A REVIEW ON THE APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS (ANNs) IN LARGE-SCALE EVALUATION OF URBAN ENVIRONMENT

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Abstract - One major limitation which currently exist with the study in urban environment is the often inconsistent and unreliable measures of urban development features across different field of studies which make large scale study difficult. The recent advances in new technologies have produced a wealth of data to help research activities by facilitating improved measurements and conducting large scale analysis. Additionally, according to the growing trend of world population the need for underground transportation is increasing. This research aimed to present the overall concept of Artificial Neural Networks (ANNs) and their role in statistical analysis part of two different but correlated field of study of Architecture and Urban planning engineering and Geotechnical Civil and transportation engineering. The advantage of machine learning in this project has focus on measuring the 1) role of ANNs on evaluation of street level urban qualities, and 2) urban underground transportation system infrastructures, in order to big data analysis in advance. The study explores the potential of big data management and big data analytics to measuring urban development features by applying different types of machine learning according to the aim of every research. Finally, the research specifically deals with optimization of time and human resource for evaluated of two correlated projects as well.

Keywords - Artificial Intelligence, Artificial Neural Networks (ANNs), Machine learning, urban environment, Settlement

I. INTRODUCTION

Researchers have just started the path to understand the true biological feature of how the neural networks performance in real practice. The observations show that the neural functions such as how the memory performs and how they are inter-connected is due to the existence of neurons. The main dilemma on the way is that if it would be possible to achieve a structure of neurons which can serve as a true example of how the human nerving systems acts. Neurons in the context of Artificial Neural Network (ANN) models mimics the role of the human body neurons. Although, the ANN models are not exactly the same of how the brain works but they can be quite close to what the human brains can perform.

Our goal in this study is to explore a review on the concept of Artificial Neural Network tools and their role and advantages in statistical analysis part of two separate research area which are as follow:

- Application of Artificial Neural Networks (ANNs) in Urban built environment and their advantages
- Application of Artificial Neural Networks (ANNs) for prediction of Ground Response Induced by Earth Pressure Balance (EPB) Tunnelling

II. BACKGROUND OF STUDY

2.1. Application of ANN

The adaptive channel equalizer which is a one-neuron neural network used for commercial purposes can be counted as one of the primary usage of artificial neural network models that was covered in full details in the study done by the end of 80s, called DARPA neural network. Some of the application scan be enumerated as follows: (1) Banking and financial fields; (2) Vehicle and auto-mobile development; (3) space and aerospace; (4) gaming and fun; (5) medical; (6) cyber security; (7) speech recognition; (8) oil industry; (9) civil engineering, (10) architecture and urban planning; and so on.

2.2. Historical background

By the seventeen century the experts in medical science started to get the notion that the heart is actually playing the role of pump and then they used this concept to mimic the action of the heart. This newly notion toward the modelling of heart changed the circulatory systems fundamentally. The first initial works on neural networks started by the end of 19th all through the beginning of 20th century. Hermann von Helmholtz, Ernst Mach and Ivan Pavlov for instance are among those researchers that worked in the context of physics, psychology and neurophysiology. Their work however did not cover the challenges and detail of ANN model formulation and design structure. To this regard, the details of the ANN models investigating the formulation of such models were involved in the work in 1940s in the study done by Warren McCulloch and Walter Pitts, who is often known as the pioneering researchers of ANN models developers. Their work was followed by a succeeding study by Donald Hebb [Hebb49], who studied the traditional conditioning which was initially proposed by Pavlov due to the properties of each neuron. Nonetheless, the first application of ANN models took place in the end of 1950s, when the learning feature was endowed to the model by the work done by Frank Rosenblatt [1]. They could

successfully develop an ANN model which is useful in the context of pattern recognition, however their application area was later known that it was limited to just solving a few number of problems in a time. Bernard Widrow and Ted Hoff [2] later developed an adaptive linear ANN models which were alike in their designed architecture and quite resembled the same ability of Rosenblatt's perceptron. Even today, the Widrow-Hoff learning strategy is being used although the other learning techniques were proposed earlier such as Rosenblatt's and Widrow's networks ad limited extent of usage which are enumerated in Marvin Minsky and Seymour Papert. The restrictions on extending the Rosenblatt and Widrow ANN model were known even during their developing time hence they attempted to overcome their models' limitation later on. Nonetheless, their modified learning algorithm was still unable to be extended for more complex problems. Since, many further attempts failed to propose any modification which can better the existing algorithms, even those succeeding Minsky and Papert thought that the ANN models will eventually be forgotten forever.

Moreover, the limited technological facilities during that time was quite a barrier in front of the researchers to undertake further researches into this field. Teuvo Kohonen [3] and James Anderson [Ande72] despite the low speed of progress in the field built up ANN models which could mimic the human memory. Stephen Grossberg [4] was also among the pioneering researchers in training the organizing networks. Although the neural network was having a highly slow progress during a decade, two main factors boosted the usage of neural networks all of a sudden. One the primary factors was the statistical analysis procedures that could help in building the recurring network, to be acted like a memory which is fully explained by John Hopfield (1982). Next factor which came into action by the end of 1980 was the development of backpropagation multiple-layer neural network. David Rumelhart and James McClelland [5] have put a significant effort on gathering and collecting the findings on how the backpropagation works.

Actually, the main motivation of the backpropagation algorithm was an earlier criticism directed toward the neural network in general mentioned by Minsky and Papert. The above-mentioned history on the ANN model development can ensure the readers that the ANN models have taken a long and often disappointing moments in their path through to getting popular as they are to date. Many of the advancements in the context of learning algorithms and the architecture of the neural networks could open a wider horizon for future works which affected significantly on the usage of ANN models. It is believed that just like what has happened to many other fields of studied the neural networks have along path ahead and yet there so many different aspects that the researchers can focus on. This might be noted that the ANN model is not a remedy for all the diseases and many cases it happens that the ability of ANN models might be used in a wrong way and thus give this feeling that the ANN models are as efficient as they should be.

2.3. Biological Inspiration

The following paragraphs discuss the unique features of the human brain which are quite the motivations behind the artificial neural network. The human brain is built of many and better to say millions of interconnected neurons serving the human body's nerve system. The neurons have the duty to be the bridge upon those the electric pulses connecting various parts of our body can pass in just a millisecond of [6]. These neurons are consisted of main components, namely, the dendrites, axon which are the two ends of a neuron while the middle part is called the cell body. The dendrites are actually like tree branches through which several pulses of electricity move and reach to other dendrites in other organs.

However, before than that an electrical signal reaches to the end of a neuron, the dendrites, the body of the cell decides that if the pulse should pass or not. The axon also plays another essential role that upon the decision of the body cell and the electricity signal in dendrites, if the signal needs to be passed to any other neurons or not [6]. In addition, it is good to mention that where an axon reaches the dendrites of other neurons is known as synapse. A very simple diagrammatic of a pair of neurons is as shown in Figure 1.

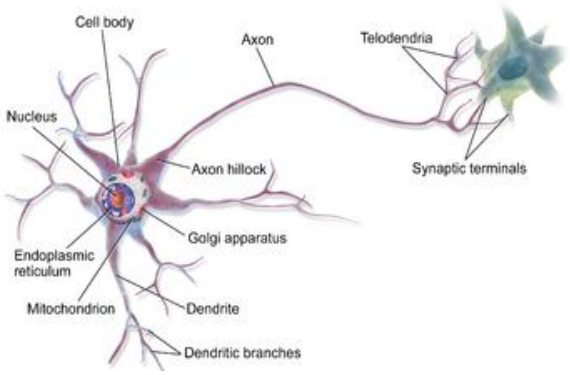


Figure 1: Schematic Drawing of Biological Neurons, [6]

2.4. Neuron Model

Figure 2 depicts the diagram of one neuron. The input in the ANN models is multiplied by the weights and then passed to the summer. Conventionally, a bias unites which is always equal to one is multiplied by its weight and be given to the summer. The output of the summer, n, known as the net input, moves to a transfer function, f, which ends to the end output of the neural network model. This is often called the activation function [6].

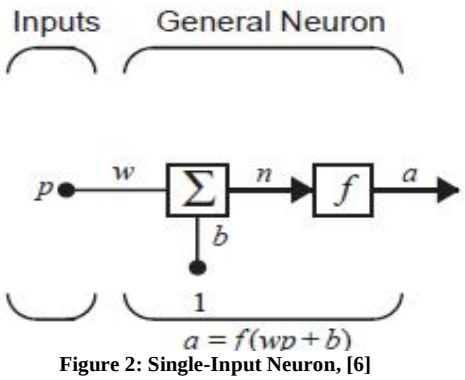


Figure 2: Single-Input Neuron, [6]

The neuron output is calculated as:

$$a = f(wp + b)$$

2.5. Basic Principles in ANN Prediction System

In general, the ground engineering has extensively used the application of ANNs which are classified into two types: (1) the non-linearity among the parameters which are derived using the available data; and (2) the other estimation model for the latter duration using the gained data and in-situ test data obtained from the previous experiences. Regarding the prediction systems, the geotechnical engineering is highly a complex mechanism. The geotechnical engineering involves a wide variety of research topics that the neural network estimation model can have plenty of applications. The advantageous feature of the application of the artificial neural network models is to predict the magnitude of the displacement and thus proved the safety of the construction site to reduce the hazards related to the changes in the ground displacement and avoid excessive deformations. Moreover, the neural network models known as soft computational models are also able to be used in a reverse direction to solve the problem when the displacement and the ground movements are given and then find out the stresses and other loads during the construction of tunnels.

III. THE APPLICATION OF ANN IN PREDICTION OF GROUND SURFACE SETTLEMENT DUE TO SHIELD TUNNELING

The popularity of the shield tunnelling owes to the facts that it is a highly inexpensive tunnelling process, great flexibility, and moreover it has little diverse impact on the traffic and other existing structure in the vicinity [7]. The primary advantageous which comes with the shield tunnelling is the highly reliable estimation of the ground displacement which is often took place in more dense regions where the population is greater than the other locations. To this regard, many shield tunnelling projects are taken places where the infrastructure systems are congested including the systems of storm drain, sewer, steam, water, gas pipes, and electrical and telephone ducts [8]. Qu (Y. L. Qu 2005) could successfully develop an artificial neural network consisting of 9 neurons for the input layer which are called the feature vector and in the last layer 2 output neurons were considered in addition to 12 neurons in the middle layer. The 2nd metro line in Shanghai, Longdong Road- Zhongyang Park, is built in soft clay, sandy silt as well muddy and silty clay. The diameter of the soil pressure is assumed to be 6340 mm. The 2nd line of Metro in Guangzhou, named Yuexiu Park-Sanyuanli, has two regional tunnels which are placed in soft low-strength rocky ground with the diameter of 6250 mm. The input variables include a wide range of properties, namely, cohesion (C), frictional angle (φ), compressive soil modulus (Es), the depth of thickness (H), TBM machine diameter of excavation (D), the grout covering pressuring (P), the rotational power of grouting (N), shield jacking force (F), and the rate of the tunnelling shield (V). These input variables are given to the neural network into the first layer and then these input variables will be mapped through several weights to be correlated to out neurons estimating the maximum of ground displacement (S max) and the tank coefficient of settlement which is denoted by i. Sun and Yuan have used the artificial neural network to investigate the mechanism of earth movements and thus the earth displacements due to soil disturbance while and after the shield tunnelling construction. The developed ANN model was able to estimate the earth displacement at the front face of the tunnel within a five-meter distance. In order to ensure that the shield tunnelling parameters are adjusted in a timely manner and the alarm system for warning the hazardous conditions, the changes in ground should be collected.

Lastly, it can be summarized that the application of ANN models is growing rapidly as the literature in tunnelling engineering shows which is due to the fact that ANN models have the ability to reach the accuracy in predicting the tunnelling parameters within a range of acceptable limits with quite much lower computational cost than any other existing approaches. One of the most important point in BP network modelling in estimating the displacements of the ground is to find the influence factors. The accuracy of the prediction can be significantly improved as when the content of samples is heightened.

IV. THE APPLICATION OF MACHINE LEARNING AND ANNSIN LARGE-SCALE EVALUATION OFURBAN STUDIES

Toward the fast growing of cities, for planners and also dwellers it is very hard to have a perspective about how every street should be looks [9]. So, human perception of urban environment is completely different, incomplete and distorted by the professions perception [10] and the city's image [9]. It also will be more significant due to the huge size of

modern cities. Therefore, it is hard to find the answer of such question as "in fast urbanizing cities, how is the city appearance changing?"

Before, the dominant methods in several studies to evaluate the city's appearance in large scale was based on sending human auditors to do filed observation and recording the data [11, 12]. However, this kinds of method has some limitation in terms of sample size, time and human resources [11].

Recently, there are many tools which has used to evaluate the city's appearance in large scale and big data evaluation. ANNs andmachine learning algorithm is one of the most famous artificial intelligent tools by significant potential to do urban environment analysis by different range of networks. The most useful methodology for this topic is image processing though availability of online street view images [13, 14, 15, 16, 17, and 18]. The combination of google street view with other tools like computer vision technics provide the possibility of large scale evaluation of the urban environment in a short time [19, 20, 21, 22, and 23].

Our goal in this part of study is to explore different types of machine learning and their possibility in terms of the physical quality of the urban environment, walkability, public transportation and spatial analysis though different features.

4.1. Different types of machine learning and ANNs to estimate urban built environment evaluation

In order to applying the machine learning algorithm in urban environment development, there is a various range of tools which have used according to the main of the studies.

In this case, there are some studies which have focused on the "automatic classification of architectural styles by capturing the morphological characteristics" to understand the transformation of architectural style over the time [24, 20, 25, 26, 27] by using geo-referenced street-level imagery from Google Street View. "The method requires iterative refinement of the patches using Support vector machine (SVMs)" [20].

Some other study aimed to understanding "people's perceptions of urban scenes, analyzed by crowd-sourcing rating on urban images" [28] Moreover Quercia et al. [28] recognized a number of aesthetic explanatory features which have positive or negative effects on people's perception of beauty and pleasurableness.

The perception of "wealth, uniqueness and safety" from street view images has been modelled on Ordonez and Berg's study [22]. Naik et al. [29] modelled the perception of safety by different method which later on was proved to be reliable with the definite socio-economic variables by Porzi, et.al [30] and Naik, Kominers, Raskar, Glaeser, & Hidalgo [21]. In such studies, street view images obtained from Google Map have used to evaluating the indicators through different machine learning (SVMs, MLPs and etc.)

Moreover, Google Street View, and Application Programming interfaces (APIs) have used to develop an algorithm for "downloading images and transforming images for the automatic detection in order to evaluation of pedestrian count in urban area" [31] .Therefore, Google Street View has an essential role to collecting the information in detail from each segment of public streets with providing a panoramic views in most of the countries around the world. Recently, it has been used to assistance audit of the built environments [32, 33, 34, 35, and 36] and for other aims of various studies.

There is another techniques in urban environment studies which is Kernel-based regularized least squares (KRLS) described in [37]. KRLS as a kind of machine learning techniques developed in the 1990s by the approach of providing the "estimates of the marginal effects of each independent variable at each data smoother functions (by reducing complexity in the optimal solution)" [37] Therefore, big data in large scale and computational analytics provide significant opportunities for interdisciplinary approach [38]. They have a potential to help the researchers in ways never before imagined and possible [38, 39]. Moreover, new data sources and technologies have simulated research on urban development [35].

CONCLUSION

According to the growing trend of world population the need for using Intelligence tools is insignificant. The main aim of this study is recommendation for researchers to transform in to the artificial intelligence tools. Additionally, the recent improvements in artificial intelligence tools as new technologies have huge advantage in order to evaluation of large amount of data at fine resolution. These new types of data evaluation can help researchers by smoothing improved measurements or new features of interest to conducting large scale study at micro and macro levels. This study is an attempted to show reduced analysis time and human resource to achieve the best result through Artificial Intelligence tools in every research area.

There are much positive advantages for prediction of surface settlement based on artificial neural network (ANN) by exploring the most effective factors on maximum surface settlement. Moreover, using different types of Artificial Intelligence tools are much more effective in urban development study in order to provide the possibility of big data evaluation in street level of urban environment. The machine learning evaluation allows to urban planners and designers to predict thebest result for future development of the cities in every cases.

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