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Artificial neural networks for the generation of a conductivity map of the ground

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ABSTRACT

In this paper a neural network is used for the generation of a contour map of the ground conductivity in Cyprus. Archived data of thermal conductivity of ground recorded at 41 boreholes are used for training a multiple hidden layer neural network with feedforward architecture. The correlation coefficient obtained between the predicted and training data set is 0.9657, indicating an accurate mapping of the data. The validation of the network was performed using an unknown dataset. The correlation coefficient for the unknown cases was 0.9553. In order to broaden the database, the 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 correlation coefficient value for this case was equal to 0.9718. A 10 × 10 km grid is then drawn over a detailed topographic map of Cyprus and the various input parameters were recorded for each grid point. This information was then supplied to the trained network and by doing so ground conductivity was predicted at each grid-point. This map will be a helpful tool for engineers in designing geothermal heat pump systems in Cyprus.

1. Introduction

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 (GCHP). 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. The usual geothermal systems employed in Cyprus are the GCHP with GHEs up to about 100 m, so the systems belong to the category of shallow geothermal systems.

The knowledge of the ground conductivity is very important for people designing geothermal energy systems for the heating and cooling of buildings. Thermal conductivity is defined as the time rate of steady-state heat flow through unit thickness of unit area of a homogeneous material, induced by a unit temperature gradient in a direction perpendicular to that unit and is mainly measured in W m^{-1} K^{-1} [1].

Ground conductivity is not usually readily available to engineers and for this purpose, normally a test borehole is drilled and samples of ground are collected at various depths to find an average thermal conductivity of the borehole. Otherwise an in-situ, thermal response test needs to be performed [2,3]. This is a time-consuming and expensive process, so people usually do not actually carry out the test and depend on rules of thumb in their design. The purpose of the work presented in this paper is to create the ground conductivity profile, for the first 100 m of depth, for dry soil and for the whole island of Cyprus using artificial intelligence techniques. Hopefully, this will ease the work of design engineers on this area.

Although the concept of artificial neural network (ANN) analysis has been discovered nearly 60 years ago, it is only in the last

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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 [4].

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 [5].

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 [6].

ANNs differ from the traditional modelling approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way. They are usually used to address problems that are intractable or cumbersome to solve with traditional methods. Neural networks are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They can learn from examples, they are fault-tolerant in the sense that they are able to handle noisy and incomplete data, they are able to deal with non-linear problems, and once trained they can perform predictions at a very high speed. ANNs have been used in many engineering applications such as in control systems, in classification, and in modelling complex process transformations [4,6].

Researchers 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. There is a large number of researches using ANNs for the former case and fewer for the latter. Ramvir et al. [7] used ANNs to predict more effectively the thermal conductivity of moist porous materials than using any other model. Yusuf et al. [8] studied the efficiency of an ANN model for estimating the thermal resistivity of soils. They showed that the results were in an extremely good agreement with experimental results. These were compared with the results obtained from the empirical relationships reported in the literature, concluding that ANNs results were superior. Elshorbagy and Parasuraman [9] investigated the efficacy of ANNs for modelling the complex soil moisture dynamics. ANNs were even used by Illiades and Maris [10] in the estimation of the average annual water supply, in each mountainous watershed of Cyprus.

Not many researchers studied the use of ANN's for predicting ground thermal properties. Some of them also used other specialized software rather than ANNs for the construction of geothermal resource maps. Kalogirou et al. [11] used ANNs for the generation of geothermal maps (contours) of temperature at three depths (20, 50 and 100 m) by considering land configuration in Cyprus while Kaftan et al. [12] used ANNs to estimate the structure parameters as location, depth, and density contrasts for gravity data in Turkey. Xue et al. [13] predicted the ground thermal conductivity by using samples from the Quaternary stratum in Tianjin. He also concluded that the model developed could also be used for the comparison and validation of in-situ TRT results during the GSHP applications.

The neural network method falls under the generic non-linear analogue techniques and has revived the idea of analogue data analysis. Neural networks have been used in the past by Kalogirou et al. [14] for time series reconstruction of precipitation records with acceptable accuracy. They have also been used in the drawing of isohyets, which are contour lines of equal rainfall [15]. Review of applications of ANNs in energy systems can be found in Refs. [4–6].

Other applications of ANNs in geothermal studies have been presented by Alvarez del Castillo et al. [16] for modelling two-phase flows in geothermal wells, by Bassan et al. [17] for the estimation of the static formation temperatures in geothermal wells and by Arslan [18] for the optimization of a Kalina cycle power generation system from medium temperature geothermal resources.

Generally, for generating surfaces from specific data sets collected though field sampling, like topographic surfaces, bedrock surfaces, groundwater tables and so forth, various interpolation methods exist. These methods include the trend surface method [19], the inverse distance weighted [20], the triangulation [21], and kriging (or Gaussian process regression) method [22]. The triangulation method generates surfaces represented by irregularly spaced points. The other three methods generate surfaces represented by equally spaced data points. No method works best for any data set and each of the above methods has its own advantages and disadvantages. Therefore, for a meaningful interpolation a good understanding of the data sets is of outmost importance.

Many researchers used different methods for producing thermal conductivity maps of a specific area. De Lima Gomes and Hamza [23] used the results of geothermal studies carried out at 72 localities in the state of Rio de Janeiro to evaluate the temperature gradient and heat flow values of the upper crust. After an analysis of the data sets and incorporation of appropriate corrections they plotted the thermal characteristics to allow a better understanding of the regional distribution of thermal gradients and heat flow within the study area. Their results indicate that most of the rock formations are characterized by thermal conductivity values varying from 2.2 to 3.6 W m^{-1} K^{-1}. They also presented two plotted patterns: (a) one similar to that depicted in geologic maps of the study area, since they assumed that the thermal conductivity is constant within any specific geologic formation and (b) a second pattern by relating the experimental data to the lithologic sequences encountered in the wells and petrologic descriptions of outcrops.

Munoz et al. [24] presented the results of a regional-scale estimation of low-enthalpy geothermal resources for district heating in the Santiago basin. The estimation was based on comparison of soil thermal properties and hydro-geological parameters. They presented information plotted on maps using the Geographic Information System (GIS). The continuous surface was estimated by interpolation using the ordinary kriging method with the geostatistical tool of ArcMap 10.0. They estimated that a drilling depth between 35 and 105 m with an average of 58 m is required to supply an energy demand of 2.7 kW, using a Borehole Heat Exchanger in the Santiago basin. Also they estimated that in case of the Ground Water Heat Exchanger, the depth to be drilled ranges between 10 and 400 m with an average value of 68 m.

Ramstad et al. [25] described the methodology for producing a thermal conductivity map of an area around Oslo, Norway. The map was based on the results of 1398 thermal diffusivity measurements of rock core samples. The thermal diffusivity was measured and used in the calculation of the thermal conductivity of the different geological units in the bedrock map of the Oslo region. The median value for the whole data set was 2.62 W m^{-1} K^{-1}, while the minimum and maximum values were 1.0 and 6.88 W m^{-1} K^{-1} respectively.