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GROUNDWATER HEAT PUMP SYSTEMS: NEURAL NETWORK APPROACH

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Introduction

The market for geothermal heat pumps has grown considerably in the last decade (Fry 2009; Bayer et al. 2012) and is one of the fastest-growing renewable energy technologies.
Computational fluid dynamic (CFD) models are widely used in this field because they offer the opportunity to calculate the time evolution of the thermal plume produced by a heat pump, depending on the characteristics of the subsurface and the heat pump. Nevertheless, these models require large computational efforts, and therefore their use may be limited to a reasonable number of scenarios. Neural networks could represent an alternative to CFD for assessing the TAZ under different scenarios referring to a specific site. The main advantage of neural network modeling is the possibility of evaluating a large number of scenarios in a very short time, which is very useful for the preliminary analysis of future multiple installations. The neural network is trained using the results from a CFD model (FEFLOW) applied to the installation at Politecnico di Torino (Italy) under several operating conditions.

Material and Methods

The test site (Politecnico di Torino) is located in the urban area of Turin the capital of the Piemonte Region in northwest Italy (geographical coordinates 45°03'45''N, 7°39'43''E, elevation 250m a.s.l.). The buildings connected to the existing GWHP plant are used for university offices and laboratories. Two 47m-deep wells, one used for groundwater extraction and the other for injection, having the same technical characteristics are present at the site. The conceptual model was set up considering the structure and geometry of the different units of the domain. Several control points were included downgradient with respect to the injection well in order to check the evolution of the thermal plumes over the space (Fig.1).
Control points 19, 21, 24, and 26 are placed along the line that connects the injection well with the piezometer, while control points 20, 22, 23, 25, and 27 are projections of previous control points along the groundwater flow direction. The horizontal angle between the two lines is almost 30°.Control points 19-23, 25, and 27 are located 10 m from the injection well while control points 24 and 26 are located 20 m from the injection well. In order to show the main effects of the thermal plume, are reported three principal scenarios in Table 1: are analyzed and modeled using FEFLOW and appropriate FEFLOW time-varying functions (TVFs) for Q and ΔT were thus defined. The TVFs have been discretized considering a time step of one day, while the automatic computational time-step has been used for FEFLOW simulations. The first two scenarios are different because of a different maximum value of the re-injection temperature (3.3 °C in the first scenario and 11 °C in the second scenario). The third scenario is similar to the first one but a small value of the reduction in mass flow rate is considered, which means that when the heating/cooling load decreases, the heat pump is primarily operating by reducing the re-injection temperature change with respect to the extraction temperature.
The neural network model can be used to predict groundwater temperatures for installations that still do not exist or that can be caused by variations in the heat pump operation (e.g. use of large storage systems or variation in the control mode). For this reason, the network should be trained considering a large variety of CFD simulations, performed by modifying the boundary conditions that refer to the heat pump operation. In the case of complex phenomena, multiple neurons arranged into layers can be used. Usually, two layers are used: in the first layer, the hidden layer, the function associated with the neuron is generally non linear (e.g. a sigmoidal function), while in the second layer a linear or non linear function is applied (Hertz et al. 1991). The neural network developed is now applied to a real case. The goal is to compare the groundwater temperatures calculated with the neural network model and with FEFLOW. To use the neural network, an equivalent semi-sinusoidal function must be obtained for the cooling load. The reason for using the equivalent function is due to the expected applications of this kind of model, which is mainly focused on non-existing installations. Since this is not a

posteriori simulation, data about the thermal request are not known, therefore it makes sense to consider approximate functions.

Results

The results deriving by the modeling of scenarios are compared by checking the groundwater temperatures at two control points downstream of the injection well. The groundwater temperatures in the three scenarios tend to converge at longer distances, where temperature gradients are small. Figure 2 shows a comparison between the temperature profile at the piezometer calculated using the neural network, the values simulated using FEFLOW and the measured temperatures. The results provided by the FEFLOW model are very close to the measurements. It is worth recalling that the input data for this model are the measured values of withdrawal mass flow rate and injection temperature. The results provided by the ANN model have similar trends and close values with respect to the FEFLOW model. There are two main sources of difference between the results: 1) the ANN model is a reduced and non-physical model which is originated from the physical model and therefore characterized by larger approximation and 2) the inputs are the semi-sinusoidal curves, which are obtained from energy equivalence, thus approximated. The temperature difference between the peak temperatures obtained with the two models is 0.34 °C, while the root mean square error in a period of 200 days is 0.46 °C. The largest temperature deviation is about 1 °C. It is worth remarking that the purpose of the ANN model is to predict the thermal impact of a possible installation, not in its vicinity, but in areas where other heat pumps operate or may be installed in the future.

Conclusions

In this paper, the use of a neural network model to predict groundwater temperature profiles at a specific site is proposed. The network is trained using simulations performed using a computational fluid dynamic model such as FEFLOW. In these simulations, theoretical profiles of the plant utilization have been considered; this allows one to characterize an application using a limited number of parameters, which is a desirable feature for the purpose of this model. Nevertheless the ANN model can be easily implemented into optimization procedures and used by people that is not expert on CFD modeling.

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Scenario	Maximum heating [kW]	Maximum cooling [kW]	Maximum temperature difference [°C]	Mass flow rate reduction [kg/s]
1	450	450	3.3	0.7
2	450	450	11	0.7
3	450	450	3	0.1

Tab.1 – FEFLOW modeling functioning scenarios

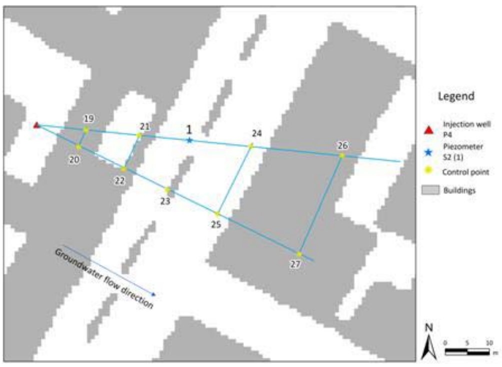

Fig. 1 – Plan view of the control points on the official cartographical map.the topographical map.

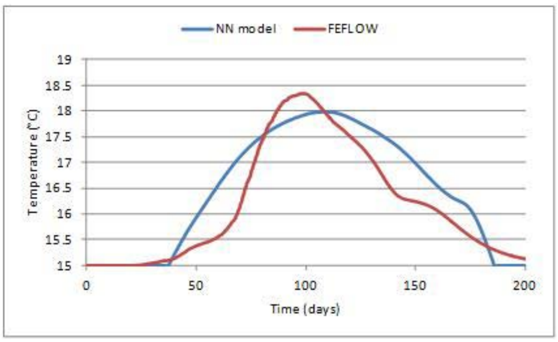

Fig. 2 – Comparison among the measured temperatures in the piezometer and those simulated with FEFLOW and calculated with the ANN model.