Time-Series Forecasting with Evolvable Partially Connected Artificial Neural Network

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ABSTRACT
In nonlinear and chaotic time series prediction, constructing the mathematical model of the system dynamics is not an easy task. Partially connected Artificial Neural Network with Evolvable Topology (PANNET) is a new paradigm for prediction of chaotic time series without access to the dynamics and essential memory depth of the system. Evolvable topology of the PANNET provides flexibility in recognition of systems in contrast to fixed layered topology of the traditional ANNs. This evolvable topology guides the relationship between observation nodes and hidden nodes, where hidden nodes are extra nodes that play the role of memory or internal states of the system. In the proposed variable-length Genetic Algorithm (GA), internal neurons can be connected arbitrarily to any type of nodes. Besides, number of neurons, inputs and outputs for each neuron, origin and weight of each connection evolve in order to find the best configuration of the network.

Categories and Subject Descriptors
I.2.6 [**Artificial Intelligence**]: Learning—*connectionism and neural nets*; G.3 [**Mathematics of Computing**]: Probability and statistics—*Times series analysis*

General Terms
Algorithms, Measurement, Performance, Design.

Keywords
Evolutionary Computation, Genetic Algorithms, Artificial Neural Networks, Evolvable topology, Time Series Forecasting

1. INTRODUCTION
Time series forecasting is an important research topic, focused on modeling and predicting the system behavior according to historical observations of the system when there is not much information about the underlying variable. Moreover, in case of chaotic time series, which involves with high degree of complexity, behavior of the systems are strongly sensitive to initial conditions such as noise and error which makes the prediction more difficult [1].

In the past, fully connected Artificial Neural Networks (ANNs) have been considered for prediction purposes, in which all inputs are fully connected to all neurons [2]. Instead of fully connected structure, it has been shown that partially connected ANNs have better storage capability per connection, improve generalization, and reduce cost of hardware and processing time [3].

With growing interest in bio-inspired computational algorithms such as genetic algorithm (GA), evolution of ANNs or Neuro-Evolution (NE) have been used to adapt the network parameters of interest [4]. Traditional NE only evolves the connection weights of the fully connected topology. However, there are other parameters that influence the performance of ANN. For this purpose, NE of augmenting topologies is proposed to evolve the structure of ANN along with connection weights to minimize the dimensionality of the search space of connection weights [5]. Similarly, minimizing the number of input nodes and neurons in pruned probabilistic ANN has also been introduced [6]. Furthermore, an ANN with evolvable topology and capability of search beyond the connection weights has been applied in cognitive systems [7].

In this paper, we introduce a new partially connected ANN with evolvable topology named PANNET which is an enhanced version of the one proposed in Marstaller et al. [7]. This structure consists of arbitrary number of neurons that make partial connections between observation nodes and hidden nodes, where hidden nodes are extra nodes that play the role of memory or internal states of the system that are not already predetermined. Using the evolutionary cycle of the proposed variable length GA with novel crossover and mutation operators, topology of the network is evolved in order to generate the best configuration of the network for modeling the underlying behavior of the system.

2. METHOD DESCRIPTION
Figure 1 illustrates the structure of a typical PANNET, which consists of two observation nodes and five hidden nodes. The arbitrary numbers of nodes are connected in the network via two neurons. Equation (1) shows the updated value of the output node l for the next time step.

$$m_l(t+1) = \sum_{k=1}^{n} W_l^{(k)} \tanh(\sum_j w_j^{(k)} \, \mathrm{m}_j^{(k)}(\mathrm{t})) \qquad (1)$$

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where $m_j^{(k)}$ and $w_j^{(k)}$ are an incoming node and its corresponding weight into the k^{th} neuron in the network respectively. Also $W_l^{(k)}$ is the output connection weight of the output node l and n is the number of incomings connections to the node l.

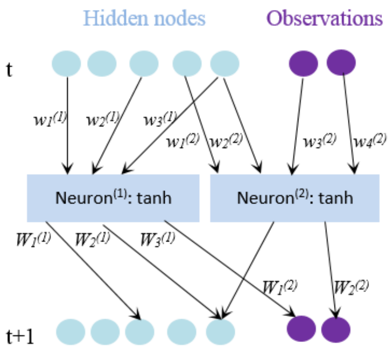

Figure 1. PANNET representation

Since the network has an evolvable topology, the number of neurons and their corresponding descriptions represent each individual in GA. Figure 2 illustrates the first and last neurons of an individual with M neurons. The number of neurons (N_N) along with number of input nodes (N_{In}), number of output nodes (N_{Out}), origin of the inputs (In), origin of outputs (Out), weight of input (In_w) and output (Out_W) nodes for each neuron are represented in the individual.

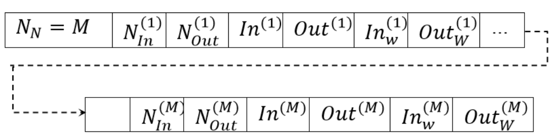

Figure 2. Individual representation

Mean sum square error between all measured outputs of the system (y_n , $n=1,..,N$) and the estimated ones ($\hat{y}_n$, $n=1,..,N$) is given by Eq. (2) over the whole set of training examples ($t=1,...,K$) is used for evaluation of the network.

$$Fitness = \frac{1}{K}\sum_{t=1}^{K}\sum_{n=1}^{N}(y_n(t) - \hat{y}_n(t))^2 \qquad (2)$$

In order to create new offspring, the proposed crossover swaps one neuron in first individual with another one in the second individual with all their components. Moreover, mutation can change number of neurons or one of components of them. This operator is developed to ensure the searching of local space of individuals and to escape from the possible local minima.

2.1 Mackey-Glass Time Series

The Mackey–Glass differential equation proposed as a model of white blood cell production and is shown in (3).

$$\frac{dy(t)}{dt} = \frac{ay(t-\tau)}{1+y^c(t-\tau)} - by(t) \qquad (3)$$

Depending on the most used parameters in Mackey–Glass analysis, where a = 0.2, b = 0.1, c = 10 and delay parameter τ =17, this equation displays a range of chaotic behaviors. The time series consists of 1000 data points ranging from t=118 to 1117 which is generated based on the fourth-order Runge–Kutta with an initial condition of $y(0) = 1.2$. The first 500 data pairs are used to train the network, and the last 500 data points are employed for testing the obtained PANNET structure.

The obtained network in generation 2478 predicts the test data of Mackey-Glass time series where the mean absolute error is 0.0056; the mean square error is 5.0501e-05; and the normalized mean square error is 8.8139e-04, which show the efficiency of the PANNET in predicting the chaotic Mackey-Glass time series without using predetermined time-delay inputs of the system. The results indicate that the proposed PANNET is effectively capable of predicting this chaotic time series, which is strongly a non-stationary and delay-differential equation without any assumption on the embedding dimension and delay of the system. In contrast, most of the previous studies selected the inputs of the ANN for modeling the dynamical behavior of the system based on their prior knowledge on embedding dimension and delay in the system.

3. CONCLUSIONS and FUTURE WORK

We proposed PANNET as a new partially connected ANN with evolvable topology, which has a capability to predict the chaotic time series without prior knowledge of underlying behavior of the system. Employing the hidden nodes as inputs or outputs of neurons give flexibility to the network to be constructed based on a set of unknown memories and internal states. In the developed variable-length GA, each candidate topology represents a set of neurons with their corresponding descriptions. Results for Mackey-Glass time series forecasting are obtained without any assumptions on embedding dimension and delay of the system, which show the effectiveness of the proposed method in chaotic time series forecasting.

4. ACKNOWLEDGMENTS

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