A Hybrid Algorithm by Incorporating Neural Network and Metaheuristic Algorithms for Function Approximation and Demand Prediction Estimation

Zen-Yao Chen(✉)

Department of Business Administration, Hungkuo Delin University of Technology, New Taipei City, Taiwan
keyzyc@gmail.com

Abstract. This study intends to heighten the training expression of radial basis function neural network (RbfN) via artificial neural network (ANN) and metaheuristic (MH) algorithms. Further, the self-organizing map neural network (SOMN), artificial immune system (AIS) and ant colony optimization (ACO)-based algorithms are employed to train RbfN for function approximation and demand prediction estimation. The proposed hybrid of SOMN with AIS-based and ACO-based (HSIA) algorithm incorporates the complementarity of exploitation and exploration potentialities to attain problem settle. The experimental consequences have evidenced that AIS-based and ACO-based algorithms can be integrated cleverly and propose a hybrid algorithm which attempts for receiving the optimal training expression among corresponding algorithms in this study. Additionally, method appraisal consequences for two benchmark nonlinear test functions illustrate that the proposed HSIA algorithm surpasses corresponding algorithms in accuracy of function approximation issue and the industrial computer (IC) demand prediction exercise.

Keywords: Metaheuristic Algorithm · Self-organizing Map · Neural Network · Ant Colony Optimization · Artificial Immune System

1 Introduction

Artificial neural networks (ANNs) have intense imitating property while indigent in deduction and argumentation [1]. Next, owing to the simply constructed topology and the capability to evidence how learning carries on a strict manner, the radial basis function (Rbf) neural network (RbfN) has been broadly adopted as the general function approximator to resolve nonlinear problems [2]. Besides, the self-organizing mapping (SOM) [3] algorithm is one of the most universal ANN model based on the unsupervised rival learning pattern [4]. Since the SOM network (SOMN) can be seen as a clustering technique [5], and it is an unsupervised imitating ANN that employs neighborhood and topology to cluster correlative data into one category [6].

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Artificial immune system (AIS) contains several calculation intelligence procedures under the joint attribute of being based on principles and actions that normally happen at the degree of the immune system (IS). AISs are obtaining enhanced regard from scientific domain as a result of their potentiality to resolve compound optimization tasks in few realms [7]. Afterwards, a popular NI-based algorithm which has a random intrinsic metaheuristic (MH) algorithm (MHA) that has been implemented to conduct much compound optimization tasks is ant colony optimization (ACO) approach. The properties of this MHA involve the following: robustness, forceful response, decentralized calculation, and lightly incorporating with distinct algorithms, induces ACO to gain more successful optimal solutions [8]. Some MHAs sustain reduction of diversity consequences in little exploration, results all answers converge into certain local optimal responses. So they invalid the occasion of finding the global optimal regions [9].

Accordingly, the aim for this study is to adopt SOMN first with auto-clustering ability to decide the initial activation neuron parameters of the hidden layer on RbfN. Consequently, through taking the advantages of ANN model and MH algorithm, this research proposes the hybrid of SOMN with AIS-based and ACO-based (HSIA) algorithm to train RbfN. In the proposed HSIA algorithm, AIS-based approach actions exploitation in local district to refrain insufficient convergence (i.e., merely to acquire the second best feasible solution) and simultaneously to make the solution space more centralize. Also, ACO-based approach actions exploration in global district to refrain the early convergence, which would make the solution space more various. Lastly, the HSIA algorithm acquired the best inspection consequences in accuracy than other relevant algorithms in literature. Moreover, the practice of empirical industrial computer (IC) demand prediction practice evidences that the HSIA algorithm has higher preciseness than other corresponding algorithms and the Box-Jenkins models.

2 Literature Review

ANNs are the most effectual category of intelligent methods for nonlinear pattern recognition, which are the material driven and global district approximators [10]. Afterwards, the recursive least-squares (RLS) or gradient search algorithm is utilized to modulate the parameters of Gaussian functions and the joined weights to heighten the modelling potentiality. To gain an expected expression, a RbfN with a great size is constantly declared. But, such a great RbfN always claim a high challenge in estimation and constantly creates numerically unreliable. Although few methods have been recommended to alleviate this issue, the supplementing accomplished is not noticeable [11].

A SOMN is a nonlinear NN model [3]. Due to its rapid imitating, self-organized and topology inherence, literature evidences that the SOMN can be effectually utilized to reduce down initial layout options [12].

In addition, various assurance optimization algorithms sustain local optimal trap. The major attributes of these algorithms are dominant supposes absence and population dependency [13]. For example, the immune system (IS) can safeguard alive organisms from intruding bacteria or virus, while be suppling with a mutually proposition between lymphocytes and in certain B cells [14]. Then, Diao & Passino [15] in 2002 proposed a based on AIS algorithm for the RbfN structure and adaptation of parameters. In addition, AIS adopts the superiority of studying principles in the airframe IS to form intelligence issue solvers [16]. Additionally, as a result of their scattered nature, AIS have been advanced concretely for resolving optimal dispersed and decision-making issues [17].

Subsequently, the ACO algorithm, introducing the pheromone concept that every ant rewards on its seek from preceding ants. Thus, for mining the global simplified path, pheromone consistence acts a necessary part for piloting the ants' conduct. In this process, efficacy and precision of algorithm are influenced via treating method of congregated information. Latter, the ACO algorithm has truly advanced potentiality of finding, excellent solution, as substantial as a stone steady, brief calculate implement. Therefore, many scholars' have presented methods which are facilitated for ACO, with intends to prevail the algorithm failing [8].

There are a various number of hybrid MHAs, which also may present very promising and excellence outcomes with correct solutions in many challenging learning topics [18]. In detail, the utility of global exploration incorporated with local exploitation not only has been demonstrated in software test data makeup but also in a variation of applications involving machine learning and its corresponding matters [19]. Moreover, the combined mode has been widely applied in many domains, such as finances [20], agribusiness [21], health [22], industry [23, 24], and etc. In the incorporated model, the superiorities of different forecast models are merged, and better forecast results are realized [25].

3 Methodology

The major point underlying SOMN is that RbfNs are local approximates, and the centres of local Rbf neurons are regulated to shift to the real centre in the meaning of feature expression [26]. Also, the conventional SOMN formulation involves a decaying neighborship width over time to generate a more greatly adjusted output mapping [27].

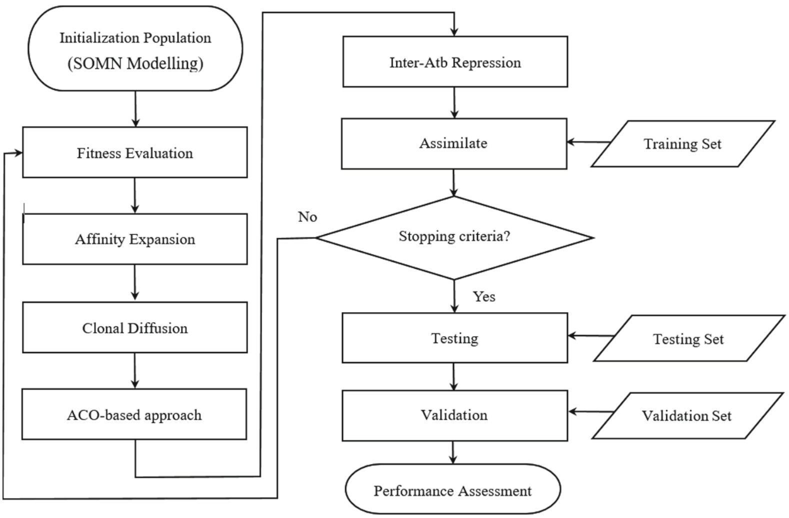

Fig. 1. The flowchart for the proposed HSIA algorithm.

Consequently, the flowchart of the HSIA algorithm is illustrated in Fig. 1, and a declaration roughly on how the evolution program for the HSIA algorithm was explained as follows. The proposed HSIA algorithm about how to train RbfN through ANN and MH algorithms will be disserted in the inferior part.

(1) *Initialization Population*

(a) Initialize build a population which involve a random amount of antibody (Atb). Next, SOMN is adopted to judge the number of centres and the relevant position values by its auto-clustering talent. The outcomes are then applied as the number of neurons on RbfN. The Atbs emerged in the population can be regarded as the neurons during the hidden layer on RbfN. With two dissimilar benchmark nonlinear test functions, different input regions will bring unlike training patterns data (i.e., antigen (Atg)) as well. These unlike training patterns data will be emerged within mapping input region on N dimension space for two benchmark nonlinear test functions.

(b) The weights w_i on RbfN are decided through resolving the linear system [28]:

$$\mathrm{A}w = u \tag{1}$$

where $\mathrm{A} = A_{ij} = \xi_i(\|x - x_i\|_2)$ and $u = u(x_i)$ are the investigated function values at the specimen points. The refined RBFs will consequence in a positive-definite matrix $\Re$, accordingly insuring an individual solution to Eq. (1) [28]. Latter, the orthogonal least squares (OLS) algorithm [29] is introduced to settle the weight value between hidden and output layers on RbfN.

(2) *Fitness Evaluation & Affinity Expansion*

The affinity expansion within Atb and Atg will be estimated during settling two benchmark nonlinear test functions. Afterward, an amount of candidate solutions with advanced fitness values will be acquired.

(3) *Clonal Diffusion*

Such clonal diffusion action tolerates more Atbs to reproduce in the inherit population, and promote the settling to be able to converge toward the global optimal solution.

(4) *ACO-based approach*

(a) In the initiating of optimization sequence, let N ants set out from their nest to seek for food. It will initialize existing equality amount of pheromone at each margin of any ant's subsequent ways. Ants go ahead from any node of ant nest, and achieved at the terminal node throughout every generation, where anyone ant may decide the next node to visit through Eq. (2):

$$P_k(r,s) = \begin{cases} \dfrac{\tau(r,s)^{\alpha} \times \eta(r,s)^{\beta}}{\sum_{u \in J_k(r)} \tau(r,u)^{\alpha} \times \eta(r,u)^{\beta}}, & if \;\; s \in J_k(r) \\ 0, & Otherwise \end{cases} \tag{2}$$

where $J_k(r)$ is the storage of all not visited nodes once ant k continues from the initiate node on margin r of passing ways in touring. $P_k(r, s)$ is the stochastic probability value of uniform distribution for ant k continuing from the initiate node on margin r to next stochastic visited node on margin s. Next, α and β are the experiential parameters to manipulate the sensitiveness for pheromone value ($\alpha \geq 0$) and heuristic value

($\beta \leq 1$) respectively. $\tau_i(r, u)$ is the pheromone value from any node on margin r to any node on margin u, while $\eta(r, u)$ is the heuristic value from any node on margin r to any node on margin u.

(b) For the developing solution, it is inescapable that it will undergo with the local and global updates on pheromone examination.

(5) *Inter-Atb Repression*
During the evolution solving action, while the affinity within any two Atbs is lower than the repression threshold, one Atb will be restrained. The Atb who has excellent affinity with Atg will be more likely to determine the characteristics of data. Once it has proliferated Atbs with advanced affinity outspread within population, more memory elements (cells) will be attracted and will prompt secondary immune reaction to determine more Atgs.

(6) *Assimilate*
To preserve the equilibrium between steadiness and divergence within population in the process of resolving, Eq. (3) can be adopted to enlist a regular percentage (%) of Atbs in the progressive population:

$$N_{En} = \mu \cdot \tau \cdot Max[2^{-1} \cdot (F_1, Z_1), 50] \tag{3}$$

where (F_1, Z_1) is the quantity of sample points within training data in the experiment, $Max[2^{-1} \cdot (F_1, Z_1), 50]$ is the maximum quantity of Atbs within population. τ is the weakening element, and it may promote the steadiness in the process of solving. Further, μ is the enlist rate, and N_{En} is the enlistment quantity of Atbs within population. The amount of new attracted Atbs within the population is dictated through the assimilate action. By this process, it can refrain excessive attracted Atbs and make untimely divergence for the solution.

(7) *Update the global optimal solution*
While the stochastic emerged population has been investigated via the HSIA algorithm and data property has been correlated with the fitness function, the global optimal solution will be settled gradually.

(8) *Stopping criteria*
The proposed HSIA algorithm will keep on to realize and backtrack to *Step (2)* until the fitness function is fulfilled or a given number of generations is accomplished.

For the object of comprehend few unalike nonlinear optimization issues, this paper proposed the HSIA algorithm which incorporated the dominances of ANN and MH algorithms. The HSIA algorithm can enforce parallel processing with exploitation and exploration in the solution space, and prompt to refrain the solution from being stray the local optimal distress. In the principle, it allows the solution to converge by degrees and to gain the global optimal solutions. Eventually, the proposed HSIA algorithm can be applied on function approximation issue and the IC demand prediction exercise.

4 Experimental Evaluation Results

This section imploded on studying and modifying the pertinent parameters on RbfN for function approximation issue. The point is to gain the excellent advisable fitness values about the parameters solution of the RbfN. The emphasis is then to settle the apposite values of the parameters set from the searching area in the examination. The proposed HSIA algorithm will regulate and thus acquire the solution sets of parameters value for RbfN.

Experimental examination function prompts prominent approximation to reimburse RbfN for the reaction of nonlinear mapping relationship. This section employs two benchmark problems that are constantly adopted in the literature to be the comparative basis of estimated algorithms. Latter, the inspection involves the latter two benchmark problems, including Mackey-Glass time series [30] and Griewank [31] nonlinear test functions.

The first nonlinear test function, the Mackey-Glass time series [30] is expounded as follows:

$$\frac{dx(t)}{d(t)} = 0.1x(t) + 0.2 \cdot x(t-17) \cdot [1 + x(t-17)^{10}]^{-1} \tag{4}$$

where $x(t)$ is the value of time series at time step t [30]. In the other problem, Griewank nonlinear test function [31] is expounded as follows:

$$GR(x_j, x_{j+1}) = \sum_{j=1}^{n} \frac{x_j^2}{4000} - \prod_{j=1}^{n} \cos(\frac{x_{j+1}}{\sqrt{j+1}}) + 1 \tag{5}$$

where one global minimum is $(x_1, x_2) = (0, 0)$, and $GR(x_1, x_2) = 0$; the search region is $-100 \le x_j \le 100$ $(j = 1)$.

4.1 Performance Estimation and Comparison

This paper combines ANN and MH algorithms to judge the optimal solution sets of parameters composition (the centre within neuron in hidden layer, width, and weight) for RbfN. According Looney [32] recommended in 1996, it stochastically produces unlike 65% training set from 1000 produces sample and distract the set into RbfN for training. By the alike action, it stochastically produces unlike 25% testing set to inquire into relevant parameters solution within population and assesses the fitness function. Until now, RbfN has introduced 90% data set in studying term. As a result of 1,000 iterations in the advance dealing, the optimal solution sets of parameters value for RbfN are gained. Lastly, it stochastically produces unlike 10% validation set to proof how the parameters solution of unit approximates the two appraisals and maintain the root mean square error (RMSE) values to clarify the studying term of RbfN. In case the data gathering term noticed above have realized, all algorithms are make ready to fulfil. The studying and validation terms referred above were carried out forty times before the average of RMSE values were evaluated. The evaluated consequences of the average of RMSE and standard deviation (SD) for all algorithms estimated from the investigation are announced in Table 1.

In Table 1, the announced outcomes evidence that HSIA algorithm acquires the reliable enough values with affirmative representation during the studying conduct of the exam checking. As the performance, RbfN may achieve the few solutions of parameters value set from the progressive procedure within population, which has carried out the circumstance with remarkable function approximation. When the modifying of RbfN via the HSIA algorithm is implemented, the unit with the optimal solutions of parameters value set during studying term is the RbfN situation in settled.

Table 1. Result examination among relevant algorithms applied in this experiment

Contrast Algorithms	Benchmark Functions			
	Mackey-Glass time series [30]		*Griewank* [31]	
	Training set	Validation set	Training set	Validation set
AIS-based [33]	2.88E-3 ± 1.68E-4	2.71E-3 ± 1.55E-4	15.63 ± 15.83	51.73 ± 16.65
ACO-based [34]	3.21E-3 ± 1.78E-4	2.67E-3 ± 2.08E-4	7.14 ± 10.30	49.14 ± 12.66
AIS-ACO [35]	2.26E-3 ± 1.91E-4	2.12E-3 ± 1.62E-4	6.59 ± 3.42	17.51 ± 4.37
HSIA	**1.85E-3 ± 1.58E-4**	**1.58E-3 ± 1.38E-4**	**4.77 ± 2.15**	**12.08 ± 2.19**

5 Case Study for Demand Prediction Estimation

This estimation tries to discuss the prediction precision on the sales specimen of the ROBO-series goods from 2008 to 2009 (227 tuples) offered by an internationally renowned industrial computer (IC) manufacturer in Taiwan. The SOMN and MH algorithms were applied to the proposed HSIA algorithm for sales specimen prediction confirmation inspection, and their precision was contrasted to relevant algorithms in literatures.

This case study expounds how specimen are feed in to RbfN for forecasting through corresponding algorithms and the contrast of results with the auto-regressive integrated moving average (ARIMA) [36] models. The specimen gathered in this practice are weekly sales specimen and thus are essential to be standardized to the training set. Consequently, (n-4)th to (n-1)th sales specimen are applied to forecast the n*th* tuple sales. After that, the following forecasted values are produced in turn by the moving-window method. The approximation expression of the RbfN forecast is inspected with the validation set (10% data). Besides, the first 90% of the specimen were adopted for model evaluation while the ultimate 10% were adopted for validation and one-step-ahead prediction. By the way, the RMSE, mean absolute error (MAE), and mean absolute percentage error (MAPE) are the majority frequently utilized error estimates in practice [37], and so were adopted to assess the prediction exercise. Thus, the prediction expressions among corresponding algorithms with the sales specimen of the ROBO-series goods are shown in Table 2.

The statistical consequences evidence that the HSIA algorithm has the best representation in terms of prediction preciseness among corresponding algorithms.

Table 2. The comparison of errors result among relevant algorithms applied in the IC case.

Contrast Algorithms	Errors		
	RMSE	*MAE*	*MAPE(%)*
AIS-based [33]	813.282	619.104	11.02
ACO-based [34]	637.923	548.257	9.71
AIS-ACO [35]	511.205	431.501	7.02
ARIMA models [36]	534.083	446.372	7.14
HSIA	**426.392**	**355.818**	**5.22**

6 Conclusions

This paper for the proposed HSIA algorithm via incorporating the SOMN, AIS and ACO-based approaches, which offers the enactment of RbfN parameters solution set, such as centre, width, and weight. The complementarity of ANN and MH algorithms that heightens the variety of populations also raises the precision of function approximation. The experimental estimation consequences have been contrasted with those achieved through the HSIA algorithm trained by several related algorithms. The HSIA algorithm has superior parameter setting and then causes RbfN to perform better learning and approximation in two benchmark nonlinear test functions. Additionally, an exercise case study has made an attempt to examine the prediction consequences on the sales specimen of the ROBO-series goods offered by an internationally renowned IC manufacturer in Taiwan. With the prediction preciseness confirmed, the verified HSIA algorithm can be applied to make forecasts in the realistic IC sales demand prediction exercise and could be gained for commerce decision managers to further heighten their benefit.

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