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Original Article

The performance of Taguchi's T-method with binary bat algorithm based on great value priority binarization for prediction

Zulkifli Marlah Marlan[1*], Faizir Ramlie[1], Khairur Rijal Jamaludin[1], and Nolia Harudin[2]

[1] *Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, Kuala Lumpur, 54100 Malaysia*

[2] *Department of Mechanical, College of Engineering, Universiti Tenaga Nasional, Kajang, 43000 Malaysia*

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Abstract

Taguchi's T-method is a predictive modeling technique under the Mahalanobis-Taguchi system that is based on the regression principle and robust quality engineering elements to predict future state or unknown outcomes. In enhancing prediction accuracy, the T-method employed Taguchi's orthogonal array as a variable selection approach to determine a subset of independent variables that are significant toward the dependent variable or output. This, however, leads to sub-optimality of prediction accuracy as the orthogonal array design lacks in offering higher-order variable interactions, in addition to its fixed and limited variable combinations to be assessed and evaluated. This paper proposes an optimization algorithm based on the Binary Bat algorithm methodology for replacing the conventional orthogonal array approach. Specifically, a Great Value Priority binarization scheme is employed to transform the continuous location of the bat into a binary bit, representing a combination of the variable in binary string form. A comparative study was conducted, and the mean absolute error metric was used as the performance measure. Experiments show that the T-method prediction accuracy with the Binary Bat algorithm based on the Great Value Priority binarization scheme is better than that of the conventional T-method-orthogonal array.

Keywords: Mahalanobis-Taguchi system, Taguchi's T-method, binary bat algorithm, great value priority, prediction model

1. Introduction

Taguchi's T-method (T-method) is one of several methods under the Mahalanobis-Taguchi system, explicitly developed to predict an unknown output or future state based on historical or available information (Teshima, Hasegawa, & Tatebayashi, 2012). The underlying theory behind the T-method involves the integration of a regression principle and Taguchi's robust quality engineering elements such as linear regression analysis, inverse regression, weighted average, unit space concept, signal-to-noise ratio (SNR) evaluation, and experimental design in formulating the T-method predictive model. The blend of statistical-mathematical analysis in formulating the T-method has resulted in superior capabilities, which are resistant to multicollinearity issues when dealing with multivariate data, and applicable to small sample data (number of samples less than the number of input variables) (Nishino, & Suzuki, 2019). As such, the T-method has been well accepted by researchers and practitioners. To date, the T-method predictive technique has been used to solve many prediction-based problems in diverse fields and sectors, such as in predicting the life of a battery in the manufacturing industry (Dasneogi, Cudney, Adekpedjou, & Kestle, 2009), predicting vehicle fuel consumption for the automotive industry (Cudney, Shah, & Kestle, 2010), estimating patient's blood pressure in the healthcare industry (Suzuki, 2015) and predicting human body fat in the biological science field (Harudin *et al.*, 2019).

In the conventional T-method, the optimization of the T-method prediction model that involves multiple independent variables is performed by utilizing Taguchi's orthogonal array (OA) to analyze and determine a subset of relevant and significant independent variables affecting the prediction outcome. The OA is employed to supply a

*Corresponding author
Email address: zulkifli49@graduate.utm.my

fractional experimental design with a balanced factor level to minimize the count of experimental runs, thus reducing the cost of experimental work (Taguchi, Chowdhury & Wu, 2005). However, there is a concern about utilizing OA for variable selection purposes, where the analysis yields sub-optimal T-method prediction accuracy. This is mainly due to the lack of higher-order variable interactions, in addition to its fixed and limited variable combination to be assessed and evaluated during variable selection (Kim, Tsui, Sukchotrat & Chen, 2009; Woodall *et al.*, 2003). This is in agreement with Abraham, & Variyath (2003), who stressed that a better variable selection approach is available than OA by capitalizing on the advances in computers for computational work. Therefore, this paper proposes a swarm-based optimization algorithm known as the Binary Bat algorithm based on Great Value Priority binarization as an alternative to the OA approach.

The practice of employing a swarm-based metaheuristic algorithm to replace the OA is not new. Under the Mahalanobis-Taguchi system for variable selection domain, Ramlie, Jamaludin, Dolah, & Muhamad (2016) reported on several past studies employing various metaheuristic algorithms such as the Binary Ant algorithm, binary Particle Swarm Optimization algorithm, and Gompertz Particle Swarm Optimization algorithm for classification problem using Mahalanobis-Taguchi method (MT-method). In addition, Ramlie *et al.* (2016) introduce a Bee algorithm as an alternative to the OA to enhance classification accuracy from MT-method through variable selection. Specifically, in the T-method, an Artificial Bee Colony algorithm, Binary Particle Swarm Optimization, and Binary Bitwise Artificial Bee Colony were introduced in Harudin *et al.* (2018), Harudin *et al.* (2020), and Harudin *et al.* (2021), respectively. These studies have demonstrated that the swarm-based metaheuristic algorithms provide a significant improvement, particularly in the variable selection problem, as opposed to the OA approach. A rigorous search through the combination of exploration and exploitation strategy of a metaheuristic algorithm does promise a better solution, although not optimal (Brezočnik, Fister, & Podgorelec, 2018). Specifically, in this paper, the Binary Bat algorithm was selected to replace the OA due to its advantages in searching and obtaining solutions based on global diversity as well as rigorous local exploitation (Uzman, Irfan, & Adeem, 2020), and to further explore the effect on the T-method prediction accuracy.

2. Methodology

2.1 Formulation of T-method prediction model

Mathematically, the T-method prediction model for any process or system is formulated in the form of the integrated estimated output, $\widehat{M}_i$, as shown in equation (1).

$$Integrated\ Estimate\ Output\ Value, \widehat{M}_i = \frac{\eta_1 \times \frac{X_{i1}}{\beta_1} + \eta_2 \times \frac{X_{i2}}{\beta_2} + \dots + \eta_k \times \frac{X_{ik}}{\beta_k}}{\eta_1 + \eta_2 + \dots + \eta_k}; \quad (i = 1, 2, \dots, l) \tag{1}$$

Where X_{i1} are the normalized data for i = 1, 2, 3 ... l number of observations on the independent variable number 1, η is the SNR value for the respective k^{th} independent variable, and β is the proportionality coefficient of the respective k^{th} independent variable. Upon gathering and tabulating the necessary data, a subset of unit space data based on the homogeneity characteristic of the dependent variable value is determined. Teshima *et al.* (2012) and Marlan, Jamaludin, Ramlie, Harudin, & Jaafar (2019) explained the detailed procedure for obtaining the unit space data. A normalized signal data consisting of all data except for the subset of unit space data is then obtained by subtracting the average value of unit space data from raw data. The normalized signal data is used to estimate the proportionality coefficient, β, and SNR for each independent variable using equations (2) and (3), respectively.

$$\begin{gathered} Proportional\ coefficient, \beta_j = \frac{M_i X_{ij} + M_i X_{ij} + \dots + M_l X_{lj}}{r} \\ Effective\ divider, r = M_1^2 + M_2^2 + \dots + M_l^2 \end{gathered} \tag{2}$$

Where M_i is the normalized dependent value of i^{th} sample (i = 1, 2, …, l), and X_{ij} is the normalized independent variable value of i^{th} sample (i = 1, 2, …, l) for j^{th} independent variable (j = 1, 2, …, k).

$$Signal-to-noise\ ratio, \eta_j = \begin{cases} \frac{\frac{1}{r}(S_{\beta j} - V_{ej})}{V_{ej}} & ; (when\ S_{\beta j} > V_{ej}) \\ 0 & ; (when\ S_{\beta j} \le V_{ej}) \end{cases} \tag{3}$$

$$\begin{gathered} Error\ variance, V_{ej} = \frac{S_{ej}}{l-1} \\ Error\ variation, S_{ej} = S_{Tj} - S_{\beta j} \\ Total\ variation, S_{Tj} = X_{11}^2 + X_{21}^2 + \dots + X_{lj}^2 \\ Variation\ of\ proportional\ term, S_{\beta j} = \frac{(M_1 X_{11} + M_2 X_{21} + \dots + M_l X_{lj})^2}{r} \end{gathered}$$

Where $\widehat{M}$ is the predicted value of the dependent variable for sample i = 1, 2, …, l. The estimated model parameters are then substituted in the integrated estimate of output in equation (1). A quality index to represent the current performance of the T-method prediction model is then computed using equation (4). The quality index in the form of a decibel value of the SNR (SNR (db)) will be used in optimizing the T-method prediction accuracy by using variable selection. Hypothetically, the exclusion of irrelevant and redundant variables from the prediction model will result in a higher value of the quality index, signifying that less variation remains in the model caused by noise variables (Taguchi *et al.*, 2005). The conventional variable selection process using Taguchi's OA is explained by Harudin *et al.* (2020).

$$Integrated\ estimate\ SNR\ (db), \eta_{est} = 10 \log \frac{\frac{1}{r}(S_{\beta j} - V_{ej})}{V_{ej}} \tag{4}$$

$$\begin{gathered} Linear\ equation, L = M_1 \widehat{M}_1 + M_2 \widehat{M}_2 + \dots + M_l \widehat{M}_l \\ Effective\ divider, r = M_1^2 + M_2^2 + \dots + M_l^2 \\ Total\ variation, S_T = \widehat{M}_1^2 + \widehat{M}_2^2 + \dots + \widehat{M}_l^2 \\ Variation\ of\ proportional\ term, S_\beta = \frac{L^2}{r} \\ Error\ variation, S_e = S_T - S_\beta \end{gathered}$$

$$Error\ variance, V_e = \frac{S_e}{l-1}$$

2.2 Binarization of the Binary Bat algorithm using Great Value Priority (GVP)

A bat algorithm is a swarm-based optimization algorithm introduced by Yang (2010) based on the echolocation characteristics of bats. Bats or microbats identify prey, avoid obstacles, and find their roosting niches in the dark using a kind of sonar called echolocation. These bats generate a very loud sound pulse and listen for the echo produced by nearby objects. Their pulses have a range of characteristics and may be linked with the species' hunting tactics. As they approach barriers or prey, the bats alter the pulse and rate of the sound. Conceptually, the exploration of food or solution in the solution space is executed by updating the bat's frequency, f_i between minimum frequency, f_{min} and maximum frequency, f_{max}, velocity, v_i, which is influenced by current best bat's position, x_*, and bat's position, x_i using equations (5), (6), and (7), respectively. The β in equation (5) is a random number drawn from a uniform distribution, $\beta \in [0,1]$. Bats further exploit solutions for a better solution by performing a local search in the region of the best solution through a random walk using equation (8), where $\varepsilon \in [0,1]$ is a random number drawn from a uniform distribution, x_{old} is the previous bat's position, and $\bar{A}^t$ is the bat's average loudness.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{5}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*)f_i \tag{6}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{7}$$

$$x_{new} = x_{old} + \varepsilon\bar{A}^t \tag{8}$$

The balance between exploration and exploitation of solution in the Bat algorithm is controlled by the loudness and pulse rate as iterations grow. Equations (9) and (10) are used for the intended purposes, where alpha, α, and gamma, γ, are constants that control the loudness and pulse rate, respectively. The *t* in equations (5) to (10) is the time step, where zero is the initial state while *t-1* and *t+1* are the previous and the new time step, respectively.

$$A_i^{t+1} = \alpha A_i^t \tag{9}$$

$$r_i^{t+1} = r_i^0\,[1 - exp(-\gamma t)] \tag{10}$$

As opposed to the Bat algorithm that searches for a solution in a continuous-valued solution space, a binary version of the Bat algorithm was introduced by Nakamura *et al.* (2013) and Mirjalili, Mirjalili & Yang (2014) by employing a sigmoid and a V-shaped transfer function, respectively, in converting continuous to binary-valued solution to solve a discrete problem such as optimal variable selection. In Nakamura *et al.* (2013), a sigmoidal transfer function was utilized to convert the continuous-valued bat's velocity into a probability value between 0 and 1 in determining the binary position of the bat (0 or 1) using a binary operator. A similar procedure was applied in Mirjalili *et al.* (2014), except that a V-shaped transfer function was utilized. Other than these two, many other discretization approaches are available to convert continuous into a binary solution string. Crawford *et al.* (2017) provide a systematic review of discretization approaches that can be employed by metaheuristic algorithms, such as Rounding off Generic Techniques, Priority Position Techniques, Binarization, and many more. Amongst many approaches, Dahi, Mezioud & Draa (2015) compare five techniques covering the nearest integer method, normalization method, angle modulation method, sigmoid function, and great value priority (GVP) methods using the Bat algorithm. The result indicated that two factors impact the efficiency of the discretization approach, which are i) the size of the problem and ii) the complexity of the problem. In a recent development, Marlan, Jamaluddin, Ramlie, and Harudin (2022), and Marlan, Ramlie, Jamaluddin, and Harudin (2022) reported on the performance of the T-method with the nearest integer based Binary Bat Algorithm and the T-method with the angle modulated Bat algorithm, and the results show improved prediction accuracy achieved in both studies.

This study employed the Great Value Priority based Binary Bat algorithm in optimizing the variable selection of the T-method prediction model. The GVP was selected due to its simple operation in transforming continuous value into binary form. Instead of converting the Bat's velocity as in Nakamura *et al.* (2013) and Mirjalili *et al.* (2014), the GVP approach converts the continuous location of the bat. Upon determination of the continuous-valued bat's position vector X using equations (5), (6), and (7), a permutation of vector P is created assigning the position of the largest element in original vector X as the first element in vector P. Subsequently, the position of the second largest element in vector X becomes the second element in vector P. The procedure continues until all elements in vector X are filled in vector P. Once vector P is obtained, transformation into a binary-valued vector is performed through equation (11) as follows:

$$x_{ij} = \begin{cases} 1, & \text{if } P_j > P_{j+1} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

Where *i* is the solution number and *j* is the number of dimensions or variables. Table 1 shows an example of the GVP procedure. Suppose that the first row is the obtained continuous-valued bat's position, the second row shows the index location of the continuous-valued bat's position in the first row, where 1 is the location of the highest continuous-valued position and 10 is the least continuous-valued bat's position. The third row is the binary bat's position obtained using equation (11). Table 2 shows the pseudocode of the Great Value Priority based Binary Bat algorithm (GVPBBA) used in this study.

Table 1. Example of GVP discretization procedure

Continuous solution, X	8.7	5.4	3.9	4.7	2.1	5.6	3.5	9.3	8.2	3.6
Index Location of X	2	5	7	6	10	4	9	1	3	8
Binary solution	0	0	1	0	1	0	1	0	0	1

Table 2. Great Value Priority based Binary Bat algorithm pseudocode

GVPBBA Algorithm

Input: Initial continuous bat population x_i, initial bat velocity v_i, initial bat frequency f_i, initial bat pulse rat r_i, initial bat loudness A_i,
Output: Optimal binary position x_*

Initialize random continuous bat population x_i (i = 1, 2, …, population size)
Initialize bat velocity, $v_i = 0$
Initialize bat frequency, f_i at x_i,
Initialize bat pulse rate, r_i, and loudness, A_i
Transform continuous-valued position, x_i into a binary-valued using equation (11)
Evaluate fitness
Find the best: fitness, binary position, x_*, continuous position, x_{**}
***While** (iteration < Maximum iterations)*
Generate new solutions:
  Adjust frequency: $f_i = f_{min} + (f_{max} - f_{min})\beta$
  Updating velocity: $v_i^t = v_i^{t-1} + (x_i^t - x_{**})f_i$
  Updating position new: $x_i^t = x_i^{t-1} + v_i^t$
  ***if** (rand > r_i)*
    Select a solution among the best solutions.
    Generate a local solution around the selected best solution
    Transform continuous-valued new position, x_i into a binary value using equation (11)
  end
  Evaluate new fitness
  ***if** (rand < A_i & $f(x_i) < f(x_*)$)*
    Accept the new solutions
    Increase pulse rate, r_i and reduce loudness, A_i
  end
Rank the bats and find the current best x_*
end while

3. Results and Discussion

3.1 Experimental design

For determining the performance of the proposed GVPBBA in T-method prediction accuracy, a set of experiments was conducted involving two benchmark datasets from the UCL Machine Learning repository, as shown in Table 3. The first dataset is for predicting the heating load based on eight building attributes, while the second dataset is used to predict Abalone's age based on seven physical measurements (Lichman, 2013). A random hold-out cross-validation was applied to each dataset, with 70% of the data used in training, and the remaining 30% allocated for validation. Specifically, in this study, the unit space data for both datasets consisted of a subset of five exemplars obtained in densely populated set of dependent variable values having homogeneous characteristics. The average values of unit space for both datasets are shown in Table 4. Subsequently, the model parameters for both datasets were successfully obtained based on the normalized signal data, as shown in Tables 5 and 6. As such, the T-method prediction model can be formulated, and the predicted value using training data can be computed to determine the quality index.

Prior to executing the GVPBBA algorithm for variable selection, the GVPBBA parameters need to be determined. In this study, a Taguchi Method was employed as a parameter optimization technique in obtaining the GVPBBA optimal parameter settings. The parameters to be determined are shown in Table 7: population size, minimum frequency, maximum frequency, pulse rate, loudness, alpha, and gamma with three levels for each. The value of each level was obtained from a compilation of past research in executing the Binary Bat algorithm, such as the works by Dahi, Mezioud, and Draa (2015), Doreswamy, and Umme (2016), Ma, and Wang (2018) and Jaafer, Bazoon, and Dawood (2020).

Table 8 shows the outcome of the Taguchi Method in parameter optimization for the GVPBBA algorithm using L_{27} OA design with integrated estimate of SNR (db) used as the objective function. The optimal setting obtained shows dissimilarity between datasets, indicating that the optimal setting will differ from one case study to another. In obtaining the optimal subset of independent variables using the GVPBBA algorithm with optimal parameters, the algorithm was independently executed for 20 runs with 500 iterations for each run. The selection of the optimal subset of independent variables was based on 50% or more of variable appearance in the optimal combination over 20 runs. Any reduction in the

Table 3. Benchmark datasets

Dataset	No. of sample	No. of independent variable	Train data set		Validation data set (30%)
			70%	Signal data	
Heating load	768	8	538	533	230
Abalone	4177	7	2924	2919	1253

Table 4. Average of unit space data for Heating load and Abalone dataset

Dataset	X1	X2	X3	X4	X5	X6	X7	X8
Heating load	0.820	612.500	318.500	147.000	7.000	3.800	0.100	1.800
Abalone	0.546	0.419	0.145	0.997	0.470	0.231	0.263	

Table 5. Computed model parameters for heating load dataset

Parameter	X1	X2	X3	X4	X5	X6	X7	X8
β	0.007	-6.203	1.814	-4.008	0.164	0.005	0.003	0.010
η	$5.18E^{-03}$	$5.23E^{-03}$	$2.18E^{-03}$	$1.29E^{-02}$	$8.12E^{-03}$	$3.71E^{-06}$	$2.17E^{-04}$	$8.48E^{-06}$

Table 6. Computed model parameters for Abalone dataset

Parameter	X1	X2	X3	X4	X5	X6	X7
β	0.021	0.018	0.007	0.085	0.031	0.018	0.028
η	0.043	0.048	0.055	0.036	0.018	0.028	0.061

Table 7. Experimental parameter settings

Parameter	Level 1	Level 2	Level 3
Population size	25	50	100
Min frequency, *fmin*	0	1	3
Max frequency, *fmax*	2	5	10
Pulse rate, *r*	0.2	0.5	0.9
Loudness, *A*	0.25	0.5	0.9
Alpha, α	0.1	0.7	0.95
Gamma, γ	0.15	0.6	0.95

Table 8. GVPBBA optimal parameters setting

Parameter	Heating load	Abalone
Population size	100	100
Min frequency, *fmin*	1	0
Max frequency, *fmax*	5	2
Pulse rate, *r*	0.5	0.2
Loudness, *A*	0.9	0.9
Alpha, α	0.95	0.7
Gamma, γ	0.95	0.6

total number of variables will be measured using a reduction rate metric, as shown in equation (12). Finally, the T-method prediction accuracy with the GVPBBA algorithm will be measured using the mean absolute error metric shown in equation (13), on the 30% validation data set.

$$Reduction\ rate, R_r = \frac{\#\ original\ features\ -\ \#\ selected\ features}{\#\ original\ features} \times 100\% \quad (12)$$

$$Mean\ Absolute\ Error, MAE\ = \frac{1}{l}\sum_{i=1}^{l}\left|M_i - \hat{M}_i\right| \quad (13)$$

For this analysis, the algorithm for the proposed method was programmed in MATLAB R2020a software run on an 8th generation Intel Core i5 processor laptop, equipped with 12 gigabytes of RAM and one terabyte of data storage.

3.1 Experimental results

Table 9 shows the optimal number of variables with their respective optimal variable combinations for the two datasets, obtained using the training data. For the cooling load dataset, the conventional T-method with OA recorded three significant variables or a 62.5% reduction, as opposed to four variables and 50% reduction obtained by the proposed T-method with the GVPBBA algorithm. The optimal combination is about the same for both approaches, except that variable 2 is included in the optimal combination of the proposed method. As for the Abalone dataset, the T-method with OA recorded three significant variables or a 57.1% reduction to variables 2, 3, and 7, while the proposed T-method with GVPBBA recorded only two significant variables or 71.4% reduction, namely variables 3 and 7. From these results, it can be concluded that both approaches successfully identify a subset of significant variables that leads to reduced dimensionality of the problem, which results in a lesser model complexity.

Table 10 shows the prediction accuracy in terms of mean absolute error (MAE) for both case studies using validation data on the three variants of the T-method. Without

Table 9. Optimal variable combination

Dataset	Item	T-method	T-method + AO	T-method + GVPBBA
Heating load	No. of feature	8	3	4
	Opt. Combination	all	3, 4, 7	2, 3, 7, 8
	Reduction rate, R_r	-	62.5%	50%
Abalone	No. of feature	7	3	2
	Opt. Combination	all	2, 3, 7	3, 7
	Reduction rate, R_r	-	57.1%	71.4%

Table 10. Mean absolute error (%) using the validation data set

Dataset	T-method	T-method + AO	T-method + GVPBBA
Heating load	8.06	5.67 (29.7%)	5.23 (35.1%)
Abalone	3.65	3.28 (10.1%)	3.23 (11.5%)

practicing any variable selection, the T-method recorded 8.06% MAE for heating load and 3.65% MAE for the Abalone dataset on the validation data set. The conventional T-method with the OA approach recorded 5.67% MAE or 29.7% improvement over the T-method without variable selection for the heating load dataset, and 3.28% MAE or 10.1% improvement over the T-method for the Abalone dataset. The proposed T-method with the GVPBBA algorithm recorded the lowest error in both case studies at 5.23% MAE or 35.1% improvement over the T-method without variable selection and 3.23% MAE or 11.5% improvement over the T-method without variable selection for Heating load and Abalone dataset, respectively. In conclusion, these results confirm that a better subset of significant variables was obtained using the proposed T-method with the GVPBBA algorithm.

4. Conclusions

This paper integrated a swarm-based Binary Bat algorithm based on the Great Value Priority discretization technique with Taguchi's T-method, as a variable selection optimizing strategy. The experimental results confirmed that the proposed method could find a better subset of significant variables, giving a reduced MAE prediction error when tested on the validation data set. Furthermore, a reduced number of independent variables in the optimal subset of significant variables leads to a less complex T-method prediction model and could reduce computational time.

As for future studies, the T-method with the GVPBBA algorithm could be further enhanced by incorporating an adaptive parameter setting as iterations progress. The relative importance of GVPBBA algorithm parameters could be identified, and a dynamic updating strategy could be implemented to further facilitate the searching mechanism.

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