

Continuous ACO in a SVR Traffic Forecasting Model

Wei-Chiang Hong

Oriental Institute of Technology, Taiwan

INTRODUCTION

The effective capacity of inter-urban motorway networks is an essential component of traffic control and information systems, particularly during periods of daily peak flow. However, slightly inaccurate capacity predictions can lead to congestion that has huge social costs in terms of travel time, fuel costs and environment pollution. Therefore, accurate forecasting of the traffic flow during peak periods could possibly avoid or at least reduce congestion. Additionally, accurate traffic forecasting can prevent the traffic congestion as well as reduce travel time, fuel costs and pollution.

However, the information of inter-urban traffic presents a challenging situation; thus, the traffic flow forecasting involves a rather complex nonlinear data pattern and unforeseen physical factors associated with road traffic situations. Artificial neural networks (ANNs) are attracting attention to forecast traffic flow due to their general nonlinear mapping capabilities of forecasting. Unlike most conventional neural network models, which are based on the empirical risk minimization principle, support vector regression (SVR) applies the structural risk minimization principle to minimize an upper bound of the generalization error, rather than minimizing the training errors. SVR has been used to deal with nonlinear regression and time series problems. This investigation presents a short-term traffic forecasting model which combines SVR model with continuous ant colony optimization (SVRCACO), to forecast inter-urban traffic flow. A numerical example of traffic flow values from northern Taiwan is employed to elucidate the forecasting performance of the proposed model. The simulation results indicate that the proposed model yields more accurate forecasting results than the seasonal autoregressive integrated moving average (SARIMA) time-series model.

BACKGROUND

Traditionally, there has been a wide variety of forecasting approaches applied to forecast the traffic flow of inter-urban motorway networks. Those approaches could be classified according to the type of data, forecast horizon, and potential end-use (Dougherty, 1996); including historical profiling (Okutani & Stephanedes, 1984), state space models (Stathopoulos & Karlaftis, 2003), Kalman filters (Whittaker, Garside & Lindveld, 1994), and system identification models (Vythoulkas, 1993). However, traffic flow data are in the form of spatial time series and are collected at specific locations at constant intervals of time. The above-mentioned studies and their empirical results have indicated that the problem of forecasting inter-urban motorway traffic flow is multi-dimensional, including relationships among measurements made at different times and geographical sites. In addition, these methods have difficulty coping with observation noise and missing values while modeling. Therefore, Danech-Pajouh and Aron (1991) employed a layered statistical approach with a mathematical clustering technique to group the traffic flow data and a separately tuned linear regression model for each cluster. Based on the multi-dimensional pattern recognition requests, such as intervals of time and geographical sites, non-parametric regression models (Smith, Williams & Oswald, 2002) have also successfully been employed to forecast motorway traffic flow. The ARIMA model and extended models are the most popular approaches in traffic flow forecasting (Kamarianakis & Prastacos, 2005) (Smith et al., 2002). Due to the stochastic nature and the strongly nonlinear characteristics of inter-urban traffic flow data, the artificial neural networks (ANNs) models have received much attention and been considered as alternatives for traffic flow forecasting models (Ledoux, 1997) (Yin, Wong, Xu & Wong, 2002). However, the training procedure of ANNs models is not only time consuming but also possible to get trapped in local minima and subjectively in selecting the model architecture.

Thus, SVR have been successfully employed to solve forecasting problems in many fields. Such as financial time series (stocks index and exchange rate) forecasting (Pai & Lin, 2005) (Pai, Lin, Hong & Chen, 2006), engineering and software field (production values and reliability) forecasting (Hong & Pai, 2006) (Pai & Hong, 2006), atmospheric science forecasting (Hong & Pai, 2007) (Mohandes, Halawani, Rehman & Hussain, 2004), and so on. Meanwhile, SVR model had also been successfully applied to forecast electric load (Pai & Hong, 2005a) (Pai & Hong, 2005b). The practical results indicated that poor forecasting accuracy is suffered from the lack of knowledge of the selection of the three parameters (σ , C , and ε) in a SVR model.

In this investigation, one of evolutionary algorithms, the ant colony optimization (ACO), is tried to determine the values of three parameters in a SVR traffic flow model in Panchiao city of Taipei County, Taiwan. In addition, as being developed for discrete optimization, the application of ACO to continuous optimization problems requires the transformation of a continuous search space to a discrete one by discretization of the continuous decision variables, which procedure is so-called CACO.

MAIN FOCUS OF THE CHAPTER

In this article, two models, the seasonal ARIMA (SARIMA) model and the SVRCACO model, are used to compare the forecasting performance of traffic flow.

Support Vector Regression (SVR) Model

The basic concept of the SVR is to map nonlinearly the original data x into a higher dimensional feature space. Hence, given a set of data $G = \{(x_i, a_i)\}_{i=1}^N$ (where x_i is the input vector; a_i is the actual value, and N is the total number of data patterns), the SVM regression function is:

$$f = g(x) = \mathbf{w}^T \phi(x_i) + b \quad (1)$$

where $\phi(x_i)$ is the feature of inputs (to map the input data into a so-called high dimensional feature space, see Fig. 1 (a) and (b)), and both w and b are coefficients. The coefficients (w and b) are estimated by minimizing the following regularized risk function

$$R(f) = C \frac{1}{N} \sum_{i=1}^N L_\varepsilon(a_i, f_i) + \frac{1}{2} \|\mathbf{w}\|^2 \quad (2)$$

where

$$L_\varepsilon(a, f) = \begin{cases} 0 & \text{if } |a - f| \leq \varepsilon \\ |a - f| - \varepsilon & \text{otherwise} \end{cases} \quad (3)$$

In addition, $L_\varepsilon(a, f)$ is employed to find out an optimum hyper plane on the high dimensional feature space to maximize the distance separating the training data into two subsets. Thus, the SVR focuses on finding the optimum hyper plane and minimizing the training error between the training data and the ε -insensitive loss function (as thick line in Fig. 1(c)).

Minimize:

$$R(w, \xi, \xi^*) = \frac{1}{2} \|\mathbf{w}\|^2 + C \left(\sum_{i=1}^N (\xi_i + \xi_i^*) \right) \quad (4)$$

with the constraints,

$$w\phi(x_i) + b - a_i \leq \varepsilon + \xi_i^*$$

$$a_i - w\phi(x_i) - b \leq \varepsilon + \xi_i$$

$$\xi_i, \xi_i^* \geq 0$$

$$i = 1, 2, \dots, N$$

The first term of Eq. (5), employed the concept of maximizing the distance of two separated training data, is used to regularize weight sizes, to penalize large weights, and to maintain regression function flatness. The second term penalizes training errors of forecasting values and actual values by using the ε -insensitive loss function. C is a parameter to trade off these two terms. Training errors above ε are denoted as ξ_i^* , whereas training errors below ε are denoted as ξ_i .

After the quadratic optimization problem with inequality constraints is solved, the weight w in Eq. (2) is obtained,

$$w^* = \sum_{i=1}^N (\beta_i - \beta_i^*) K(x, x_i) \quad (5)$$

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