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*Original research article*

# Artificial Neural Network Trained 'Simultaneous Extent Analysis' as a Logical Tool in Computation of Urban Heat Island Intensity

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**ABSTRACT**

Researchers have evolved several empirical studies with numerous statistical operations for processing of vast Climatic data. However, certain short-comings exist in the methodologies as the efforts to quantify the high resolution observations is at most times inappropriate, inaccurate, tedious, complex and expensive. One of the most documented anthropogenic impressions on urban climate is the 'Urban Heat Island Intensity' (U.H.I.I.). To facilitate a simpler and yet scientific understanding of this urban phenomenon; the current study introduces an accurate approach in terms of estimation. The present effort highlights the development of a new technique 'Simultaneous Extent Analysis' (S.E.A.) as a precise representation of U.H.I.I., from the 'population characteristics' of a huge parallel variable climatic database. It orients about the forecasting more specifically with the inception of Neural Network, and training upon a three-year continuous knowledge database, using Levenberg - Marquardt Backward Propagation method, and the Inference engine as Backward Chaining. The climatic data was a part of meteorological studies collected at half-hourly intervals to analyze U.H.I.I. at Bangalore (India). The knowledge base upon training was tested and validated with the real-time data for forecasting. The coefficient of correlation of 0.93 between the predicted and actual values is extremely good, thereby depicting that the efficiency of the model is good".

**Keywords:** Analysis; Empirical; Magnitude; Urban; Neural

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## 1. Introduction

Researchers in the field of urban climate studies have developed innumerous empirical models to establish the temperature difference between urban and rural areas, avidly referred to as 'Urban Heat Island intensity' (U.H.I.I.).

This is of paramount interest to environmentalist, town planners, meteorologist etc. However, in any of the active and passive climate researches involving primary and secondary data; sample design is always a vital component [1].

The present study tries to showcase 'Simultaneous Extent Analysis' (S.E.A.) as an accurate technique for representation of U.H.I.I. from 'population characteristics' of a huge parallel variable climatic database. It is an improvement over a previously 'author' defined logic 'Relative Magnitude Analysis' (RMA), with the inception of Artificial Neural Network (ANN). An effective knowledge representation paradigm inspired by biological nervous system, ANN has remarkable ability to derive relation, extract patterns and detect problems from complicated or imprecise data [2, 3].

RMA essentially advocated the analysis of 'simultaneous variables' for any form of calculation involving parallel dataset, and considered only 'arithmetic mean' averaged over the logging interval of entire dataset [2]. In RMA, in order to determine the 'true temperature intensity', complete sample (data of 31 days and of 24 hours each day) across the stations was subjected to simultaneous evaluation and finally averaged for the particular month(s) as presented in Equation (1.1) [2].

$$\sum_{i=1to24,\, j=1to31} \Delta T_{ij} = \sum ({}^{urban}T_{ij} - {}^{Rural}T_{ij}) \quad (1.1)$$

Wherein; '$i$' represents the respective hour of observation, '$j$' represents the respective day of observation, and '$k$' is the total number of entries recorded in 24 hours over 31 days [2]. The role of ANN in this context is to improvise the efficiency upon the logic of RMA, by forecasting more precisely.

The training upon knowledge base was achieved using Levenberg - Marquardt Backward Propagation method, with Backward Chaining as the Inference engine [3].

## 2. Materials and Methods

Voluminous data of air temperature values for a metropolitan city was collected over a period of 3 years (2010 - 2013) at 12 stations simultaneously, with the recording interval maintained as half hourly. For the current study, the 'sample' constituted air temperature values of 11 stations for training with the 12th station being employed for validation of efficiency in model prediction.

Primarily a dataset (ANN Model) was developed in MATLAB with Temperature, Green Cover, Open Space, Water Cover, Built up Space and Paved Surface as input parameters, and U.H.I.I. as output parameter. The Neural network performance was improved by normalizing the data between 0 and 1 to assist in data convergence, using simple normalization technique as depicted in Equation (2.1).

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (2.1)$$

The Neural Network architecture consisted of three layers; Input Layer, Hidden Layer and Output Layer as showcased in Fig. 2.1.

The outputs were transformed into its original data format and the dataset was divided into three samples for Training, Testing and validation. The data was fed into the network as an array of 12 factors × 1095 values, wherein 12 was the number of factors (Temperature, Green Cover, Open Space, Water Cover, Built up Space and Paved Surface) and 1095 was the number of readings recorded. In order to train the network, an output of size 1 × 1095 was constituted. The network was primarily subjected to training as using 3 different training functions namely; Levenberg-Marquardt (trainlm), Scaled conjugate gradient (trainscg) and Gradient descent (traingd). Training ensures that the network is adjusted according to its error.

Among these, Levenberg-Marquardt Backward Propagation method was found to perform well for the given dataset, with the Inference engine as Backward Chaining.

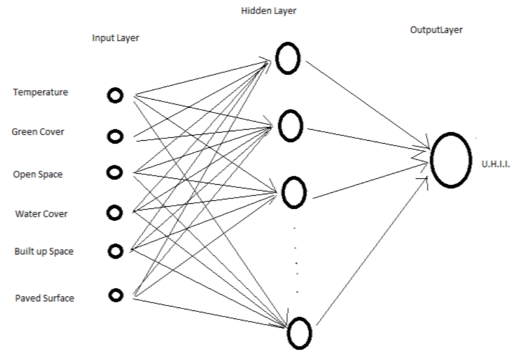


**Fig. 2.1.** Schematic Diagram for Feed forward Neural Network.

Initially the network was trained for 5 hidden neurons. Due to lower performance of the network the number of hidden neurons was increased up to 10 to enhance maximum performance. Finally the trained network was tested for its performance with real-time data collected from 12th station.

While testing enables provision of an independent measure of network performance during and after training; Validation allows measurement of network reasoning and to halt training when reasoning from detailed facts stops improving.

## 3. Results and Discussion

As can be observed from Performance Graph in Fig. 3.1., the Mean Square Error has reduced and got saturated at an Epoch 2. At this point Training, Testing and Validation sets have got converged.

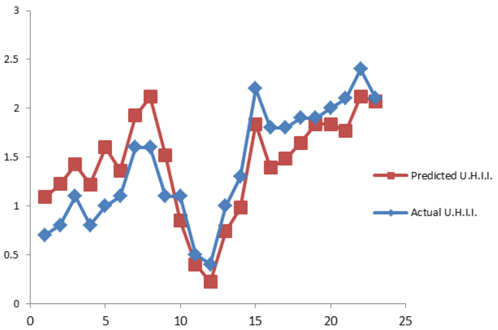


**Fig. 3.1.** Performance graph.

The graph depicts that training is perfect at epoch 2, and that the validation performance has reached a minimum. The training was continued for 5 more iteration before the training stopped.

Also, there are no major problems with the training. The validation and test curves are very similar and the test curve has increased significantly before the validation curve increased.

As also observed from Fig. 3.2., the trained network when tested with real-time data of 12th station shows a difference of nearly 0.1°C to 0.2°C between predicted and actual values.

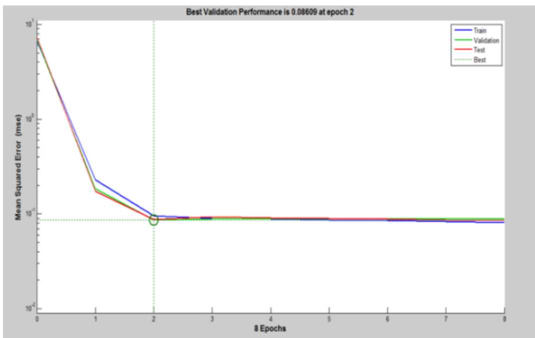


**Fig. 3.2.** Graph showing Predicted and Actual U.H.I.I.

Fig. [3.3.-3.6.] shows plots that represent the relationship between the outputs of the network and the targets. The four plots represent the training as indicated in (Fig. 3.3.), validation (Fig. 3.4.), testing data (Fig. 3.5.), and combined plot (Fig. 3.6.).

In the graph, the dashed line in each plot represents the perfect "Result - outputs = targets". The solid line represents regression between outputs and targets as an exact linear relationship, and as a good fit.

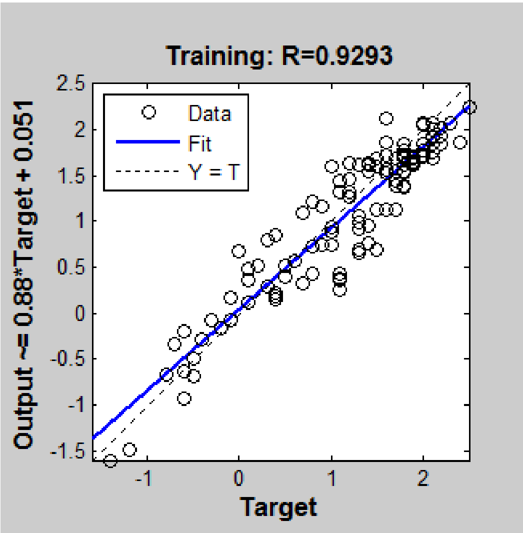


**Fig. 3.3.** Plot for Training of Data.

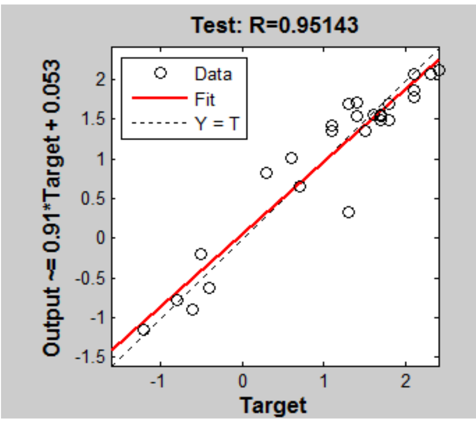


**Fig. 3.4.** Plot for Testing of Data.

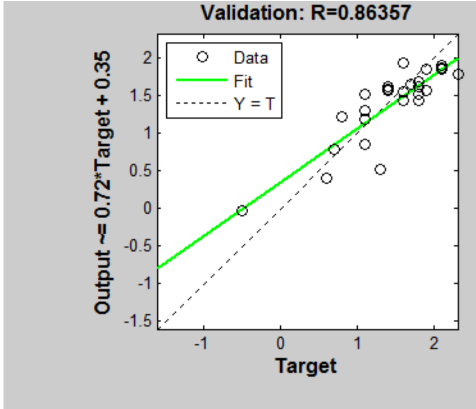


**Fig. 3.5.** Plot for Validation of Data.

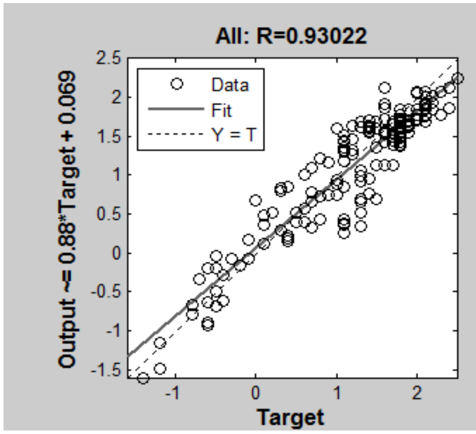


**Fig. 3.6.** Combined Plot.

The validation plot presented in Fig. 3.5., shows that though certain data points do have negligible poor fits; however, as the coefficient of correlation of 0.93 as shown in Fig. 3.6., between the predicted and actual values is extremely good, thereby indicating the difference is quite negligible and the efficiency of the model is good.

## 4. Conclusion

The current study introduces 'S.E.A.' as an approach on how to calculate U.H.I.I. with more precision and accuracy, using 3 years datasets collected from Bangalore. Statistical revelations and practical findings confirm that ‘S.E.A.’ presented far more precision with respect to actual conditions both quantitatively and qualitatively. This newer means of estimation with more precision can assist the policymakers to regard U.H.I.I. as a significant parameter while combating Global Warming and Climate Change.

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