Artificial Neural Network Based Evaluation Method of Urban Public Security

Zheng Xu, Qingyuan Zhou, Haiyan Chen and Fangfang Liu

Abstract In a Smarter City, available resources are harnessed safely, sustainably and efficiently to achieve positive, measurable economic and societal outcomes. Enabling City information as a utility, through a robust (expressive, dynamic, scalable) and (critically) a sustainable technology and socially synergistic ecosystem could drive significant benefits and opportunities. In this paper we propose a model based on Grid Management System. This model is based on grid cycle providing grid capturing, grid sharing, grid enhancing and grid preserving. Moreover, our model shares grid that supports the law of knowledge dynamics. Later we illustrate a scenario of Pudong District of Shanghai for independence issues. An Artificial Neural network (ANN) based simulation applying the proposed Grid Management System model is also described at the end of this paper to validate its applicability.

Keywords Artificial neural network · Public security, grid management system

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1 Introduction

In a Smarter City, available resources are harnessed safely, sustainably and efficiently to achieve positive, measurable economic and societal outcomes. Data (and then information) from people, systems and things in cities is the single most scalable resource available to City stakeholders but difficult to publish, organize, discover, interpret, combine, analyze, reason and consume, especially in such an heterogeneous environment [1–4]. Indeed data is big and exposed from heterogeneous environments such as water, energy, traffic or building. Most of the challenges of Big Data in Smart Cities are multi-dimensional and can be addressed from different multidisciplinary perspectives e.g., from Artificial Intelligence (Machine Learning, Semantic Web), Database, Data Mining to Distributed Systems communities. Enabling City information as a utility, through a robust (expressive, dynamic, scalable) and (critically) a sustainable technology and socially synergistic ecosystem could drive significant benefits and opportunities. While research efforts in Big Data have mostly focused on the later stages of the process of making sense of the sea of data (e.g. data analytics, query answering, data visualization, etc.), in the context of Smart Cities, where heterogeneous data originates from multiple municipal and state agencies with little to no coordination, major hurdles and issues continue to impede progress toward these later stages. These key unaddressed issues are often related to information exploration, access, and linking.

Recent research and experiments suggest that artificial neural network (ANN) can be a candidate for nonlinear series forecasting [5]. ANN is typical intelligent learning paradigm, widely used in some practical application domains including: pattern classification, function approximation, optimization, forecasting and many others [6]. Opposed to traditional forecasting approaches, ANN has a strong self-learning and self-organizing ability so it can tackle any nonlinear problem. As a classic method of ANN, BP neural network model is widely used in forecasting area. Using neural networks has the limitations of large complexity and also fails because of over-fitting, local optima. On the other hand, RBFNNs, with only one hidden layer, have the ability to find global optima. In addition to less computational complexity, simulations performed in the literature reveal that the RBFNN produces superior performance as compared to other existing ANN-based approaches. Hence the works on task scheduling using RBFNN became an established and an active area of academic research and development [7]. In this paper we propose an E-Governance model based on Grid Management System. This model is based on grid cycle providing grid capturing, grid sharing, grid enhancing and grid preserving. Moreover, our model shares grid that supports the law of knowledge dynamics. Later we illustrate a scenario of Pudong District of Shanghai for independence issues. An Artificial Neural network (ANN) based simulation applying the proposed Grid Management System model is also described at the end of this paper to validate its applicability.

2 Related Work

Data Grids primarily deal with data repositories, sharing, access and management of large amounts of distributed data. Many scientific and engineering applications require access to large amounts of distributed data; however, different data could have their own format. In such Grid systems many types of algorithm, such as replication, are important to increase the performance of Grid-enabled applications that use large amounts of data. Also, data copy and transfer is important here in order to achieve high throughput. To successfully realize the vision of scientific Grid applications, the commission of the Next Generation Grid (NGG) [8] recognized the challenging research topics in future Grid systems including guaranteed QoS, reliability, and service performance, which are of vital importance in the Grid-computing service. Nevertheless, most commercial vendors in reality endeavor to increase commercial interests by efficient Grid-computing service and cost-effective Grid trade, but if the Grid system were utterly driven by commercial interests rather than QoS, a commercial buyer would not embrace the Grid-computing service to deal with critical computing jobs. Therefore, a number of RMS concerning service efficiency, service cost, or the requirements of QoS have been recommended in various complex Grid environments [9]. Grid computing was conceived to connote the idea of a “power grid:” namely, applications can plug into the Grid to draw computing resources in the same way electrical devices plug into a power grid to draw power. Analogous to a power grid, it views geographically distributed computing capabilities, storage, data sets, scientific instruments, knowledge, and so on as utility resources to be delivered over the Internet seamlessly, transparently, and dynamically as and when needed. The Grid is built upon two fundamental concepts: virtualization, i.e., individuals and/or institutions with the required resources or common interests can dynamically form a virtual organization (VO) that enables rapid assembly and disassembly of resources into transient confederations for coordinated problem solving, and dynamic provisioning, i.e., resources provision is transient, dynamic, and volatile without guarantee of availability, central control for accessibility, and prior trust relationships. Grid computing offers a promising distributed computing infrastructure where large-scale cross organizational resource sharing and routine interactions are commonplace.

3 Basic Methodology

The Back Propagation (BP) neural network with self-adaptive and self-organizing characteristics can be very effective in dealing with nonlinear problems. Over the years, BP neural network model is widely applied in forecasting area. A BP neural

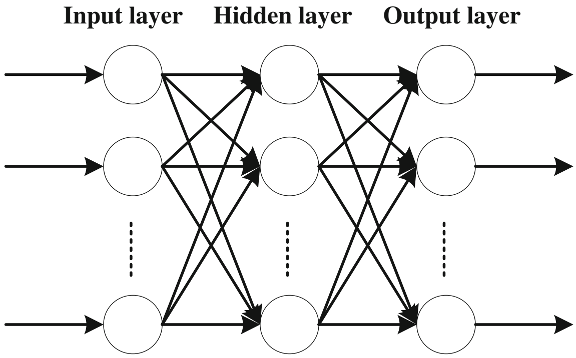

Fig. 1 The structure of BP neural network

network model comprises an input layer, one or more hidden layers and an output layer. Each layer comprises a number of nodes connected by weight-value. The BP network structure is shown in Fig. 1. BP network learning process consists of forward propagation and backward propagation. During the process of forward propagation, input samples are sent from the input layer to the hidden layer and finally to the output layer. The output results are produced after this process. Then turn to the back propagation stage if there is a big difference between output results and expected results. In the back propagation, output error is reversed back to input layer, by modifying connection weights between neurons of each layer. These two propagations repeat iteratively to adjust connection weights and node biases in order to eventually minimize the error function. It's known that BP neural network is trained by Back Propagation (BP) algorithm [10].

RBF neural network is a kind of three-layer static feed-forward neural network consists of input layer, hidden layer and output layer. A typical RBF network structure is similar as Fig. 1 shows. The difference between RBF network and BP network is that it uses Gaussian function as the transfer function from the input layer to the hidden layer. Gaussian function is a local activation function and it is activated within a small extent so that the network has the local learning ability [11]. For the same problem, a RBF neural network requires more modes in hidden layer but it has shorter training time and higher learning speed than a BP neural network.

Elman neural network is a regression neural network consists of four layers: input layer, hidden layer, undertake layer and output layer, as shown in Fig. 2. The input layer, hidden layer and output layer are similar as forward network. Its special feature is that the undertake layer has the ability to remember output value of hidden layer a time before and then use it as input value to hidden layer next time [12]. This type of network has a function of remembering dynamically so it can deal with dynamic information accurately.

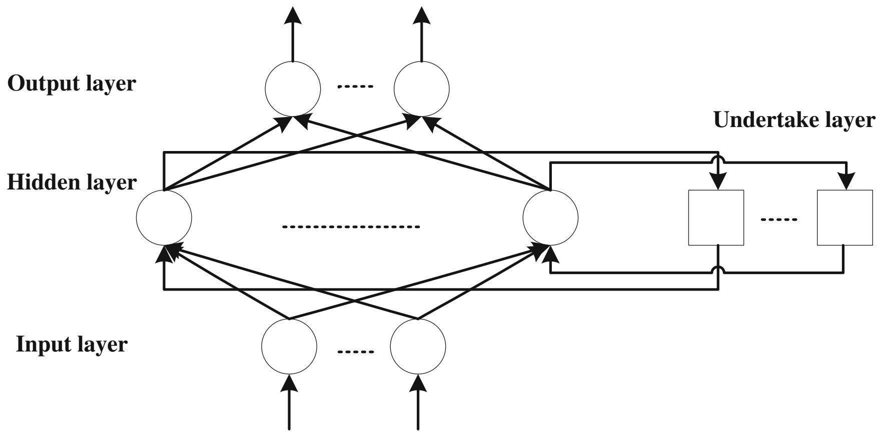

Fig. 2 The structure of Elman neural network

4 Urban Public Security Management Network Platform

Urban public security management network platform can be divided into three levels, the most above level is urban public security emergency response commanding center, the second level is management center, emergency preplan management center, database, information briefing center, and the third level is made up of safety and prevention system, firefighting control center, and a monitoring terminal of different danger sources from business and enterprises. Among them, the third level is the key of urban public security management network, safety and prevention systems and firefighting control centers of business and enterprises should make effective monitoring and management of various firefighting facilities under their protective area, and transmit their effective status to urban public security management center. In addition, monitoring terminals should be built to various dangerous sources, and transmit their status to the center.

In this way, the status of dangerous sources can be enquired from this center, and if the dangerous sources are in a wrong or non-regular state, evaluations shall be made and conclusions and corrective measures against can be made and sent to respective management departments. If corrections have not been made within validity, then the grade of danger shall be raised, and the evaluation report shall be delivered to emergency response commanding center. The safety and prevention system, firefighting control center, and a monitoring terminal of different danger sources shall make regular self-inspection and maintenance, and send reports to the public security database for central processing. By the effective management of third level information terminal, various dangerous sources can be investigated and made effective monitoring and control, thus a solid groundwork of urban public security management system can be laid eventually.

5 Conclusions

In a Smarter City, available resources are harnessed safely, sustainably and efficiently to achieve positive, measurable economic and societal outcomes. Enabling City information as a utility, through a robust (expressive, dynamic, scalable) and (critically) a sustainable technology and socially synergistic ecosystem could drive significant benefits and opportunities. In this paper we propose a model based on Grid Management System. This model is based on grid cycle providing grid capturing, grid sharing, grid enhancing and grid preserving. More-over, our model shares grid that supports the law of knowledge dynamics. Later we illustrate a scenario of Pudong District of Shanghai for in-dependence issues. An Artificial Neural network (ANN) based simulation applying the proposed Grid Management System model is also de-scribed at the end of this paper to validate its applicability.

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