Improved Intelligent Method for Traffic Flow Prediction Based on Artificial Neural Networks and Ant Colony Optimization

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Abstract

Real time traffic flow is often difficult to predict precisely because of the complexity, nonlinearity and uncertainty characteristics of the traffic flow data. Intelligent prediction methods such as artificial neural network (ANN), support vector machine (SVM), etc. have been proven effective to discover the nonlinear information hidden in the traffic flow data. Nevertheless, a single prediction model is difficult to ensure the prediction accuracy and efficiency. To overcome the lack of the single prediction method, this paper uses a prediction method that combining artificial neural networks (ANN) with ant colony optimization (ACO), called ANN-ACO, by exploiting complementary advantages of both approaches. Firstly, this method uses the ANN theory for data reduction pretreatment, and then constructs the traffic flow prediction model based on ACO according to the information structure. The analysis results show that the proposed method can extract the underlying rules of the testing data and decrease prediction error or better when compared with single ANN or ACO approach. Besides, the combined prediction model not only has fault tolerant and anti-jamming capability, but also can shorten the operation time and improve the speed of the system and also forecast accuracy. Hence, it can be used to forecast real-time traffic flow.

Keywords: Traffic flow prediction; Artificial neural network; Ant colony optimization

1. Introduction

With the increasing complexity of nonlinear system, the accurate mathematical model of nonlinear system is hard to construct. The universal approximation capability of a neural network is one of the most exciting properties and has potentials for applications to problems such as system identification, signal processing, prediction, control, and pattern recognition [1-3]. A multilayer artificial neural network can approximate any nonlinear continuous function to an arbitrary accuracy [4-6]. Among various kinds of neural networks, the feedforward neural networks, based on the backpropagation learning algorithm, is the most widely used model. However, we meet many problems in application of feedforward neural networks, such as the longtime training, easy convergence to the local minimum points and low prediction precision. To overcome this drawback, many researchers have done a great deal of works to improve the algorithm. The major improve algorithms consist improving the backpropagation learning algorithm [7-8] and preprocessing the training samples. The error between the approximation function base on neural network and actual function is large near every peak, especially at the large slope difference on both side of the peak. The above improvement algorithms are hard to obtain high prediction precision when the predicted nonlinear function has many peaks. So the approximation function values near peaks must be adjusted.

Short-term traffic flow forecasting, which is to determine the traffic volume in the next time interval usually in the range of five minutes to half an hour, is one of the important problems in the research area of ITS. In the past years, some approaches ranging from simple to complex were proposed on the theme of short-term traffic flow forecasting. Simple ones, such as random walk (which is informed only by the current conditions), historical average (whose prediction is solely based on the average of all corresponding observed flow rates), and informed historical average (which combines the above two methods) can only work well in specific situations [9]. One class of the complex approaches, UTCS (Urban Traffic Control System) prediction method is based on forecasting philosophies similar
to the above methods, and it would either bring along similar drawbacks or become highly complex [10]. There are also other elaborate methods including approached based on time series models (including ARIMA, seasonal ARIMA), Kalman filter theory, neural network approaches, non-parametric methods, simulation models, local regression models and layered models known as the ATHENA model and the KARIMA model [11].

The great complexity and difficulties encountered in geotechnical engineering such as traffic management and congestion control have motivated researchers to use powerful new optimization algorithms and methods. The most popular of these new algorithms include genetic algorithms (GAs), simulated annealing (SA), ant colony optimization (ACO), and artificial neural networks (ANNs). These algorithms have been identified as potential solutions to traffic flows or transportation forecasting problems.

One of the most popular prediction methods is the ANN which simulates the biological neural network structure and the learning system. The ANN is a family of massively parallel structures that solve various problems via the cooperation of highly interconnected but simple computing elements called neurons. This allows the assessment of non-linear relationships between any of the soil and foundation parameters and also gives faster and better results compared to previous traditional methods[12]. ANNs have been applied to many geotechnical engineering problems. Some of the above mentioned studies include the prediction of the ultimate bearing capacity of shallow foundations on cohesionless soils.

ACO algorithms have been applied to solve a number of engineering problems in the literature. However, ACO applications in the field of geotechnical engineering are very limited[13]. Changfu et al. adopted the modified ant colony algorithm to locate critical slip surfaces. In these studies, their common reason for using the ACO algorithm was to find the slip surface with the minimum safety factor.

Furthermore, to the best our knowledge no study related to determine the ultimate bearing capacity by using the ACO algorithm has been reported in the available literature. However, the ACO algorithm could be a useful method for developing an alternative ultimate bearing capacity computation formula.

In this study, two different approaches are proposed to determine the ultimate bearing capacity of shallow foundations on granular soil.

Firstly, a black box model based on ANN is proposed to predict the ultimate bearing capacity. The performance of the proposed neural model is compared to that of other prediction methods in the literature. Secondly, by using the ACO algorithm, an improved Meyerhof formula is proposed for the computation of the ultimate bearing capacity. The results achieved from the proposed formula were compared with those obtained from the Meyerhof, Hansen and Vesic formulas.

This paper is organized as follows. In section 2 we will analyze problems in nonlinear function approximation based on neural network. In section 3 we will analyze theory of ant colony optimization. In section 4 we will introduce the prediction model based on ANN-ACO, followed by application in traffic flow forecasting in section 5. The conclusions are given in section 6.

2. Problem in nonlinear function approximation based on neural network

2.1. Neural network based nonlinear function approximation analysis

Supposed an approximating nonlinear function is showed as real curve in Figure.1. The four layers feed-forward neural network is selected to predict it and the predicted result is showed as broken curve in Figure.1. The predicted errors are showed as Figure.2. The Figure.2 showed that the errors of the predicted nonlinear function output by neural network are large near its peaks, such as, A, B, C, D, E, F, G and H, especially when the large slope difference on both side of the peaks, such as, A, B, C, D and E. So, the nonlinear function values near peaks must be corrected or compensated to improve the prediction precision. The r ant colony optimization theory can extract knowledge from data as a tool of knowledge discovery, data mining and data processing. The predicted the nonlinear function by neural network can be compensated by using ant colony optimization theory.
2.2. Solution Scheme

The structure of error compensation system based on ant colony optimization is showed as Figure 3. Firstly, all kinds of data features are extracted from the historical data. Then, according to these data features, the next time value of the predicted nonlinear function is predicted by neural network. Finally, the predicted values by neural network are compensated by ant colony optimization. So, the high accuracy prediction results are obtained.

3. Ant colony optimization

Ant algorithm was first proposed by Dorigo and Gambardella as a multi-agent approach for difficult combinatorial optimization problems such as traveling sales man problem (TSP) and the quadratic assignment problem (QAP). From then, researchers have applied ACO to many discrete optimization problems. ACO is a meta-heuristic approach which has been applied to various NP hard problems such as static/ dynamic combinatorial optimization[14]. ACO applications in static combinatorial optimization problems include job shop scheduling (flow shop, open shop, group shop), vehicle routing, sequential ordering, graph coloring and shortest common super sequences. ACO application to dynamic combinatorial optimization problems includes connection oriented network routing and connection less network routing.

In Ani, an ACO approach was presented for feature selection problems. In this paper, the author calculates a term called “updated selection measure (USM)” which is used for selecting features, a function of the pheromone trail and the so called “local importance” which has replaced the heuristic
function. A major application of the algorithm developed in this paper is in the field of texture classification and classification of speech segments. Similarly, another application of ACO can be found in Jensen and Shen where an entropy-based modification of the original rough set-based approach for feature selection problems was presented. Other applications include Schreyer and Raidl where an ACO approach is used for labeling point features, a pre-processing step which reduces the search space.

This paper presents a relatively simpler model of ACO. The major difference from previous works is in the calculation of the heuristic values. Heuristic value calculations are application specific and help the algorithm reach the optimal solution quickly by reducing the search domain. In medical diagnosis applications heuristic value can be a function of diagnostic value, cost or risk. Generally, the value of these parameters, except cost, is fuzzy and the function cannot be generalized for different applications.

In this paper, the heuristic value is treated as a simple function of cost. Clearly, the features associated with lesser costs will be preferred by the algorithm. The algorithm uses ANNs as a classification function to evaluate the “goodness” of the subset developed at each stage, instead of the nearest neighborhood algorithm used otherwise.

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**Figure.3** Structure of ant colony optimization based error compensation system

4. **Prediction Model Based on ANN-ACO**

4.1. **Error Compensation Algorithm**

The prediction data outputted by the neural network prediction model are adjusted as

\[
\begin{align*}
V_t' &= \hat{V}_t + s|k_{t+1} - k_t| \\
k_{t+1} &= \hat{V}_{t+1} - \hat{V}_t \\
k_t &= \hat{V}_t - \hat{V}_{t-1}
\end{align*}
\]  

(1)

Where \( \hat{V}_t' \) denotes the adjusted prediction data, \( \hat{V}_{t+1}, \hat{V}_t \) and \( \hat{V}_{t-1} \) denotes the output of neural network prediction model at \( t+1, t \) and \( t-1 \) time respectively, \( k_{t+1} \) and \( k_t \) denotes the prediction
curve slope on both sides of the peak respectively and \( s \) denotes the scale factor. The scale factors will be determined by ant colony optimization.

### 4.2. Training a Neural Network Using ACO Method

ACO is a general optimization method and in this work, numerical weights of neuron connections represent the solution components of the optimization problem and minimizing the MSE of output neurons is the performance criterion. Search domain is \((-1, 1)\), i.e. solution components may assume any real value in this range.

In positive update stage, weights of the normal PDFs are assigned based on the quality of solutions which is evaluated according to the MSE of output layer.

Two approaches for pheromone positive update can be exploited. In the first approach, MSE of NN for each solution is calculated and the weights of corresponding normal PDFs are assigned in inverse relation to MSE. For the remaining part of this text we will name this approach MSE-function method. Considering \( \text{ith} \) solution component and \( \text{jth} \) single normal PDF, mixture is represented as:

\[
P_i(x') = \sum_{j=1}^{K} w_j \cdot g(x', \mu_j, \sigma_j)\tag{2}
\]

\[
w_j = \frac{S}{MSE_j}, \quad j = 1, \cdots, K\tag{3}
\]

Where \( K \) represents total number of normal distributions in kernel mixture and \( S \) is a constant. The MSE of a neural network represents the quality of a solution found by an ant. Therefore same MSE and weight is assigned to all components of a certain solution.

\[
P_i(x') = S \sum_{j=1}^{K} \frac{S}{MSE_j} \cdot g(x', \mu_j, \sigma_j)\tag{4}
\]

In the second approach for positive pheromone update, solutions are sorted according to their performance and a “rank” value is assigned to them. Then the weight of each solution is calculated according to the Rank-function defined as

\[
w = \frac{1}{(\pi q K)^{\frac{r}{2}}} e^{\frac{(r-1)\bar{y}^2}{2qK^2}}\tag{5}
\]

where \( K \) is the number of distributions in the mixture, \( q \) is a parameter and \( r \) represents the rank of corresponding solution. In compare to MSE-function method, Rank function technique is less sensitive to MSE variances and hence, it converges faster but may suffer from stagnation which results in poor outputs. In the simulations carried out, both techniques are accomplished and compared.

The mean of normal PDFs are equal to the solution component values which are selected by ants. The standard deviation of normal PDFs is calculated as

\[
\sigma_i = \frac{\max(x_{i,m}) - \min(x_{i,m})}{\sqrt{c}}\tag{6}
\]

where \( c \) represents the iteration and \( m \) is the number of ants used in the simulation. Standard deviation is inversely proportional to the iteration number \( c \) and it implies that solutions found in the first iterations are less useful than the outputs of the final iterations. Note that less standard deviation leads to the higher probability for selection of values around \( x_i \). In this work following equation for standard deviation is proposed.
\[
\sigma' = \frac{\max(x^{'}_{1,m}) - \min(x^{'}_{1,m})}{c''/MSE^v}
\]  

(7)

where \( u \) and \( v \) are parameters. In the proposed equation, \( \sigma' \) is proportional to MSE, therefore superior solutions which have lower MSE, lead to smaller standard deviations and more probability of selection. Large MSE and standard deviation is almost equivalent to uniform distribution and it results in decreasing the effect of bad solutions. Proposed equation for \( \sigma' \) is evaluated in simulations.

5. Traffic Flow Forecasting Based on ANN-ACO

5.1. Structure of Traffic Flow Forecasting Based on ANN-ACO

The structure of traffic flow forecasting based on ANN-ACO is showed as Figure 4. The historical data inputs the neural network based traffic flow forecasting model and the model outputs the forecasting data in the following time interval. Then the forecasting data are adjusted by using ant colony optimization to obtain the final forecasting data.

5.2. Simulation

The spring traffic flow data input the neural network forecasting model. The original data table is showed as Table 1. After the characteristics are discredited and the decision table is obtained, showed as Table 2. According to equation (5), the error compensation scale factors of neural network outputs are determined. Then the neural network outputs are adjusted by using of equation (1). The adjusted traffic flow data are showed as the dashed line curve in Figure 5. The adjusted forecasting data errors are showed as Fig 6 and the error-squared sum are 2525.4. The result shows that the proposed method can improve the traffic flow forecasting accuracy significantly.
### Table 1: Original Data Table

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### Table 2: Decision Table

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**Figure 5** Real and forecasting summer traffic flow data
6. Conclusion

The prediction errors of approximated nonlinear function based on neural network are large near peaks, especially when the large slope difference on both side of the peak. To overcome this drawback, the predicted the nonlinear function by neural network can be compensated by using ant colony optimization. The algorithm is applied into realize the traffic flow forecasting. The simulation results show that the proposed prediction model based on ANN-ACO can improve the prediction accuracy significantly.

7. References


