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THEORETICAL INVESTIGATIONS FOR THE VERIFICATION OF SHEAR CENTRE AND DEFLECTION OF SIGMA SECTION BY BACK PROPAGATION NEURAL NETWORK USING PYTHON

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The most important challenges in the construction field is to do the experimentation of the designing at real time. It leads to the wastage of the materials and time consuming process. In this paper, an artificial neural network based model for the verification of sigma section characteristics like shear centre and deflection are designed and verified. The physical properties like weight, depth, flange, lip, outer web, thickness, and area to bring shear centre are used in the model. Similarly, weight, purlin centres with allowable loading of different values used in the model for deflection verification. The overall average error rate as 1.278 percent to the shear centre and 2.967 percent to the deflection are achieved by the model successfully. The proposed model will act as supportive tool to the steel roof constructors, engineers, and designers who are involved in construction as well as in the section fabricators industry.

Keywords: Artificial Neural Network (ANN), Back Propagation Neural Network (BPNN), Sigma section, Shear Centre, Deflection, Roof Construction

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1. Introduction

Artificial Neural Network (ANN) is the electronic form of logical Neuron system with simplified models. ANN is an efficient parallel distributed processing system made up of enormous interconnected artificial neural computing elements. As like human brain function, ANN is employed in several applications like controlling dynamical networks as mentioned by Jason Z. Kim et al (2017).They have the ability to learn and thereby acquire knowledge to make it available for use in the Industrial purpose. Industrial agent based industrial systems under the conditions of productivity; re-configurability, robustness, and scalability were employed as stated by Paulo Leitao et al. (2013). For acquiring knowledge, different ANN Architectures exists nowadays as stated by Iman Mansouri et al. (2018). ANN schemes are employed in different domains even from our daily life for glucose measurement in the field of medical diagnosis as mooted by V. Ashok and A. Nirmal Kumar (2013).Architectures of ANN have been classified into different models based on their features and learning mechanism as proposed by Bernard Widrow and Michael Lehr (1990) and Samson B.Cooper and Dario Di Maio (2018) using ANN for pragmatic approach to static load on a wing rib estimation and calibration of Finite Element (FE) model for training using random data as inputs. ANN based model has been trained and designed to verify the dimensions of sigma sections with Python language and its accessories as the programming environment due to the advantages mentioned as follows.Anaconda is an open source tool which provides cross platform and package manager services to different environments. It provides the common platform for the future Large Scale Structure (LSS) data as kick off by Nick Hand et al (2018).Jupyter is also one of the open source interactive programming software which provides better editing environment for data science and scientific computing models. It is one of the tools in Anaconda which provides web based interactive language as used in Neuro Physiology research by David M. Rosenberg and Charles C. Horn (2016). Python is an object oriented high level programming language. There are some benefits like code readability, functionality and procedure oriented flow. It has community support and large amount of standard libraries / library function. A technique for the axis symmetric shell systems modelled in 3D for buckling analysis using ABAQUS, Isight and Python is presented by Adam J. Sadowski et al (2018). Numpy is one of the library functions which provides packaging for scientific computing operations as used in simulating the response of seismic by structural and geotechnical systems by Minjie Zhu et al. (2018) To analyse the material characteristics between actual and simulated design value with respect to environment, processing technology, and other uncertain factors optimization techniques were employed as mentioned by Jianhua Zhou etal. (2018).

2. DATA PREPARATION TO IMPLEMENT NEURAL NETWORK MODEL

Neural network have some common features such as disseminated representation of information, representation free judgment, capability to handle data with ambiguity and imperfection**.** Moreover, in this research work ANN is employed for the Sigma Section properties verifications. The sigma purlin system is designed and fabricated for supporting the roofing sheet as secondary item in the construction. In this research work, sigma section is fabricated for maximum roof slope of 25degrees and bay widths of up to 15 meters are simulated, tested and verified by ANN using Python language. The sigma section is manufactured by using the cold roll forming pre-hot dipped galvanized steel material. It is having the characteristics of minimum yield strength of 345Mpa (Mega pascal). Here in this research, ANN using Python is used for the verification of shear centre and deflection under the conditions of ultimate load as limitations. All the data for verification of shear centre and deflection are acquired, collected, and observed from the fabrication of sigma section with different dimensions and properties at real time implementation of roofing constructions. For the verification of shear centre as well as for the deflection of sigma section properties, Back Propagation Neural Network (BPNN) is employed which is one of the supervised ANN algorithm as optimization technique employed by Ashok et al. (2010). The collected real time data from various sections are grouped into the five with minimum of six sections and maximum of nine sections in each which are totally thirty eight sections. The properties of sigma section for the shear centre verification are area, depth, flange, lip, outer web, thickness, and weight are collected and tabulated in Table 1.

TABLE 1 SIGMA SECTION SHEAR CENTRE PROPERTIES

S. No.	Sigma Section Groups	No. of Sections	Area (cm^2)	Depth (mm)	Flange (mm)	Lip (mm)	Outer Web (mm)	Thickness (mm)	Weight (Kg/m)	Shear Centre Y_{sc} (cm)
01.	G1	9	6.756± 2.485	200± 0	62.5±0	20± 0	60± 0	1.926± 0.65	5.301± 1.95	0.663± 0.055
02.	G2	9	7.188± 2.645	225± 0	62.5±0	20± 0	60± 0	1.926± 0.65	5.642± 2.08	0.414± 0.055
03.	G3	7	8.873± 2.73	240± 0	62.5±0	20± 0	60± 0	1.926± 0.5	6.966± 2.14	0.45± 0.05
04.	G4	7	9.39± 2.89	265± 0	62.5±0	20± 0	70± 0	1.926± 0.5	7.373± 2.27	0.411± 0.045
05.	G5	6	12.29± 3.015	300± 0	75±0	20± 0	70± 0	1.926± 0.35	9.648± 2.37	0.681± 0.045

TABLE 2 SIGMA SECTION DEFLECTION PROPERTIES

Sl. No.	Profile	Weight Kg/m	Purlin Centres in Meters							Deflection
			1	1.375	1.5	1.675	1.8	2	2.5	
			±Allowable Loadings (kN/m^2)							
1.	Profile1	4.65± 1.09	4.92± 1.88	3.58± 1.37	3.28± 1.26	2.94± 1.13	2.73± 1.05	2.46± 0.94	1.97± 0.75	28.75± 11.20
2.	Profile 2	56± 1.21	47.4± 1.42	34.47± 1.03	31.59± 0.95	28.31± 0.85	26.32± 0.79	23.71± 0.71	18.95± 0.57	286.98± 7.40
3.	Profile 3	4.76± 1.21	3.36± 1.25	2.44± 0.91	2.24± 0.84	2.00± 0.75	1.87± 0.70	1.68± 0.63	1.35± 0.5	21.27± 8.05
.	.	.	.	.	.	.	.	.	.	.
14.	Profile 14	9.58± 2.37	1.42± 0.58	1.03± 0.42	0.95± 0.38	0.85± 0.34	0.79± 0.32	0.71± 0.29	0.57± 0.23	20.28± 7.33
15.	Profile 15	9.65± 2.37	1.53± 0.43	1.08± 0.55	1.02± 0.27	0.89± 0.30	0.85± 0.23	0.76± 0.17	0.61± 0.16	21.07± 5.94
16.	Profile 16	9.65± 2.37	1.27± 0.43	0.82± 0.55	0.84± 0.27	0.76± 0.30	0.70± 0.23	0.60± 0.17	0.51± 0.16	18.91± 5.94
17.	Profile 17	9.65± 2.37	1.05± 0.34	0.76± 0.25	0.70± 0.23	0.63± 0.2	0.68± 0.27	0.53± 0.17	0.44± 0.14	17.12± 5.40

3.METHODOLOGY

Back Propagation Neural Network basically (BPNN) consists of three layers, one is input layer, the second is hidden layer and the third is output layer. It functions based on two phases, one is the feed forward phase and the other is feedback phase. In the feed forward phase, the data from the input is propagated to the output layer through input layer and the hidden layer. When the error range is not in the limit as the target value set in the output neuron of the output layer, the output data is resent back to the input layer via hidden layer. The general BPNN architecture as a sample is displayed in the figure 1

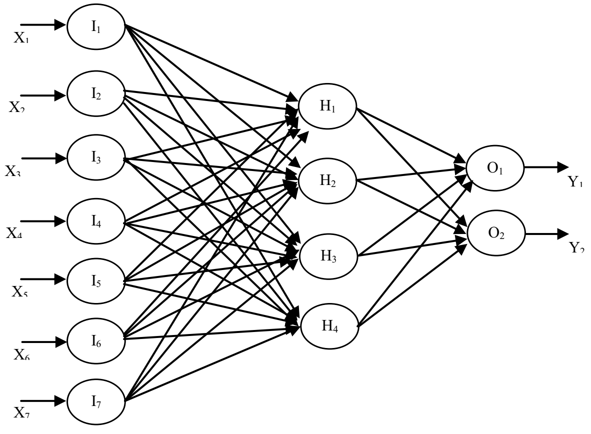

Fig. 1. General BPNN Architecture

Initially, the algorithm uses the normalised values of the sigma section properties as inputs to verify the shear centre. It is verified using five different groups comprising thirty eight sections with various parameters like lip, flange, weight, etc as mentioned in Table 1. Similarly, for the deflection verification, the purlin centres with seven different allowable loadings conditions with weights as mentioned in the Table 2 are given as inputs. Moreover, weights and bias of the architecture network which are calculated randomly from a set of values with three digit values as precision before and after the decimal point. The inputs to the network are for the verification and comparison of sigma section between simulated and fabricated process. In this, the learning rate (α) is used for the weight updating element as well as same procedure follows for the bias fixing too. The proposed work for the verification of Sigma section shear centre and deflection is as in the figure 2.

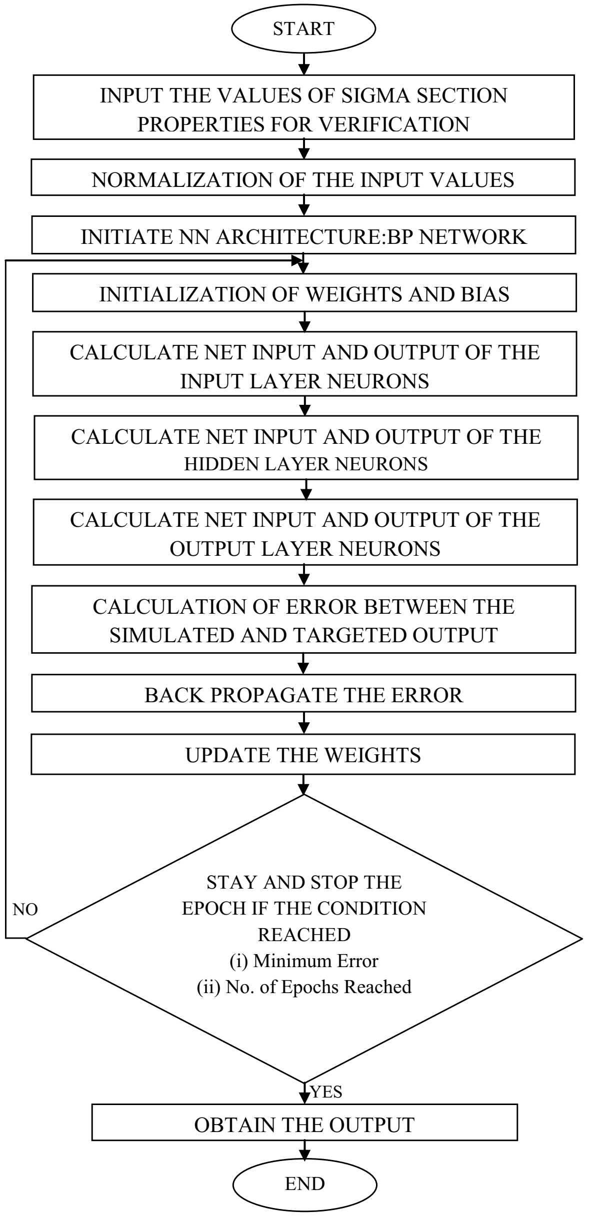

Fig. 2 Flowchart of BPNN Algorithm.

Over the single layer network, the feed forward network is more advantageous in solving more complex problems. BPNN provides an efficient methodology for the alteration of parameters of the structure values in the feed forward network like weight updation between the layers with different functions. The updations are with different mathematical functions according to the applications, similarly for learning the input and output training data set also. Here, the network is trained by the Back Propagation algorithm, through which the error is calculated. The training will be terminated by an end condition such as when the error value begins to rise beyond the tolerance and later it gets deteriorated. In this work, the weight is assigned initially between -1 to +1 with the bias factor as 1 to the neurons in the Hidden layers. The training process begins with n x n matrix in which the input values are between 0 and 1. The weights between the layers are updated and propagated to the hidden and input layers back until the error rate is reduced to the least value or upto the maximum epoch is accomplished. After the simulation model created as in the figure 4.3, the performance can be appraised with different sets of inputs given by the design engineers

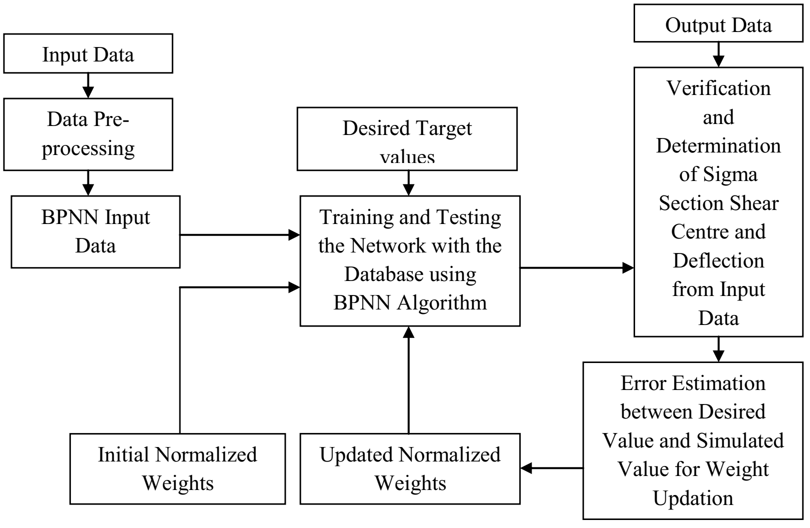

Fig. 3. Block Diagram of BPNN for the proposed model

Figure 4 is the exact BPNN architecture structure of this work with three layers, the input layer with eight neurons from I_1 to I_8, hidden layer with thirteen neurons as H_1 to H_{13} respectively and output layer with one neuron as O_1. The weights V_{11} to V_{813} are between input layer to hidden layer, similarly, W_{11} to W_{113} are the weights between hidden layer to output layer.

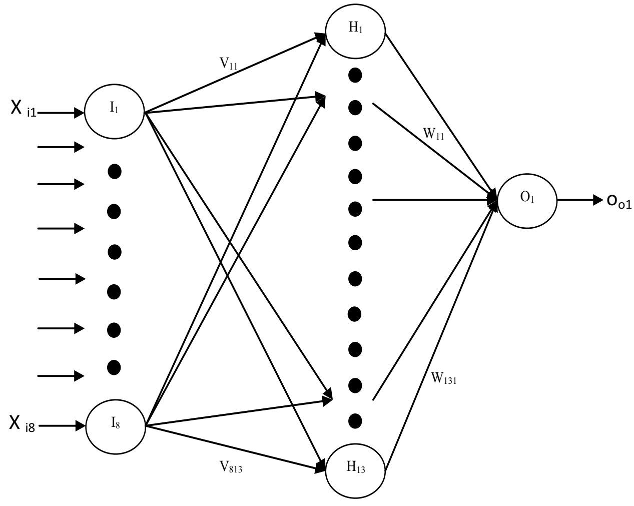

Fig. 4. BPNN Architecture Diagram for the proposed work

3.1. ROLE OF BPNN ALGORITHM IN THE VERIFICATION OF SIGMA SECTION PROPERTIES

The flow design of a Artificial Neural Network creates its own internal mapping creating a hierarchical network that is both linearly separable and capable of learning any given mappings. Now a three-layer network with an output layer of 'n' nodes, hidden layer being 'm' nodes and input layer 'I' nodes is considered. The training procedure is as follows, Initialise random weights at the start, Repeat, For every cycle of training method, Perform training with the given method, Stop, Repeat the procedure until the error is acceptably low.

The processed data is applied as inputs to neural networks after desired signal separation, The two schemes like Back Propagation Neural Network (BPNN) feed forward networks have been applied with great success to the functions of deflection and shear centre of a sigma section.The three layered Back Propagation Neural Network (BPNN) uses Gradient Descent algorithm with Learning Rate η=0.9, momentum coefficient α=0.9.

3.2. RESULTS AND DISCUSSION

The feasibility of the back propagation network in estimating the shear centre of a sigma section with respect to different sectional properties like weight, depth, flange, lip, outer web, thickness, area are shown in Table 3

TABLE 3 SHEAR CENTRE SIMULATED RESULTS OF THE PROPOSED METHOD

Sl. No.	Groups	No. of Sections	Desired output	Simulated output	Error Rate
1	G1	9	0.915±0.073	0.926±0.120	0.028±0.020
2	G2	9	0.903±0.055	0.890±0.089	0.025±0.017
3	G3	7	0.905±0.047	0.907±0.093	0.026±0.020
4	G4	7	0.909±0.065	0.919±0.116	0.035±0.026
5	G5	6	0.900±0.084	0.920±0.093	0.048±0.013

The subsequent graph in figure 5 gives the error rate plot of five groups and thirty eight sections for the verification of shear centre of a sigma section.

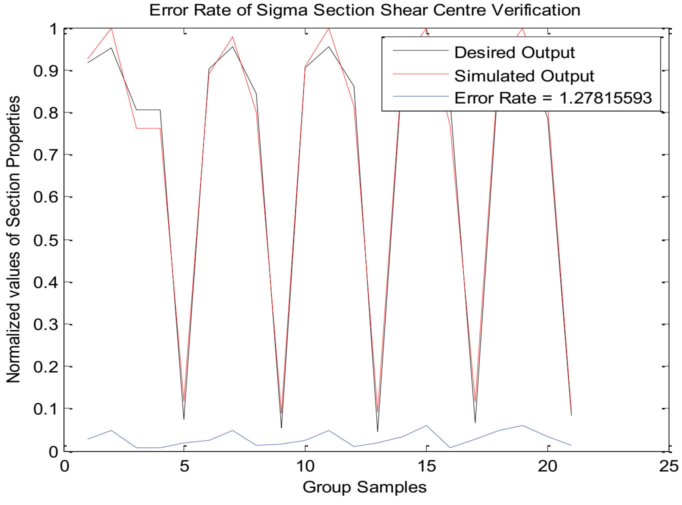

Fig. 5 Verification of Simulated Shear Centre Output with Error Rate.

The feasibility of the back propagation network in estimating the deflection of a sigma section with respect to different sectional properties like weight and seven different types of purlin centres are shown in Table 4

TABLE 4 SIMULATED DEFLECTION OUTPUT VERIFICATION WITH ERROR RATE

Sl. No.	Profiles	No. of Models	Desired output	Simulated output	Error Rate
1	P1	6	0.079±0.078	0.174±0.174	0.107±0.107
2	P2	5	0.102±0.102	0.208±0.207	0.084±0.084
3	P3	3	0.044±0.044	0.013±0.012	0.032±0.031
.	.	.	.	.	.
14	P14	17	0.133±0.132	0.230±0.250	0.126±0.131
15	P15	11	0.137±0.137	0.210±0.210	0.086±0.716
16	P16	7	0.171±0.171	0.257±.257	0.089±0.089
17	P17	6	0.043±0.085	0.141±0.141	0.077±0.076

The subsequent graph in figure 6 gives the error rate plot of seventeen profiles and one hundred and twenty eight models for the verification of shear centre of a sigma section.

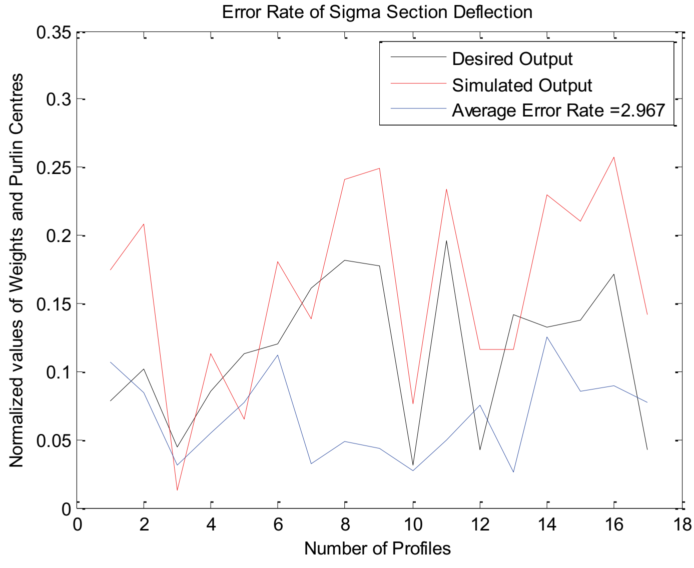

Fig. 6 Verification of deflection of sigma section.

In this back propagation neural network model, network trains and adapts quickly to give the error rate of 1.278 for shear centre and 2.967 to the deflection verification and remains constant after 450 epochs. The overall performance of this model is 97% to 98%. If the record models are increased, the training performance increases which results in reducing the error.

4. CONCLUSION AND SCOPE FOR THE FUTURE

The BPNN model using python language for this research work verification will act as supportive tool for steel roof constructors, engineers, and designers who are involved in construction as well as in the section fabricators industry. This model helps in error calculation and verification of sigma section design. For the bpnn model training, testing, verification, and validation process for the shear centre and deflection of sigma sections different samples are used. approximately, five groups of shear centre with 38 sections in each set minimum of six and maximum of nine sections in different groups were used for verification as mentioned in table1. the model predicts the shear centre of the sigma section with respect to the section properties as the overall average error rate as 1.278 percent. moreover, the overall average square error rate is 0.049 percent. likewise, seventeen profiles of sigma section deflection verification with two hundred and fourteen models with minimum of six and maximum of eighteen were mentioned in table 2 is used. Similarly, the prediction of sigma section deflection under allowable loading conditions, the overall average error rate is 2.967 percent and the overall average square error rate is 0.34 percent. In future, this model can be enhanced using machine learning algorithms for the sigma section design and verification by the engineers and constructors of steel roof constructions.

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LIST OF FIGURES AND TABLES:

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