation time, and the predictive closest distance between the typhoon center and the Amami archipelago.

VII. Prediction by GP Posterior Distribution

Let the amount of electric power damage corresponding to the estimated typhoon weather data $\boldsymbol{x}_* = [x_{1*}, x_{2*}]^{\mathrm{T}}$ in the Amami archipelago be y_*. Then, we can get the joint Gaussian distribution of $\boldsymbol{y}$ and y_* under the GP prior as

$$\begin{aligned} &\begin{bmatrix} \boldsymbol{y} \\ y_* \end{bmatrix} \sim \\ &\mathcal{N}\left(\begin{bmatrix} \boldsymbol{m}(\boldsymbol{X}) \\ m(\boldsymbol{x}_*) \end{bmatrix}, \begin{bmatrix} \boldsymbol{K} & \boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{x}_*) \\ \boldsymbol{\Sigma}(\boldsymbol{x}_*, \boldsymbol{X}), & s(\boldsymbol{x}_*, \boldsymbol{x}_*) + \sigma_n^2 \end{bmatrix} \right) \end{aligned} \tag{21}$$

where $\boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{x}_*) = \boldsymbol{\Sigma}^{\mathrm{T}}(\boldsymbol{x}_*, \boldsymbol{X})$ is the N-dimensional covariance vector evaluated at all pairs of the training input $\boldsymbol{X}$ and the new input $\boldsymbol{x}_*$. From the formula for conditioning a joint Gaussian distribution [24], the posterior distribution for y_* is obtained as

$$y_* \mid \boldsymbol{X}, \boldsymbol{y}, \boldsymbol{x}_* \sim \mathcal{N}(\hat{y}_*, \hat{\sigma}_*^2) \tag{22}$$

where $\hat{y}_*$ is the predictive mean and $\hat{\sigma}_*^2$ is the predictive variance, which are given as follows:

$$\hat{y}_* = m(\boldsymbol{x}_*) + \boldsymbol{\Sigma}(\boldsymbol{x}_*, \boldsymbol{X}) \boldsymbol{K}^{-1} (\boldsymbol{y} - \boldsymbol{m}(\boldsymbol{X})) \tag{23}$$

$$\hat{\sigma}_*^2 = s(\boldsymbol{x}_*, \boldsymbol{x}_*) - \boldsymbol{\Sigma}(\boldsymbol{x}_*, \boldsymbol{X}) \boldsymbol{K}^{-1} \boldsymbol{\Sigma}(\boldsymbol{X}, \boldsymbol{x}_*) + \sigma_n^2 \tag{24}$$

$\hat{y}_*$ is the predicted amount of electric power damage by the typhoon and $\hat{\sigma}_*^2$ is utilized as the confidence measure of the predicted amount of damage.

VIII. Simulations

We predict the amount of electric power damage using the actual data of 18 typhoons that hit or came close to the Amami archipelago from 1996 to 2009. These 18 typhoon data are divided into 17 typhoon data for training and 1 typhoon datum for prediction. Namely, we can predict the amount of electric power damage with 18 combinations of training and prediction data. The amount of electric power damage is taken to be the number of the power failure circuits. The setting parameters of ABC algorithm are chosen as follows:

(i) employed bee size $N_s = 50$ (50% of the colony size)
(ii) maximum iteration number $l_{max} = 100$

The prediction result obtained by the proposed method is shown in Fig. 5. In this figure, the circles show the true number of the power failure circuits, the squares show the predicted number of the power failure circuits, and the shaded areas give the double standard deviation confidence interval (95.5% confidence region). The actual damages of 15 typhoons are included in the double standard deviation confidence interval. The probability that the actual damages are included in the double standard deviation confidence interval is 83.3%, which is quite close to the expected value 95.5%. This indicates that the proposed method yields quite reasonable confidence region of the predicted amount of damage.

For comparison, the two-stage prediction method [8] is applied to this prediction problem. The prediction result obtained by the two-stage prediction method is shown in Fig. 6. The average error rate:

$$E = \frac{1}{18} \sum_{k=1}^{18} |y_*(k) - \hat{y}_*(k)| / y_*(k) \tag{25}$$

is calculated for the proposed method and the two-stage prediction method, where $y_*(k)$ is the actual damage, i.e., the true number of the power failure circuits, and $\hat{y}_*(k)$ is the predicted number of the power failure circuits. As a result, the average error rate is 0.506 for the proposed method and 0.665 for the two-stage prediction method. The average error rate of the proposed method is 23.9% smaller than that of the two-stage prediction method. Therefore, we conclude that the accuracy of the propose method is superior to that of the conventional two-stage prediction method.

It should be noted that any confidence measures of the predicted amount of damage could not be obtained in the two-stage prediction method. On the other hand, the proposed method can give not only the predicted values but also the confidence regions of the predicted values. Therefore, in effect, we can utilize the upper value of the confidence region $\hat{y}_{*max} = \hat{y}_* + 2\hat{\sigma}_*$ as the predicted value of the worst case. This

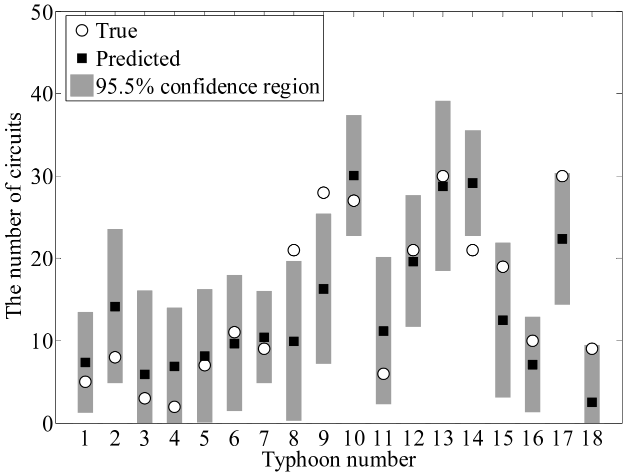

Fig. 5 Prediction result of power failure circuits (proposed method)

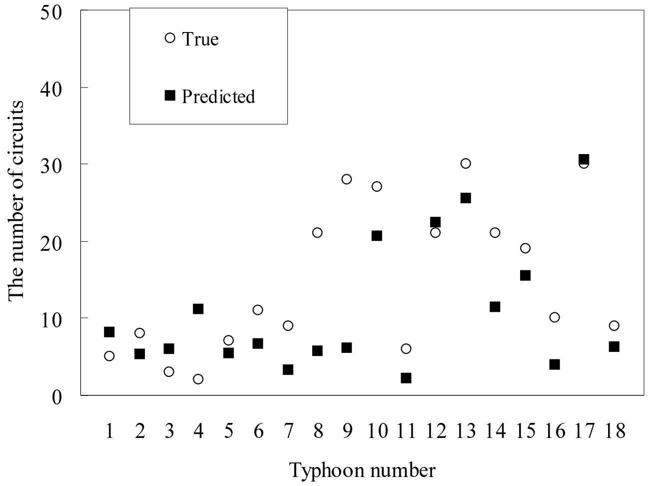

Fig. 6 Prediction result of power failure circuits (two-stage prediction method)

suggests that the proposed method can reduce the possibility that the staff and materials necessary for restoration are lacking in the Amami archipelago. This is also one of the advantages of the proposed method.

IX. Conclusions

In this paper a novel prediction method for the electric power damage caused by typhoon has been proposed using the GP model. The separable LS approach combining the linear LS method with ABC algorithm is presented for training the GP prior model. Since ABC algorithm has a few setting parameters, the proposed training algorithm is efficient for construction of the prediction system. Simulation results show that the proposed prediction method yields accurate predicted amount of damage and reasonable confidence region. Examination of another weather data that affect electric power damage is one of the future works.

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