Improvement of Gaussian Process Predictor of Electric Power Damage Caused by Typhoons Considering Time-Varying Characteristics

T. Hachino, S. Okubo, H. Takata, S. Fukushima, and Y. Igarashi
Kagoshima University, Kagoshima, Japan
Email: {hachino, takata, fukushima, igarashi}@eee.kagoshima-u.ac.jp, k9756977@kadai.jp

***Abstract*—Damage of electric power facilities caused by typhoons is one of the most common meteorological disasters in Japan. 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 ensure the speedy restoration of the electric power supply, it is important to predict the amount of damage accurately for an approaching typhoon. This paper presents an improvement of Gaussian process (GP)-based predictor of electric power damage caused by typhoons. The electric power facilities have been maintained so that they are robust to the disasters, and the robustness changes with time. Therefore, the proposed predictor uses the information of the arrival date of typhoons as well as the typhoon weather information. Simulation results based on actual data show that the proposed predictor improves the accuracy of prediction compared with the conventional GP-based predictor.**

***Index Terms*—prediction, damage by typhoon, electric power systems, gaussian process, time-varying characteristics**

I. Introduction

Electric power systems in Japan have suffered from major damage from typhoons almost every year [1]-[3]. Typhoons are defined as intense tropical cyclones that have an extremely high wind speed when they are formed in eastern Asia [4]. Once a blackout is caused by the typhoon, the influence to the civil life becomes extremely serious. To ensure the speedy restoration of the electric power supply, it is necessary to predict the amount of damage accurately for an approaching typhoon. Since there are many islands in Japan, developing an accurate prediction method is particularly urgent. This is because the staff and materials necessary for restoration must be appropriately arranged and sent to isolated islands from the mainland according to the predicted amounts of damage just before ships and airplanes are canceled due to the typhoon.

Although significance of the accurate prediction has been recognized, the reasonable method of prediction has been seldom reported. In the field, empirical predictions based on past typhoon weather information and electric power damage have been utilized. However, it is difficult for such predictions to keep the objectivity. On the other hand, the authors have presented two-stage predictors that consist of neural networks and linear or second-order regression from the viewpoint of nonlinear prediction [5]-[7]. However, these prediction methods require 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, we proposed the nonparametric prediction methods based on the Gaussian process (GP) model [8]-[11]. The GP model is a nonparametric model and fits naturally into the Bayesian framework [12]-[14]. This model has recently attracted much attention for system identification [15], [16], time series forecasting [17], [18], and predictive control [19]. The GP-based predictors include far fewer parameters to describe the nonlinearity than the two-stage predictors, and moreover they can give not only predicted amounts of damage but also their confidence measures. However, the accuracy of the GP-based predictors is not necessarily enough for practical realization. This paper focuses on an improvement of the GP-based predictor [8] in the view point of prediction accuracy. In general, electric power facilities have been reinforced by maintenance by the power suppliers such as electric power company. The robustness of electric power facilities to the disasters increases year after year. Considering the fact that the robustness of electric power facilities changes with time, the proposed predictor uses the information of the arrival date of typhoons as well as the typhoon weather information, as inputs to the predictor. This means that the relation between the typhoon information and the amount of damage is assumed to be time-varying.

This paper is organized as follows. In Section II, the problem is formulated. In Section III, the numeric conversion of the typhoon information is described. In Section IV, the GP prior model for prediction is derived. In Section V, the separable least-squares (LS) approach using the linear LS method with particle swarm optimization (PSO) is presented for training of the GP

Manuscript received May 22, 2014; revised July 24, 2014.

doi: 10.12720/ijeee.3.4.263-268

prior model. In Section VI, the prediction of the electric power damage is carried out using the GP posterior distribution. In Section VII, the performance of the proposed prediction method is demonstrated through numerical simulation using actual data of damage for the Amami archipelago in Japan. Finally, conclusions are given in Section VIII.

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, as shown in Fig. 1.

The input of the predictor is the typhoon information:

$$x = [x_1, x_2, x_3]^{\mathrm{T}} \tag{1}$$

where x_1 is the typhoon track, x_2[m/s] is the maximum instantaneous wind speed, and x_3 is the information of the arrival date of typhoons. The input x_3 is introduced to represent the time-varying relation between the typhoon information and the amount of damage. It is possible to choose other weather information as the input, but this 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. The output from the predictor is the amount of electric power damage y, such as the number of circuits with power failure.

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

$$X = [x(1), x(2), \cdots, x(N)]^{\mathrm{T}}$$
$$x(j) = [x_1(j), x_2(j), x_3(j)]^{\mathrm{T}} \tag{2}$$

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

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

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 data of a new approaching typhoon.

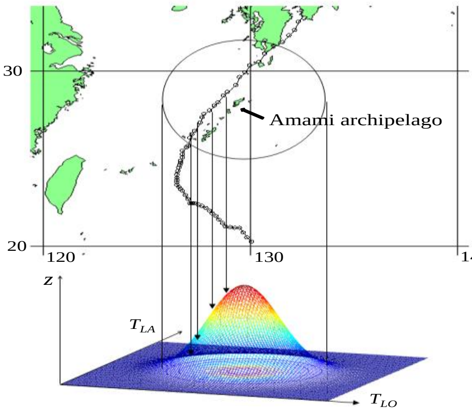

Figure 1. Quantification of the typhoon track

III. Numeric Conversion of Typhoon Information

The typhoon track x_1 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 a 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 a 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:

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

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 $\theta_p = [\alpha, \beta]^{\mathrm{T}}$ suboptimally will be discussed in Section V.

The maximum instantaneous wind speed x_2[m/s] can be directly available from the Meteorological Agency. The information x_3 of the date when typhoons hit the Amami archipelago is determined usingthe period between the date prespecified as initial point and the arrival date of typhoons.

IV. GP Prior Model for Prediction

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

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

where $f(\cdot)$ is a function which is assumed to be smooth. ε is assumed to be a zero-mean Gaussian noise with variance σ_n^2 . Note that the input x contains the information of the arrival date of typhoons x_3. Therefore, the description of (5) means that the nonlinear function $f(\cdot)$ is regarded as the time-varying function. The assumption of smoothness means that the amounts of electric power damage have a high correlation and become similar values for the typhoon data that are close to each other.

Let the vector of function values corresponding to the typhoon data given by (2) be

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

Then this vector f is represented by the GP. 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 variableswith a joint multivariable Gaussian distribution. Therefore, the vector of function values f can be represented by the GP as

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

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

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

$$m(x) = \bar{x}\theta_m \tag{8}$$

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

$$m(X) = \left[m\big(x(1)\big), m\big(x(2)\big), \cdots, m\big(x(N)\big)\right]^{\mathrm{T}} = \bar{X}\theta_m \tag{9}$$

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

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

$$\Sigma(X, X) = \begin{bmatrix} \Sigma_{11} & \cdots & \Sigma_{1N} \\ \vdots & \ddots & \vdots \\ \Sigma_{N1} & \cdots & \Sigma_{NN} \end{bmatrix} \tag{10}$$

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

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

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):

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

where

$$K(X, X) = \Sigma(X, X) + \sigma_n^2 I_N$$

$$I_N\text{: } N \times N \text{ identity matrix} \tag{13}$$

and $\theta_c = \left[\sigma_y, \ell, \sigma_n\right]^{\mathrm{T}}$ is called the *hyper parameter* vector. In the following, $K(X, X)$ is written as K for simplicity.

V. TRAINING BY PSO

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

$$J = -\log p(y|X, \theta)$$

$$= \frac{1}{2}\log|K| + \frac{1}{2}(y - \bar{X}\theta_m)^{\mathrm{T}} K^{-1} (y - \bar{X}\theta_m) + \frac{N}{2}\log(2\pi) \tag{14}$$

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 θ_c and adjusting parameter vector θ_p are given, the weighting parameter vector θ_m can be estimated by the linear LS method putting $\partial J / \partial \theta_m = 0$:

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

However, even if θ_m is known, the optimization with respect to θ_c and θ_p is a complicated nonlinear problem and might suffer from the local optima problem. Therefore, in this paper, we determine the unknown parameter vector θ by the separable LS approach combining the linear LS method with PSO. Only $\Omega = \left[\theta_c^{\mathrm{T}}, \theta_p^{\mathrm{T}}\right]^{\mathrm{T}} = \left[\sigma_y, \ell, \sigma_n, \alpha, \beta\right]^{\mathrm{T}}$ is represented with the particles and is searched for by PSO.

The detailed training algorithm is as follows:

Step 1: Initialization

Generate an initial population of Q particles with random positions $\Omega_{[i]}^0 = \left[\theta_{c[i]}^{\mathrm{T}}, \theta_{p[i]}^{\mathrm{T}}\right]^{\mathrm{T}}$ and velocities $V_{[i]}^0$ $(i = 1, 2, \cdots, Q)$.

Set the iteration counter$l = 0$.

Step 2: Numeric conversion of the typhoon information

Convert the typhoon information to a numerical value by the technique given in Section III.

Step 3: Construction of the covariance matrix

Construct Q candidates for the covariance matrix $K_{[i]}$ using $\theta_{c[i]}$ $(i = 1,2,\cdots Q)$.

Step 4: Estimation of θ_m

Estimate Q candidates for $\theta_{m[i]}$ $(i = 1,2,\cdots Q)$ from (15).

Step 5: Evaluation value calculation

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

$$J\left(\Omega_{[i]}^{l}\right) = -\log p\left(y \middle| X_{[i]}, \theta_{[i]}\right)$$

$$= \frac{1}{2}\log\left|K_{[i]}\right| + \frac{1}{2}\left(y - \bar{X}_{[i]}\theta_{m[i]}\right)^{\mathrm{T}} K_{[i]}^{-1}$$

$$\times \left(y - \bar{X}_{[i]}\theta_{m[i]}\right) + \frac{N}{2}\log(2\pi) \tag{16}$$

Step 6: Update of the best positions pbest and gbest

Update $pbest_{[i]}^{l}$, which is the personal best position,and $gbest^{l}$, which is the global best positionamong all particles, as follows:

If $l = 0$, then

$$pbest_{[i]}^{l} = \Omega_{[i]}^{l}$$

$$gbest^{l} = \Omega_{[i_{best}]}^{l} i_{best} = \arg\ \min_i J(\Omega_{[i]}^{l}) \tag{17}$$

otherwise

$$pbest_{[i]}^{l} = \begin{cases} \Omega_{[i]}^{l}\left(J\left(\Omega_{[i]}^{l}\right) < J\left(pbest_{[i]}^{l-1}\right)\right) \\ \quad pbest_{[i]}^{l-1}(\text{otherwise}) \end{cases} \tag{18}$$

$$gbest^{l} = pbest_{[i_{best}]}^{l}$$

$$i_{best} = \arg\min_i J(pbest_{[i]}^{l})$$

Step 7: Update of positions and velocities

Update the particle positions and velocities using (19):

$$V_{[i]}^{l+1} = w^{l}\cdot V_{[i]}^{l} + c_1\cdot rand_1\left(pbest_{[i]}^{l} - \Omega_{[i]}^{l}\right)$$

$$+ c_2\cdot rand_2\left(gbest^{l} - \Omega_{[i]}^{l}\right)$$

$$\Omega_{[i]}^{l+1} = \Omega_{[i]}^{l} + V_{[i]}^{l+1} \tag{19}$$

where w^l an inertia factor, c_1 and c_2 are constants representing acceleration coefficients, and $rand_1$ and $rand_2$ are uniformly distributed random numberswith amplitude in the range [0, 1]. Fig. 2 shows the update of particle positions.

Step 8: Repetition

Set the iteration counter to $l = l + 1$ and go to *step 2* until the prespecified iteration number l_{max}.

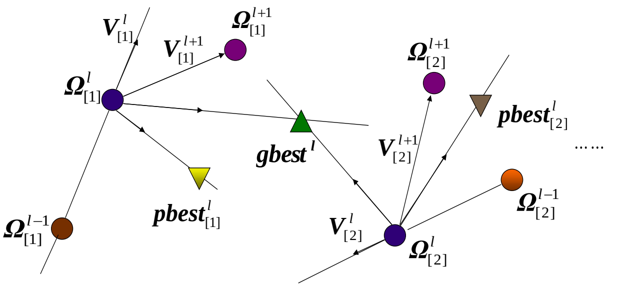

Figure 2. Update of particle positions

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

VI. Prediction by GP Posterior Distribution

Let the amount of electric power damage corresponding to the estimated typhoon data $x_* = [x_{1*}, x_{2*}, x_{3*}]^{\mathrm{T}}$ in the Amami archipelago be y_*. Then, we can get the joint Gaussian distribution of y and y_* under the GP prior as

$$\begin{bmatrix} y \\ y_* \end{bmatrix} \sim N\left(\begin{bmatrix} m(X) \\ m(x_*) \end{bmatrix}, \begin{bmatrix} K & \Sigma(X, x_*) \\ \Sigma(x_*, X) & s(x_*, x_*) + \sigma_n^2 \end{bmatrix}\right) \tag{20}$$

where $\Sigma(X, x_*) = \Sigma^{\mathrm{T}}(x_*, X)$ is the N-dimensional covariance vector evaluated at all pairs of the training input X and the new input x_*. From the formula for conditioning a joint Gaussian distribution [20], the posterior distribution for y_* is obtained as

$$y_* | X, y, x_* \sim N(\hat{y}_*, \hat{\sigma}_*^2) \tag{21}$$

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

$$\hat{y}_* = m(x_*) + \Sigma(x_*, X)K^{-1}(y - m(X)) \tag{22}$$

$$\hat{\sigma}_*^2 = s(x_*, x_*) - \Sigma(x_*, X)K^{-1}\Sigma(X, x_*) + \sigma_n^2 \tag{23}$$

$\hat{y}_*$ 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.

VII. 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. Among the 18 typhoons, 17 typhoons are used for training data and one typhoon is used for prediction data. 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 circuits with power failure. The initial point for numeric conversion of x_3 is set to be January 1, 1990. The design parameters of PSO are chosen as follows:

particle size: $Q = 100$
maximum iteration number: $l_{max} = 100$
inertia factor:

$$w^l = w_{max} - (w_{max} - w_{min})l/l_{max}$$
$$(w_{max} = 0.8,\ w_{min} = 0.4)$$

acceleration coefficients: $c_1 = 0.7,\ c_2 = 0.7$

The prediction results obtained by the proposed method and the conventional GP-based method [8] in which only typhoon weather information is utilized as input, are shown in Fig. 3 and Fig. 4, respectively. In these figures, the circles show the actual number of circuits with power failure, the squares show the predicted number of circuits with power failure, and the shaded areas give the double standard deviation confidence interval (95.5% confidence region). The mean absolute error $E = \sum_{k=1}^{18} |y_*(k) - \hat{y}_*(k)|/18$ is 3.80 for the proposed method and 4.60 for the conventional GP-based method, where $y_*(k)$ is the actual number of circuits with power failure and $\hat{y}_*(k)$ is the predicted number of circuits with power failure.The proposed method improves the accuracy of prediction. The actual amounts of damage of 15 typhoons are included in the double standard deviation confidence interval for the conventional GP-based method, whereas the actual amounts of damage of 16 typhoons are included in the interval for the proposed method. Namely, the probability that the actual amounts of damage are included in the double standard deviation confidence interval is 88.9% for the proposed method and 83.3% for the conventional GP-based method. This indicates that the proposed method can also improve the confidence region.

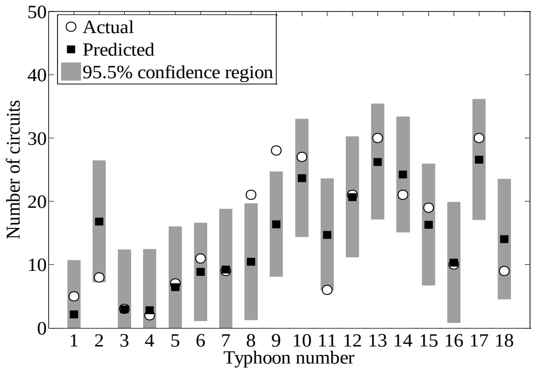

Figure 3. Predicted number of circuits with power failure (proposed method)

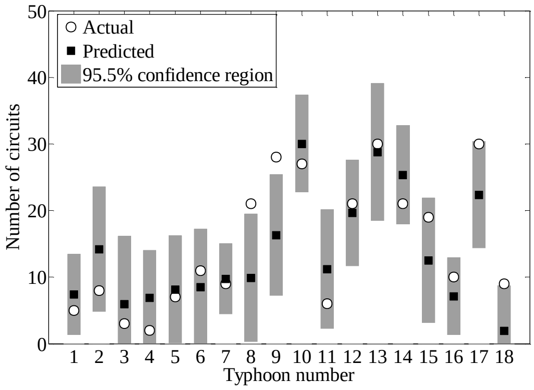

Figure 4. Predicted number of circuits with power failure (conventional GP-based method)

For comparison, Monte Carlo simulations with10 experiments are implemented for the proposed method and the conventional GP-based method, where 10 setups of the initial population are generated for PSO. The mean absolute error is shown in Table I for both the proposed method and the conventional GP-based method. The average of the mean absolute error is 3.89 for the proposed method and 4.84 for the conventional GP-based method. The average of the mean absolute error of the proposed method is 19.6% smaller than that of the conventional GP-based method. Therefore, we can confirm that introducing the information of the arrival date of typhoons improves the prediction accuracy well.

TABLE I. MEAN ABSOLUTE ERRORS

Population No.	Proposed method	Conventional GP-based method
1	3.89	4.79
2	3.93	4.86
3	3.81	4.89
4	3.88	4.87
5	3.95	4.89
6	3.93	4.89
7	3.91	4.91
8	3.88	4.86
9	3.80	4.81
10	3.86	4.60
average	3.89	4.84

VIII. CONCLUSIONS

In this paper, an improvement of the GP-based predictor of electric power damage caused by typhoons has been presented. Taking the maintenance of the electric power facilities into consideration, the proposed predictor uses the information of the arrival date of typhoons as well as the typhoon weather information, as inputs to the predictor. Simulation results show that the proposed prediction method yields more accurate predicted amount of damage than the conventional GP-based method. Examination of another weather data that affect electric power damage is one of the future works.

ACKNOWLEDGMENT

The authors would like to express sincere thanks to Kyushu Electric Power Company, Kagoshima Branch, for offering their data and support in this research.

This work was partially supported by JSPS KAKENHI Grant Number 24560524.

REFERENCES

[1] S. Miyazawa, *Disaster Prevention and Weather (in Japanese)*, Asakura Publishing, 1982.

[2] K. Yamamoto, *Report on the Investigation of Observation, Forecasting and Information Dissemination Systems to Reduce Tropical Cyclone Disasters in the Asian and Pacific Countries*, Japan Meteorological Agency, 1999.

[3] *White Paper on Disaster Management 2012 (in Japanese)*, Cabinet Office, Government of Japan, 2012.

[4] D. Longshore, *Encyclopedia of Hurricanes, Typhoons and Cyclones*, Facts on File, Inc., 1998.

[5] H. Takata, K. Sonoda, T. Hachino, and Y. Minari, "A prediction method of damage by typhoons to power systems in Kagoshima via linear regression model and neural network (in Japanese)," *J. Signal Processing*, vol. 3, no. 6, pp. 455-461, 1999.

[6] H. Takata and T. Hachino, "A prediction method of electric power damage by typhoons in Kagoshima via the second-order polynomial model and NN (in Japanese)," *Trans. of the ISCIE*, vol. 16, no. 10, pp. 513-519, 2003.

[7] H. Takata, K. Komatsu, and T. Hachino, "Prediction of electric power damage by typhoons in Amami archipelago," *J. Signal Processing*, vol. 9, no. 6, pp. 465-471, 2005.

[8] T. Hachino, H. Asai, and H. Takata, "Prediction of electric power damage by typhoons in Amami archipelago via Gaussian process model (in Japanese)," *IEEJ Trans. Electronics, Information and Systems*, vol. 132, no. 12, pp. 1966-1972, 2012.

[9] T. Hachino, T. Ueda, and H. Takata, "Gaussian process regression for prediction of electric power damage caused by typhoons considering non stationary of damage," *J. Signal Processing*, vol. 17, no. 3, pp. 61-68, 2013.

[10] T. Hachino, H. Takata, S. Nakayama, S. Fukushima, and Y. Igarashi, "Application of firefly algorithm to Gaussian process-

based prediction of Electric power damage caused by typhoons," *Int. J. Computer Science and Electronics Engineering*, vol. 1, no. 3, pp. 445-449, 2013.
[11] T. Hachino, H. Takata, S. Fukushima, and Y. Igarashi, "Gaussian process-based predictor of electric power damage caused by typhoons in Japan using artificial bee colony algorithm," *Int. J. Energy and Environment*, vol. 7, no. 5, pp. 189-196, 2013.
[12] A. O'Hagan, "Curve fitting and optimal design for prediction (with discussion)," *J. Royal Statistical Society B*, vol. 40, pp. 1-42, 1978.
[13] C. K. I. Williams and C. E. Rasmussen, "Gaussian processes for regression," *Advances in Neural Information Processing Systems*, vol. 8, pp. 514-520, 1996.
[14] C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning*, MIT Press, 2006.
[15] J. Kocijan, A. Girard, B. Banko, and R. Murray-Smith, "Dynamic systems identification with Gaussian processes," *Mathematical and Computer Modelling of Dynamical Systems*, vol. 11, no. 4, pp. 411-424, 2005.
[16] T. Hachino and H. Takata, "Identification of continuous-time nonlinear systems by using a Gaussian process model," *IEEJ Trans. Electrical and Electronic Engineering*, vol. 3, no. 6, pp. 620-628, 2008.
[17] A. Girard, C. E. Rasmussen, J. Q. Candela, and R. Murray-Smith, "Gaussian process priors with uncertain inputs -application to multiple-step ahead time series forecasting," *Advances in Neural Information Processing Systems*, vol. 15, pp. 542-552, 2003.
[18] T. Hachino and V. Kadirkamanathan, "Multiple Gaussian process models for direct time series forecasting," *IEEJ Trans. Electrical and Electronic Engineering*, vol. 6, no. 3, pp. 245-252, 2011.
[19] B. Likar and J. Kocijan, "Predictive control of a gas-liquid separation plant based on a Gaussian process model," *Computers and Chemical Engineering*, vol. 31, no. 3, pp. 142-152, 2007.
[20] R. von Mises, *Mathematical Theory of Probability and Statistics*, Academic Press, 1964.

Tomohiro Hachino received the B.S., M.S. and Dr. Eng. degrees in electrical engineering from Kyushu Institute of Technology in 1991, 1993, and 1996, respectively. He is currently an Associate Professor at the Department of Electrical and Electronics Engineering, Kagoshima University. His research interests include nonlinear control and identification, signal processing, and evolutionary computation. Dr. Hachino is a member of IEEJ, SICE, and ISCIE.

Shin Okubo received the B.S. degree in electrical and electronics engineering from Kagoshima University in 2014. He is currently a master's student at the Department of Electrical and Electronics Engineering, Kagoshima University. His research interests include the prediction of nonlinear systems and evolutionary computation.

Hitoshi Takata received the B.S. degree in electrical engineering from Kyushu Institute of Technology in 1968 and the M.S. and Dr. Eng. degrees in electrical engineering from Kyushu University in 1970 and 1974, respectively. He is currently a Professor Emeritus and a part-time lecturer at Kagoshima University. His research interests include the control, linearization, and identification of nonlinear systems. Dr. Takata is a member of IEEJ and RISP.

Seiji Fukushima received the B.S., M.S., and Ph.D. degrees in electrical engineering from Kyushu University in 1984, 1986, and 1993, respectively. He is currently a Professor at the Department of Electrical and Electronics Engineering, Kagoshima University. His research interests include photonics/radio hybrid communication systems and their related devices. Dr. Fukushima is a member of IEICE, IEEE/Photonics Society, Japan Society of Applied Physics, Japanese Liquid Crystal Society, and Optical Society of America.

Yasutaka Igarashi received the B.E., M.E., and Ph.D. degrees in information and computer sciences from Saitama University in 2000, 2002, and 2005, respectively. He is currently an Assistant Professor at the Department of Electrical and Electronics Engineering, Kagoshima University. His research interests include optical CDMA communication systems and the cryptanalysis of symmetric-key cryptography. Dr. Igarashi is a member of IEICE and RISP.