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Traffic Signal Prediction Using Elman Neural Network and Particle Swarm Optimization

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ABSTRACT

Prediction of traffic is very crucial for its management. Because of human involvement in the generation of this phenomenon, traffic signal is normally accompanied by noise and high levels of non-stationarity. Therefore, traffic signal prediction as one of the important subjects of study has attracted researchers' interests. In this study, a combinatorial approach is proposed for traffic signal prediction, based on Neural Networks and Particle Swarm Optimization algorithm. Elman Neural Network is chosen from amongst many types of Neural Networks due to its feedbacked structure. To this purpose, Particle Swarm optimization algorithm is utilized for adequate training of the Neural Network, instead of common gradient descent based methods. In this work, wavelet transform is employed as a part of the preprocessing stage, for the elimination of transient phenomena as well as for more efficient training of the Neural Network. Simulations are carried out to verify performance of the proposed method, and the results demonstrate good performance in comparison to other methods.

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1. INTRODUCTION

The growth in the numbers of cars, besides providing comfort to society also brings about its own complications. Among the problems caused by the increasing numbers of cars on roads are traffic issues. Therefore, investigation of optimized traffic control methods constitutes one of the important research objectives for researchers. A variety of methods are employed in traffic control, including the use of traffic lights, commute restrictions, transmission of radio messages, etc.

One of the most important parameters affecting the success of the above mentioned methods is the numbers of cars passing on the relevant routes. In fact, having adequate predictions (estimates) on the numbers of future vehicles passing in a particular lane can be beneficial for the success of traffic management methods. As formation of traffic is based on human decisions, the traffic signal is considered as a random process with high nonstationarity and large noise.

Until now, various methods such as Fixed Model, Linear Model, Statistical Model, Fuzzy Systems, and Hidden Markov Model have been used for short-term traffic prediction [1-5]. In several recent studies, authors suggested fuzzy Dempster–Shafer models for the prediction of traffic signal [6]. In these studies, with the goal of eliminating transient events in mind, the traffic signal was denoised using wavelet transform, and then prediction was accomplished based on Theory of Evidences.

In parallel with these methods, the exploitation of time series estimation capabilities of neural networks as one of the main research areas of traffic signal prediction has always attracted attentions from researchers [7-10].

Transient phenomena or noises are among the properties of the traffic signal, which in the proposed methods are usually eliminated through a single preprocessing stage. One of the important considerations in designing neural networks is

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determining the appropriate learning procedure to achieve optimal weights of the network. In overall, learning in the neural networks can be regarded as an optimization problem. In fact, finding of the best network weights is an optimization problem in the space of weights. According to this point, various methods of finding weights have been proposed, a majority of which are based on back propagation algorithms and the gradient descent based methods. Along with and considering the drawbacks of gradient descent based methods, numerous researchers have proposed meta-heuristic approaches for the tackling of optimization problems [11]. Finding optimal weights for the neural networks is not an exception, and various studies exist seeking optimal network weights using meta-heuristic methods such as genetic algorithm [12-15]. In this research, recurrent Elman neural network is utilized for prediction of traffic signal. Moreover, particle swarm optimization (PSO) algorithm is employed here for a better training of Elman neural networks. Recurrent neural networks make use of feedback connections [16], and among the characteristics of these networks is the ability to learn patterns which bear correlations [17].

The rest of this paper is organized as follows: In section 2, such utilized tools in this research as recurrent Elman neural networks and particle swarm optimization algorithm are introduced. In section 3, the proposed method is presented, which is followed by section 4 where the procedure of applying the proposed method on traffic data as well as the obtained results are investigated. Finally, the paper ends by conclusions in section 5.

2. METHODS AND MATERIALS

The proposed system in this study is based on recurrent Elman neural networks and particle swarm optimization algorithm. These tools are therefore introduced in this section.

2. 1. Neural Networks and Recurrent Elman Neural Networks In recent decades, thanks to developments in computers, the neural networks inspired by the brain structure have found many applications as intelligent modeling tools [18, 19]. Based on their organization these networks are categorized either as feedforward or recurrent networks. Considering the feedback structure of the recurrent networks, these networks have been widely utilized in applications which deal with time series.

Among the most well-known recurrent neural networks is the Elmann network, which was first introduced in 1991 by Elman [16]. It is a partial type neural network, which is a combination of the classic perceptron neural network and the fully recurrent neural network. In contrast to the perceptron neural network which involves input, hidden and output layers as well as the weighted connections among neighboring layers, the recurrent layer of the Elman network employs a context layer which is sensitive to the history of input data [16]. Internal connectivity of Elman network guarantees the dynamical capability of network, and makes it superior compared to the feedforward networks. Figure 1 shows a schematic of the Elman network.

As seen from Figure 1, the network has four layers of input layer, hidden layer, context layer, and output layer. The context layer is used for memorizing the output from the hidden layer, and can be considered as a unit delay. The joint action of these four layers is sensitive to the past events of the input data. Furthermore, the internal feedback network increases the capability of processing temporal changes in data.

In order to investigate the relationships governing the Elman network, consider a network with n neurons in the input layer, m neurons in the hidden layer, and r neurons in the intermediate context layer. Moreover, name the input-to-hidden layer weights as w_1, context-to-hidden layer weights as w_2, and hidden-to-output layer weights as w_3. Also assume $u(t)$ as the set of inputs at time t, $x(\mathrm{t})$ as the output of the hidden layer, $x_c(t)$ as the output of the context layer, and $y(\mathrm{t})$ as the final output of the network. We have:

$$x(t) = \xi(w_2 x_c(t) + w_1(u(t-1))) \qquad (1)$$

As seen from the above equation, $x_c(t) = x(\mathrm{t}-1)$. Also, ξ denotes the transfer function of the hidden layer, for which the hyperbolic tangent is generally considered. The final output of Elman network is obtained as:

$$y(t) = \xi(w_3 x(t)) \qquad (2)$$

In Equation (2), ξ is again the transfer function of the output layer, for which a linear function is normally opted.

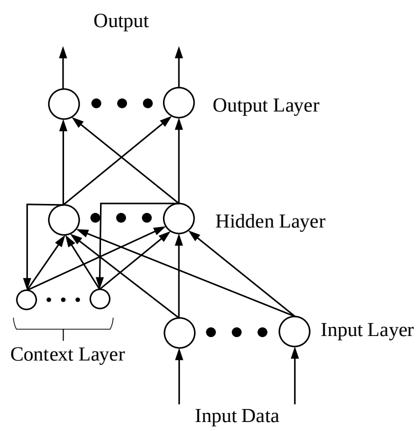

Figure 1. Schematic illustration of an Elman Network

2. 2. Particle Swarm Optimization (PSO) Algorithm PSO was first introduced in 1995 by Kennedy and Eberhart [20]. Inspired by swarm behavior of the groups of animals such as birds, fishes and so on, this algorithm provides an optimization method [21]. PSO incorporates a population of particles in an n-dimensional space. The corresponding n-dim space constitutes the solution space for the intended optimization problem, and dimensions of this space contain all possible solutions. Each particle holds a specific location X in the search space, representing a possible solution for the problem. Each particle has also a velocity vector v. Additionally, each particle has some memory where it keeps the local best p (so far) and the global best g (so far). In every iteration, the global best is diffused among the whole population, and particles try to relocate towards this global best discovered in the search space. At any moment t, the velocity of particles are updated, and particles are moved from their previous locations towards new points by incorporating updated velocities. Therefore:

$$\vec{X}(t+1) = \vec{X}(t) + \vec{v}(t+1) \tag{3}$$

The following equation is utilized for updating to new velocities:

$$\begin{aligned}\vec{v}(t+1) = \omega.\vec{v}(t) + U(0,\phi_1).(\vec{p}(t) \\ -\vec{x}(t)) + U(0,\phi_2).(\vec{g}(t) - \vec{x}(t))\end{aligned} \tag{4}$$

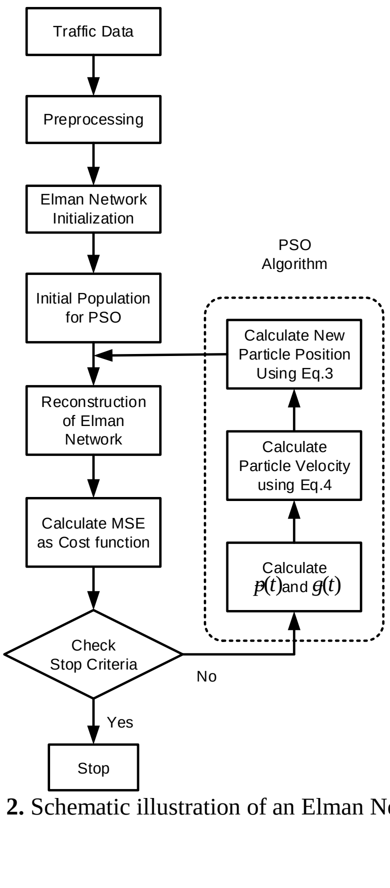

Figure 2. Schematic illustration of an Elman Network

where $U(a,b)$ is a random number from [a,b] interval. ω is known as inertia parameter [22] and indicates the contribution of the previous velocity in determining the new velocity. Also ϕ_1 and ϕ_2 imply the importance of p(t) and g(t) respectively.

Furthermore, in every iteration the velocity vector of all particles are limited by the parameter $v_{\max}$. The PSO algorithm is initiated by assigning all particles with random locations from the search space, through ϕ_1 and ϕ_2 uniform distribution. Moreover, elements of the initial velocity vector should be chosen from the [$-v_{\max}$, $+v_{\max}$] interval.

3. PROPOSED METHODOLOGY

The proposed method of this research is based on the time series prediction capabilities of artificial neural networks, and consists of the major steps of data preprocessing, finding optimal weights for the Elmen neural network using PSO optimization algorithm, and eventually testing of the proposed system.

Before proceeding to the demonstration of system details, consider the block diagram of the proposed method in Figure 2. In this block diagram, we have tried to present the various stages of PSO algorithm separately, so as to facilitate the overall comprehension of the proposed method. As seen from Figure 2, first the input traffic signal sample of which is depicted in Figure 3 is preprocessed.

Because of the human intervention in traffic event generation process, traffic signal cannot be expressed according to a specific rule. Traffic signal is therefore usually considered as a random process with high degree of non-stationarity and large noise level.

In the case of time series prediction, when data contains high levels of noise, efforts are normally made to preprocess the input data in order to eliminate the effects of noise and transient events. In the proposed system, wavelet transform is utilized for the elimination of transient events.

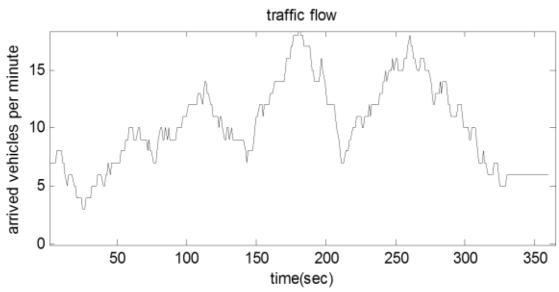

Figure 3. A sample of traffic signal involving transient phenomena

Moreover, since in time series prediction using artificial neural networks specific patterns are searched within input data, input data for neural network is generated by applying proper delays to the input signal. Considering the property of recurrent Elman neural network, in deriving temporary patterns (also existing in the traffic signal as a time series), this network was chosen from amongst various network types. Among the issues related with artificial neural networks is the training of these types of networks [23]. In general, the training of artificial neural networks to obtain optimized weights can be considered as an optimization task within a high dimensional search space. Traditionally, gradient descent based methods such as back propagation are employed for training of the network and to find the optimal weights [23]. However, although the reduced gradient methods are listed among the best training methods for small dimension search spaces, but cannot achieve adequate solutions for high dimensional optimization problems. Overall, considering the NP-Hardness nature of the problem of finding optimized weights for neural networks, motivated authors to utilize meta-heuristic algorithms. Among these methods, PSO is a good and efficient algorithm for seeking optimal solution points, and therefore is employed here.

The cost function related to PSO algorithm is selected as the mean squared error (MSE) between the response of neural network and the real data used during network training. The procedure of PSO algorithm for optimizing Elman network involves supplying PSO algorithm with weights and thresholds of the Elman network, calculation of the cost function and finding of the optimal points until the stop criterion is reached.

Also, as it will be discussed in the section for results, in addition to error criterion the numbers of iterations is also used as another factor to stop optimization of the network.

4. SIMULATION AND RESULTS

Before proceeding to the results, it should be noted that data was denoised using a three level wavelet transform scheme [6]. A sample traffic signal as well as its denoised counterpart are shown in Figure 4 for comparison. It is clear from Figure 4 that transient events are eliminated as the noise signals. This process facilitates system training. The utilized Elman network for the prediction of traffic signal is a three-layer artificial neural network.

The number of input and output neurons will be completely dictated by the problem. The number of input neurons depends on the dimension of delays embedded on input data. In this study, the number of delays is selected from 4 to 10 and the results are evaluated. Hence, the data suitable for training and testing of neural network is formed as Equation (5):

$$database = \begin{bmatrix} n_1 & n_2 & n_3 & \cdots & n_r \\ n_2 & n_3 & n_4 & \cdots & n_{r+1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ n_{d-r} & n_{d-r+1} & n_{d-r+2} & \cdots & n_d \end{bmatrix} \qquad (5)$$

In Equation (5), d represents the total number of samples and $r = \{4,5,6,7,8,9\}$ indicates the embedded delay dimension. Also, based on above descriptions the number of output neurons is considered as 1. In this regard, the proposed system tries to predict the future sample based on the values of the past samples. The numbers of neurons in the hidden and context layers are also available as the degree of freedom for design. To avoid excessive complexity of the system on one hand and to guarantee obtaining of optimal weights on the other, the number of neurons in hidden and context layers were varied from 3 to 10. The parameters of particle swarm algorithm utilized in finding the optimal weights for the neural network included inertia parameter ω, and the coefficients of contributions from the local best and global best ϕ_1 and ϕ_2. We selected ω as 0.5, while the remaining two parameters were chosen from [0,2] interval ($\phi_1 = \phi_2 = 2$). Moreover, two stop criterions of maximum 100 algorithm iterations and the MSE cost function value of 0.001 were opted. Simulation results are presented in TABLE 1 as well as Figure 5. It should be noted that since the resulting error values are very close to each other, logarithmic scaling is used for the z-axis of Figure 5 in order to achieve a more detailed view.

By considering the results shown in Table 1 and Figure 5, the best answer is obtained for 6 neurons in the input, hidden and context layers. Hence, in the proposed system the delay dimension was selected as r=6. Overall and according to above explanations, traffic signal prediction is achieved by the proposed method combining an Elaman neural network having 6 neurons in hidden and context layers, and 6 neurons in the input layer with the PSO algorithm for training of this network. Convergence results of the proposed method, comparison of the system output with the traffic signal data and the error diagram are all depicted in Figure 6. As shown in Figure 6, performance of the proposed system in estimating of traffic signal is desirable.

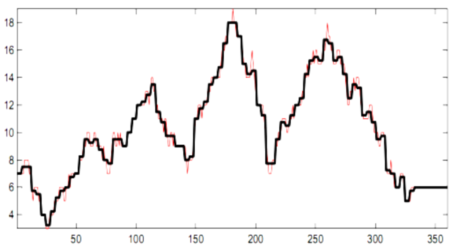

Figure 4. A sample of the original signal as well as its denoised version

TABLE 1. Mean Square Error (MSE) of the proposed method with respect to changes in the number of hidden and input layer neurons

Hidden Layer	Input Layers						
	4	5	6	7	8	9	10
3	0.0205	0.0117	0.0115	0.0120	0.0121	0.0227	0.0302
4	0.0203	0.0103	0.0102	0.0106	0.0105	0.0223	0.0223
5	0.0203	0.0093	0.0072	0.0075	0.0095	0.0135	0225/0
6	0.0111	0.0083	**0.0061**	0.0063	0.0063	0.0073	0.0093
7	0.0111	0.0083	0.0074	0.0074	0.0091	0.0083	0.0095
8	0.0111	0.0088	0.0091	0.0094	0.0094	0.0144	0.0189
9	0.0111	0.0099	0.0092	0.0094	0.0112	0.0161	0.0197
10	0.0121	0.0107	0.0120	0.0122	0.0122	0.0169	0.0230

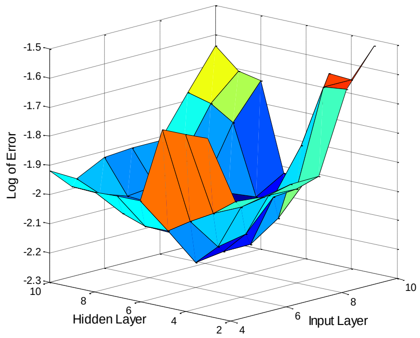

Figure 5. Logarithm of the errors achieved in simulation with respect to the numbers of neurons in the intermediate and input layers

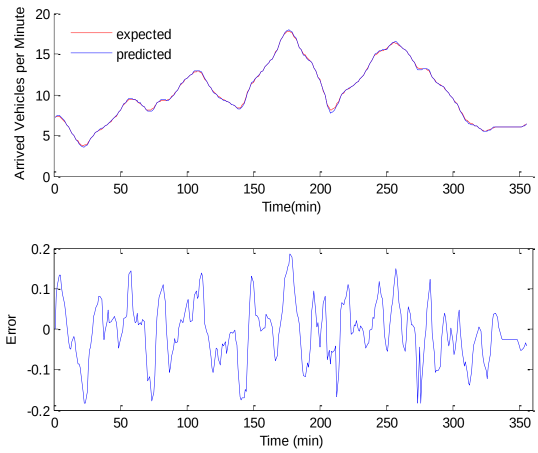

Figure 6. The outcome of applying proposed method on traffic signal and the resulting error

For further investigation and comparison of the results obtained from our proposed method with the results achieved from other two methods, the corresponding mean squared error values are presented in Table 2.

TABLE 2. Comparison of the Mean Square Errors of the proposed method with two different reference methods

Method	Mean Square Error
Reference Method [8]	0.0081
Reference Method [6]	0.0083
Neural Network without PSO	**0.0193**
Proposed Method	0.0061

The simulation results of back propagation based Elman recurrent neural network are also provided in Table 2 to demonstrate the advantages of PSO algorithm.

A quick investigation of Table 2 shows that compared to the other two methods, our proposed method has predicted the traffic signal by a favorable mean squared error.

5. DISCUSSION AND CONCLUSION

In this paper, we have proposed the combination of recurrent Elman neural network with particle swarm optimization algorithm for traffic signal prediction. Elman neural network is able to model past events due to its particular structure which accommodate feedback connections. The main scientific contribution of this paper is the use of optimization algorithm in finding weights for the recurrent network employed in traffic signal prediction, which more precisely can be categorized in two areas of tools and applications. From the tools perspective, usually the training of recurrent neural networks is somehow difficult due to the existing internal delays in these networks, and therefore the use of PSO algorithm in training was suggested. As we have demonstrated in this work, particle swarm optimization is able to adequately answer this requirement, proving the success of the proposed methodology. Also in the applications part, as discussed in the introduction section traffic signal prediction constitutes one of the challenging problems attracting interests from many researchers across the world. Overall, the proposed method can predict traffic signal with a relatively favorable accuracy, and the results outperform those without utilizing PSO algorithm. In fact, the use of PSO algorithm has resulted in an improved training of neural network and thereby in better results.

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Traffic Signal Prediction Using Elman Neural Network and Particle Swarm Optimization

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چکیده

پیش بینی ترافیک در مدیریت آن بسیار مهم است. سیگنال ترافیک با توجه به دخالت انسان ها در شکل گیری این پدیده، معمولا حاوی نویز و عدم ایستایی بالایی می باشد. به همین دلیل پیش بینی سیگنال ترافیک به عنوان یکی از مسایل مهم پژوهشی، همواره مورد توجه پژوهشگران است. در این پژوهش یک سیستم ترکیبی، مبتنی بر شبکه عصبی و الگوریتم بهینه سازی ازدحام ذرات برای پیش بینی سیگنال ترافیک پیشنهاد شده است. در بین شبکه های عصبی، شبکه عصبی المن با توجه به ساختار فیدبکی آن انتخاب شده است. همچنین به منظور آموزش مناسب شبکه عصبی، به جای روش های متداول مبتنی بر کاهش گرادیان، از الگوریتم بهینه سازی ازدحام ذرات استفاده شده است. در این پژوهش به منظور حذف پدیده های گذرا و برای آموزش بهتر شبکه عصبی از تبدیل موجک به عنوان بخشی از پیش پردازش اولیه اطلاعات نیز استفاده شده است. به منظور بررسی عملکرد روش پیشنهادی، شبیه سازی هایی صورت گرفته است که نتایج حاصل، حاکی از عملکرد مناسب روش پیشنهادی در مقایسه با دیگر روش ها می باشد.

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