Using Artificial Neural Networks for the construction of contour maps of thermal conductivity

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Abstract: - In this paper a neural network is used for the construction of a contour map. The particular case of the thermal conductivity map of the ground of the island of Cyprus is considered, with archived data at a number of boreholes throughout Cyprus being used for training a suitable artificial neural network. The data were randomly divided into a training and a validation dataset for a multiple hidden layer feed-forward architecture. The correlation coefficient obtained between the predicted and the training dataset is 0.966, indicating an accurate mapping of the data, while the validation (unknown) dataset exhibits an also satisfactory correlation coefficient of 0.955. The dataset was broadened by embedding the patterns used for the validation into the training dataset with the correlation coefficient equalling a higher 0.972. The available input parameters were then recorded for each grid point on a detailed topographic map of Cyprus, whereby the neural network was used to predict the thermal conductivity at each point. The coordinates and the estimated conductivity were then used as input to a specialized contour drawing software in order to draw the geothermal contour map.

Key-Words: - Artificial neural networks, geothermal maps, thermal conductivity, boreholes

1 Introduction

Although the concept of artificial neural network (ANN) analysis has been discovered nearly 60 years ago, it is only in the last 30 years that application software has been developed to handle practical problems. ANNs are good for some tasks while lacking in some others. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems, where humans usually decide on an intuitive basis [1].

ANNs have been applied successfully in various branches of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and so forth. Some of the most important ones are pattern, sound and speech recognition, analysis of medical signatures, identification of military targets and of explosives in passenger suitcases. They have also been used in weather and market trends forecasting, prediction of mineral exploration sites, electrical and thermal load prediction, adaptive and robotic control, and so forth [2].

ANNs are systems of weight vectors – whose component values are established through various machine-learning algorithms–, which take a linear set of pattern inputs and produce a numerical pattern representing the actual output. ANNs mimic somewhat the learning process of the human brain. Instead of complex rules and mathematical routines ANNs are able to learn key information patterns within a multi-information domain. In addition, inherently noisy data do not seem to present a problem as ANNs are tolerant of noise variations [3].

Researchers have used ANNs for the prediction of the thermal properties of materials when parameters affecting them vary and for the prediction of the temperature and thermal properties of the ground in places where limited information is available [4-7].

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Not many researchers studied the use of ANNs for predicting ground thermal properties. Some of them also used other specialized software rather than ANNs for the construction of geothermal resource maps [8-10]. This can actually be a very useful application of ANNs as the knowledge of the ground conductivity is very important for people designing geothermal energy systems for the heating and cooling of buildings. As ground conductivity is not usually readily available to engineers and drilling a test borehole is a time-consuming and expensive process, people usually do not actually carry out the test and depend on rules of thumb in their design. The purpose of the work presented here this paper is to try to create ground conductivity profiles for the whole island of Cyprus using artificial intelligence techniques. Hopefully, this will ease the work of design engineers on this area.

Ground Heat Exchangers (GHEs) are used to exploit effectively the heat capacity of the ground. The knowledge of the thermal properties of the ground is essential for the design of GHEs for Ground Coupled Heat Pumps. In small plants like residential houses these parameters usually are estimated or calculated with the aid of calculation models. In such a case, the morphology of the ground in the area, the thermal conductivity, the density and the specific heat capacity of the different soil formations as well as the temperature of the ground in various depths need to be known. This kind of information is usually available from the Geological Survey Departments of each country or by geologists that perform geotechnical studies in the area. Unfortunately in Cyprus the available data are inadequate due to the limited interest showed by people in the previous decade in the exploitation of geothermal energy and similar applications.

2 ANN Methodology on archived data

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights are associated with the knowledge [11].

ANN models constitute a novelty in system prediction. An ANN operates like a *black-box* model, requiring no detailed information about the system. Instead, it learns the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way in which a non-linear regression might perform. An advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters [1-3].

A neural network consists of a number of processing elements called neurons, each of which has many inputs but only one output. In a typical network, there are three layers of neurons, i.e., an input layer that receives input from the outside world, a hidden layer or layers that receive inputs from the input layer neurons, and an output layer that receives inputs from the hidden layers and passes its output to the outside world and in some cases back to the preceding layers. The strength of the network lies in the interconnections between the neurons, which are modified during training. The training is done by exposing the network to a specific data set of information and by applying a training algorithm to enable the network to produce the desired output [1].

Archived data of ground conductivity recorded for 41 boreholes were then used for training a suitable artificial neural network. For the eight "new" boreholes, the ground conductivity was estimated from samples obtained during drilling, whereas for the rest, data from a study carried out in the seventies were used.

The parameters used for the training of the network are (i) the lithology class at the area of each borehole, (ii) the borehole elevation, (iii) the mean, minimum and maximum ambient air temperature at the location of the borehole, (iv) rainfall at the location of the borehole, (v) the x- and y-coordinates for each borehole, measured from some reference point, (vi) The average conductivity of the borehole.

Table 1. Sample of the data used for the training and validation of the ANN.

Lithology Class	Elevation (m asl)	Mean Annual Ambient Temp.	Min Annual Ambient Temp.	Max Annual Ambient Temp.	Rainfall (mm)	East (m)	North (m)	Thermal Cond. (W/K)
14	52	17.9	11.6	25.8				
16	734	18.4	10.3	28.1				
16	369	18.4	10.3	28.1				
8	330	18.3	9.1	27.6				
….	…	…	…	…				

300	193322	71772	1.58
350	151823	106462	3.14
350	152719	108685	3.14
400	120892	80701	1.27
…	…	…	…

From the 41 borehole sets of data that were available 33 were used for the training of the network and 8 (20%) were randomly selected for its validation. A sample of the data used for the training and validation of the ANN is shown in Table 1.

All data were then normalized in the range [0, 1] before being used in the ANN to increase prediction accuracy.

Various network architectures were investigated for finding the one that could provide the best overall performance. The architecture, among those tested, that gave the best results and was adopted for the present work is shown in Fig. 1. This architecture, used in a number of engineering problems with very good results, is a feed-forward architecture composed of five slabs, three of which are hidden. There are different activation functions in each slab, as can be seen in Fig. 1.

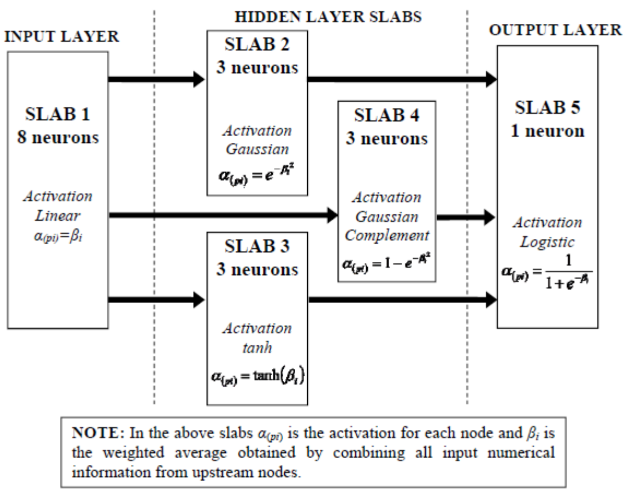

Fig. 1. Employed ANN architecture.

Different activation functions were applied to the hidden layer slabs in order to detect different features in a pattern processed through the network. Eight element inputs were used corresponding to the values of the input parameters. The learning procedure was implemented by using the back-propagation algorithm. For the training of the network, a learning rate and a momentum factor needs to be specified by the user. Both of these constant terms are specified at the start of the training cycle and determine the speed and stability of the network. For this purpose, the learning rate was set to a constant value of 0.1 and the momentum factor to 0.3. The weights were initialized to a value of 0.3. The back-propagation learning algorithm used is described in [12, 13].

The training was stopped when the average error obtained by comparing the actual and the ANN modelled data remained constant for 100,000 events (i.e. about 2380 iterations through all data – epochs – in the training dataset). This is considered a good value, enabling the network to learn the input patterns satisfactorily and to give good predictions while avoiding overtraining.

The correlation coefficient obtained between the predicted and training data set is 0.966, very close to 1, indicating an accurate mapping of the data. Then the network training was frozen and a set of completely unknown test data was applied for verification. The validation of the network was performed by using the “unknown” data for 8 cases, giving a satisfactory correlation coefficient of 0.955.

After the network was trained and achieved a satisfactory level of performance, it was ready to be used for the prediction of the ground thermal conductivity at a number of points all over Cyprus, where recorded data are not available. This was done in order to allow one to obtain information for the whole island, which was then used to produce the required map. For this purpose, a 10×10 km grid was drawn over a detailed topographic map of Cyprus, as shown in Fig. 2, and the lithology class, elevation, mean, minimum and maximum ambient air temperature, rainfall, the x- and y- coordinates for each borehole, measured from the same reference point (at the low left corner), and the conductivity were recorded. A total of 95 grid points was obtained this way.

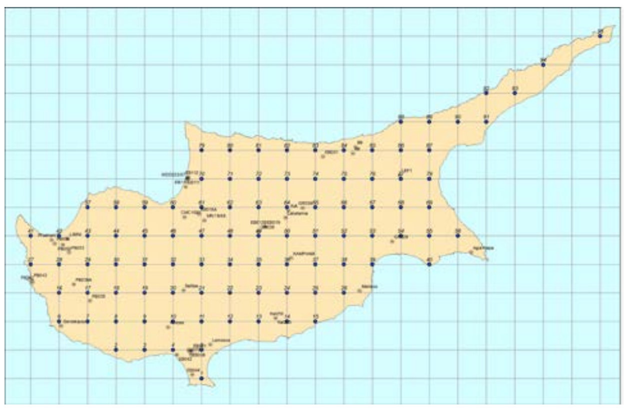

Fig. 2. The 10×10 km grid. The random reference point is at the low left corner.

In order to broaden the database, the 8 patterns used for the validation of the technique were embedded into the training data set and a new training of the network was performed. The architecture of the network, the momentum, the learning rate and the initial weight values were the same as in the validation phase. The correlation coefficient for the training dataset was equal to 0.972, an improvement from the previous training value (0.966), due to the increase in the size of data used. It is worth mentioning that the accuracy of predictions also increased due to the increased size of data used to train the ANN.

3 The geothermal map

As mentioned before, a 10×10 km grid was drawn over a detailed topographic map of Cyprus and the lithology class, elevation, mean, minimum and maximum ambient air temperature, rainfall, and the x- and y-coordinates for each borehole were recorded. This information was then supplied to the trained network and, by doing so, the conductivity was predicted at each grid-point. The x- and y-coordinates and the estimated conductivity for both the original boreholes (41 boreholes) and the grid-points (95 in total), were then used as input to a specialized contour drawing software in order to draw the geothermal map. The map was drawn using ArcGIS 3D Analyst software, which is available through the Geological Survey Department using the Natural Neighbour algorithm. The map obtained is shown in Fig. 3.

It should be noted that on the map, the dots shown represent the points for which data were available. So dots which do not fall on the actual grid points show the actual location of the 41 boreholes.

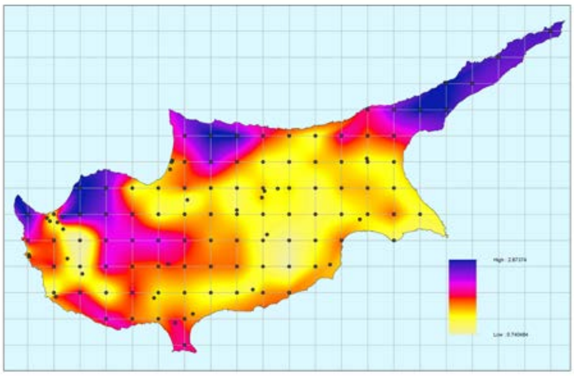

Fig. 3. Geothermal map for thermal conductivity

Now, to evaluate the potential of a site for the installation of shallow geothermal systems and the exploitation of this renewable source of energy by the use of borehole heat exchangers coupled with a heat pump for heating and cooling purposes, additional information will be needed, like the knowledge of the thermal properties of the ground at the particular installation site. These properties are based on geological, hydrogeological and lithological information and influence the specific heat extraction rates [14-16]. The ground conductivity however, is also very important for the designing of such systems [17].

4 Conclusions

In this paper, it has been demonstrated how Artificial Neural Networks can be used for the generation of the ground conductivity map in Cyprus. It is believed that the proposed method of explicitly involving the lithology class, elevation, ambient temperatures and rainfall in drawing the geothermal map, realistically produced a valid map of conductivity. The map will be a helpful tool for engineers designing geothermal systems in Cyprus and in the future, with drillings in areas that no actual data were used for the generation of the ground conductivity map, will further improve further its accuracy.

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