Available online at www.sciencedirect.com
ScienceDirect
Procedia Environmental Sciences 25 (2015) 50 – 57
Procedia Environmental Sciences

7th Groundwater Symposium of the
International Association for Hydro-Environment Engineering and Research (IAHR)

Uncertainty-based analysis of variations in subsurface thermal field due to horizontal flat-panel heat exchangers

V. Ciriello[a]*, M. Bottarelli[b] and V. Di Federico[a]

[a] *Dipartimento di Ingegneria Civile, Chimica, Ambientale e dei Materiali, Univeristà di Bologna, Italy*
[b] *Dipartimento di Architettura, Univeristà di Ferrara, Italy*

Abstract

Geothermal energy is produced by coupling a heat pump with the ground, resorting to ground heat exchangers (GHEs) that can be installed in vertical or inclined boreholes or horizontally in shallow ground. Horizontal GHEs are easy to be installed and maintained, more compliant with environmental regulations, and generally do not interfere with groundwater systems. To overcome this deficiency, the shape of the exchangers plays a relevant role. Here, we consider a new shape devised in the form of a flat-panel, positioned horizontally and edgeways in a shallow trench. Its energetic performance compares favourably with other advanced shapes. In order to design and verify geothermal systems, it is crucial to predict accurately the soil thermal field around the exchanger. This prediction is generally compromised by the uncertainty associated with (i) the thermo-physical properties of the soil and (ii) the solar impact on surface energy balance, that mainly controls the thermal energy storage in the first layer of the subsurface environment. In this context, global sensitivity analysis (GSA) may be performed to delineate the most significant sources of uncertainty and address measurements accordingly. Sensitivity studies of other horizontal GHEs have been developed without resorting to GSA. Here, we present an effective approach for the characterization of the uncertainty associated with the variations in the soil thermal field induced by a flat-panel. We show that the variability associated with the climate parameters plays the most relevant role. It impacts the length of the exchanger for fixed specific power required at the flat-panel, thus affecting the overall design of the geothermal system.

Peer-review under responsibility of the Scientific Committee of the IAHR Groundwater Symposium 2014

Keywords: horizontal ground heat exchangers, ground thermal field, global sensitivity analysis, polynomial chaos.

* Corresponding author.
E-mail address: v.ciriello@unibo.it

Peer-review under responsibility of the Scientific Committee of the IAHR Groundwater Symposium 2014
doi:10.1016/j.proenv.2015.04.008

1. Introduction

Ground-coupled heat pump (GCHP) systems are regarded as a sustainable energy technology for heating and cooling purposes, as well as a profitable solution when properly designed [1-3]. In these installations the heat pump is coupled via a closed loop with the ground by means of ground heat exchangers (GHEs), which can be settled vertically or horizontally at diverse depths. Horizontal installations are placed in shallow diggings a few meters of depth, conversely to vertical solutions in which GHEs are installed in boreholes drilled down up to a hundred meters deep. Owing to their different depths of installation, the vertical technology exploits a real geothermal source, while for the horizontal one, the ground mainly constitutes a solar energy buffer [4]. Nevertheless, both these technologies require an accurate estimation of the soil thermal properties, i.e. the thermal conductivity and the volumetric heat capacity, since the heat transfer in the ground is generally dominated by conduction. For vertical GHEs, the thermal response test is the most widespread method to evaluate the average soil thermal properties; though the limits of this approach are well known [5-7], the cost of other surveying methods is rarely justified. In case of horizontal GHEs, the soil thermal properties can be estimated through laboratory tests or estimated based on literature-derived reference values according to the lithology. However, other variables play an important role in the design of shallow systems. Conversely to deep GHEs, horizontal devices are subjected to diverse energy balances occurring at the soil surface from year to year. Furthermore, due to infiltration, the soil thermal properties vary significantly following the changes in soil humidity [8,9].

In this work we employ global sensitivity analysis (GSA) to characterize the influence of the uncertainty associated with the main parameters that control heat transfer in shallow soils. To do this we adopt the Sobol indices [10,11] as sensitivity measures and resort to the Polynomial Chaos theory [12,13] for an effective computational approach [14]. We focus our analysis on the soil thermal properties and the surface energy balance, identifying four key parameters. In particular, we account for the uncertainty associated with two domain parameters: (i) the thermal conductivity, and (ii) the volumetric heat capacity. Especially for shallow GHEs, both these parameters are commonly surveyed without great accuracy. Regarding to the surface energy balance, we consider (i) the yearly average ground temperature, and (ii) the amplitude of its oscillation to be the main parameters associated with the climate zone. Note that from year to year climate conditions may change significantly; these thermal trends may affect the behaviour of the system.

Our methodology is based on the following steps. First we model the four parameters subjected to uncertainty as independent random variables of assigned distribution. Then, we approximate the thermal field (computed by means of a numerical finite element model) via Polynomial Chaos Expansion, in the domain of interest. This allows to effectively perform GSA almost continuously in space and time. For more details regarding to this approach refer to [15,16]; a comparison of accuracy and computational cost with respect to traditional Monte Carlo simulations is provided in, e.g., [17]. Our sensitivity results show the importance, especially for shallow installations, of resorting to a statistical approach able to account for the main uncertainties affecting predictions of the soil thermal field, whose value in turn influences the design of the GHEs.

2. Case study

In this section, the energy behaviour of a shallow GHE flat-panel [18] is investigated by means of a numerical model. The numerical finite element code FEFLOW® (version V6.1, 2013) is employed to solve the heat transfer equations in porous media under unsteady-state and saturated conditions. As depicted in Fig. 1, we consider a 2D domain (10 m x 10 m) in which the flat-panel, having a height of 1 m, is located on the left side at a depth of 1 m; the panel, through which the working fluid of the closed-loop flows, is installed in a trench whose thermal properties are supposed similar to those of the surrounding ground.

Hydraulic and thermal boundary conditions of the 1st and 2nd kind are fixed at the outer domain limits in order to represent realistic operating conditions. At the bottom of the domain, constant temperature of 15°C and hydraulic head of -4.0 m are assumed, representing undisturbed conditions. Heat and mass transfer are neglected at the vertical boundaries, except for the GHE activity. At the surface boundary, a temperature time series is fixed, as prescribed by the International Ground Source Heat Pumps Association for the design of GHEs and employed by the Italian Regulation UNI11466 [19]:

$$T(z,t) = T_M - A \cdot \cos[\omega(t - D)] \tag{1}$$

where $\varpi = 2\pi/365$, T is the ground temperature at the Julian day t and depth z, and T_M is the yearly average temperature; α is the soil thermal diffusivity, A is the semi-amplitude of the yearly oscillation of ground temperature and D is the Julian day of the year correspondent to the minimum of ground temperature at the working depth.

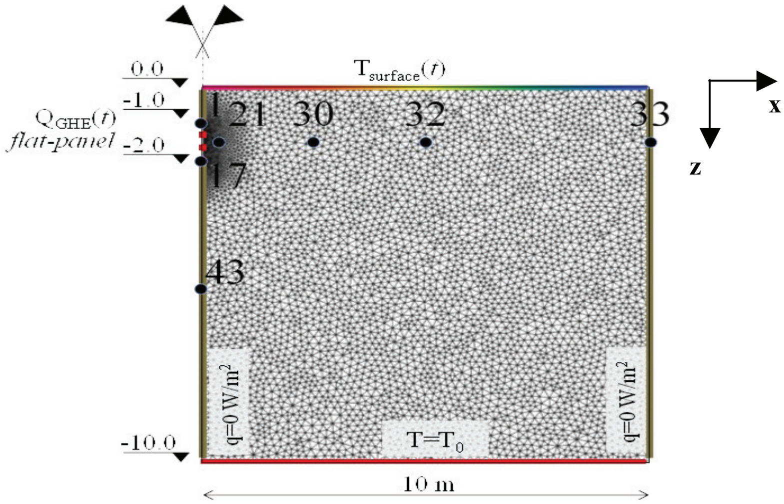

Fig. 1. Domain schematic.

Operation of the GHE is modeled by considering the energy requirements both in heating and cooling conditions for a given residential building, simplified as a lumped system [3]. The hourly time series of the GHE heat flux is related to the energy requirement of a GCHP, working to maintain a target temperature of 20°C in winter and 26°C in summer inside the building. Through several simplifications, the energy requirement has been linked only to the outdoor air temperature and the building physics (described by, e.g., the overall thermal transmittance and the global mass). The resulting heat flux is depicted in Fig. 2a for a whole year, to show the heating and cooling mode, and in Fig. 2b for a winter week, to detail the hourly operation mode. Both these figures show also the maximum and minimum daily temperatures occurring over the ground surface. For simplicity, the GHE is supposed to start operating in heating mode in an undisturbed ground thermal field on the first Julian day; more realistically, the operation would start about two months in advance.

Within this numerical framework we consider, as sources of uncertainty, the key parameters collected in Table 1, i.e. (i) the soil thermal conductivity, λ, (ii) the soil volumetric heat capacity (given by the product $\rho \cdot c = \lambda / \alpha$ between the density and the specific heat of soil), (iii) the yearly average ground temperature, T_M, and (ii) the semi-amplitude of its oscillation, A. Adequate statistical distributions have been chosen by means of a preliminary statistical analysis of soil thermal properties and temperature time series related to the area of Ferrara (Italy).

In order to set the initial temperature condition in the domain, we run the model for a whole year, with the GHE not operating and for average values of the parameters collected in Table 1.

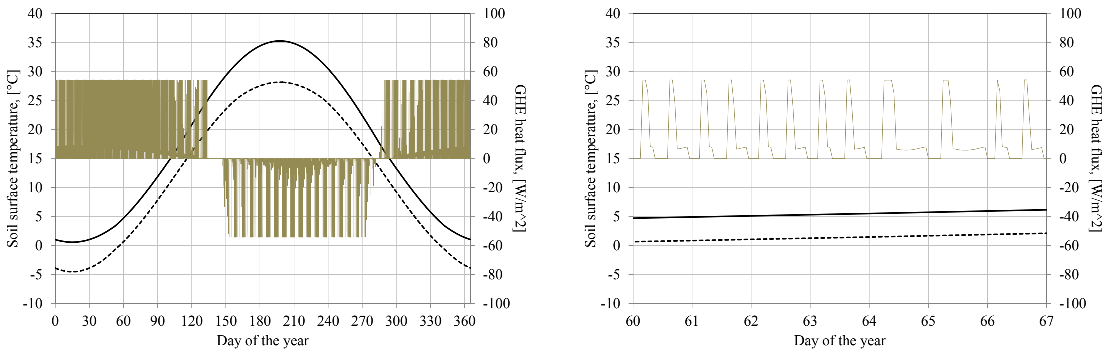

Fig. 2. (a) Soil surface temperature (in two simulated cases) and GHE heat flux versus time; (b) enlarged image at hourly scale.

Table 1. Key model parameters and respective probability distribution.

Parameter	Distribution
Thermal conductivity (λ, in W/mK)	~ N (1.20, 0.20)
Volumetric heat capacity (ρ c, in J/m^{3}K)	~ N (1840100, 201780)
Semi-amplitude (A, in °C)	~ N (16.34, 1.47)
Yearly average temperature (T_M, in °C)	~ N (14.37, 1.17)

3. Methodology

Consider a model function $y = f(\mathbf{x})$, y being a target random response (at a prescribed space-time location) depending on the vector $\mathbf{x}$ of independent random parameters defined in the n-dimensional unit hypercube, I^n. If $f(\mathbf{x})$ is integrable, the following representation holds [10]:

$$f(\mathbf{x}) = f_0 + \sum_i f_i(x_i) + \sum_{i<j} f_{ij}(x_i, x_j) + \ldots + f_{1,2,\ldots n}(x_1, x_2, \ldots x_n), \quad \int_0^1 f_{i_1,\ldots i_s}(x_{i_1}, \ldots x_{i_s}) dx_k = 0, \tag{2}$$

where $k = i_1,..i_s$, $1 \le i_1 < ... < i_s \le n$ $(s = 1,...,n)$ are the indices specifying the parameters upon which each term depends and the 2^n summands in (1) are orthogonal functions that can be expressed as integrals of $f(\mathbf{x})$. Equation (2) is typically termed ANOVA decomposition [10]. The generic s-order Sobol' index $S_{i_1,...i_s}$ is defined as [10,11]:

$$S_{i_1,..i_s} = V_{i_1,..i_s} / V, \tag{3}$$

$V = \int f^2(\mathbf{x})d\mathbf{x} - f_0^2$ being the total variance associated with y, and $V_{i_1,...i_s} = \int f_{i_1,...i_s}^2 dx_{i_1}..dx_{i_s}$ the partial variance expressing the contribution due to the subset $\{x_{i_1},..x_{i_s}\}$ of model parameters. These quantities can be computed if $f(\mathbf{x})$ belongs to the space of square-integrable functions. The indices defined in (3) sum up to unity. The first-order or principal sensitivity indices, S_i, describe the significance of each parameter when individually considered. Higher-order indices describe the effects of interactions among parameters. The overall effect of a given parameter x_i is described by the total sensitivity index $S_{T_i} = \sum_{\eta_i} S_{i_1,...i_s}$, $\eta_i = \{(i_1,..i_s): \exists k, 1 \le k \le s, i_k = i\}$.

In order to drastically reduce the onerous computational cost associated with a complete GSA, traditionally performed via Monte Carlo simulation [11], we resort to model reduction techniques and in particular we employ the Polynomial Chaos approach [12]. In this framework, one starts by noting that any square-integrable random model response, y, may be approximated by the following chaos representation [13]:

$$y \cong \tilde{y} = \sum_{j=0}^{P-1} a_j \Psi_j(\mathbf{x}), \; P = (M+p)!/(M!p!), \tag{4}$$

where Ψ_j denotes the generic multivariate orthogonal polynomial and P is the number of (unknown) polynomial coefficients, a_j. Note that the choice of the polynomial basis is linked to the distribution of the independent random parameters [20]. Assessment of the coefficients a_j can be performed by means of the probabilistic collocation method [21] that requires a limited number (proportional to P and depending on the complexity of the response surface) of full model runs. Once the PCE surrogate model is defined, GSA can be performed with no additional computational cost. Orthogonality of the polynomial basis allows recognizing that the mean of the model response coincides with a_0; the total variance is $V = Var\left[\sum_{j=0}^{P-1} a_j \Psi_j(\mathbf{x})\right] = \sum_{j=1}^{P-1} a_j^2 E\left[\Psi_j^2(\mathbf{x})\right]$, and the Sobol indices can be effectively derived as [14]:

$$S_{i_1,...i_s} = \sum_{\alpha \in \varphi_{i_1...i_s}} a_\alpha^2 E\left[\Psi_\alpha^2\right] / V. \tag{5}$$

We employ the technique summarized above to reduce the numerical model described in Section 2. In our case study, the target model response is given by the temperature at diverse space-time locations, i.e. $T(x,z,t)$. Following the probabilistic collocation method, a number of 15 full model runs are required to derive the PCE meta-model of order 2, given that four parameters are taken to be uncertain. In particular, we resort to the Hermite Chaos since the parameters are normally distributed.

4. Discussion

Fig. 3 depicts the total sensitivity indices of Sobol, associated with the parameters collected in Table 1, versus time. This is done for six points inside the domain of interest (see Fig. 1). Specifically, points 1, 17 and 43 (first column in Fig. 3) are vertically aligned along the direction of the flat-panel, while points 21, 30 and 32 (second column in Fig. 3) are aligned horizontally along its axis of symmetry.

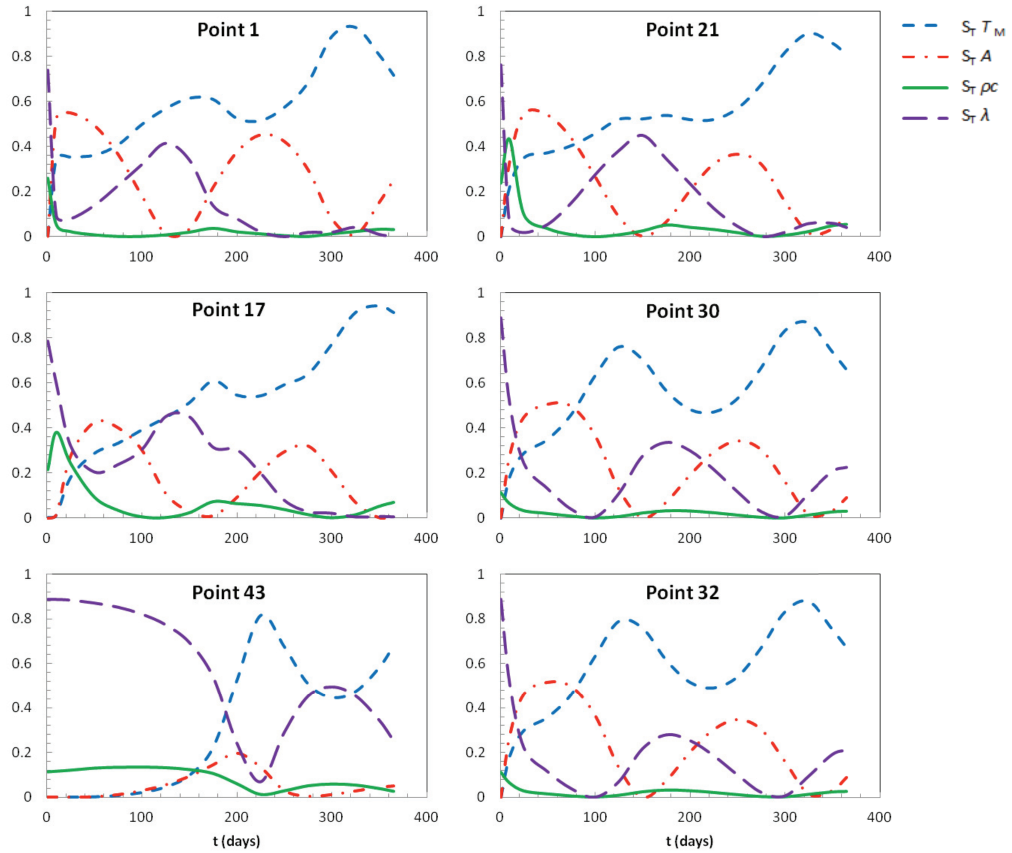

Fig. 3. Total Sensitivity Indices of the uncertain model parameters versus time at different points in the domain (Fig. 1).

One can observe that uncertainty in T_M mainly affects the variability of the thermal field almost everywhere in the domain and during the whole simulated year. Only at point 43 the trend is quite different, and the uncertainty associated with the thermal conductivity, λ, dominates in the first half of the year. This makes sense since the farther from the soil surface, the smaller the influence of climate parameters is. In this part of the domain, heat conduction is significantly affected by the soil thermal properties; nevertheless, note that the influence of the volumetric heat capacity is generally negligible for the selected case study. Regarding to A, its uncertainty controls the variability of the thermal field across the full layer where the shallow GHE operates, especially during the heating period. For all the parameters, the oscillations of the sensitivity indices over time are related to the time shift of the thermal wave as it advances downward, and to the operating mode of the flat-panel (on/off, heating/cooling). The thermal inertia of soil induces a fast attenuation and a time shift of the surface thermal wave even in presence of the GHE. Along the horizontal direction, similar results at points 30 and 32 denote that the radius of influence of the device is relatively small.

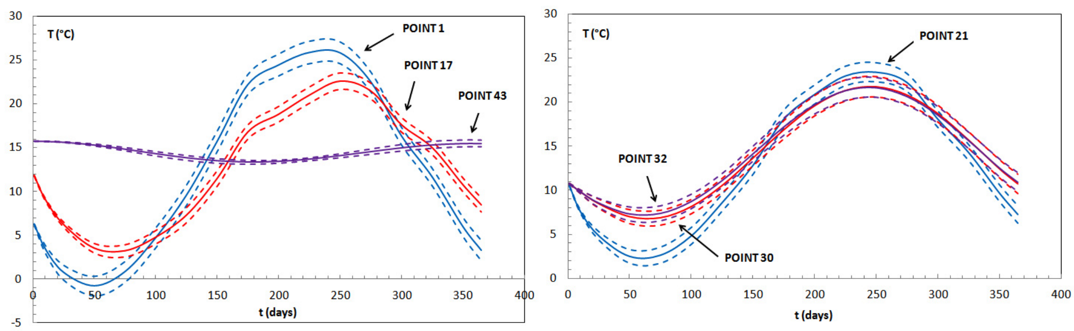

Fig. 4. Mean values of temperature versus time for diverse points in the domain (Fig. 1) with confidence intervals of amplitude equal to one standard deviation.

In Fig. 4 the mean values of temperature are shown versus time at selected domain points; confidence intervals, of amplitude equal to one standard deviation, are also depicted for all cases examined. Note that the variance associated with temperature is due to the propagation of the uncertainty in model parameters; information regarding the contribution of each parameter may be derived by means of results represented in Fig. 3. One may observe that the temperature variance significantly decreases with depth, being reduced by at least one order of magnitude in a few meters. At the same depth of the GHE, uncertainty in the soil thermal field does not vary significantly, thus pointing out the primary contribution of climate parameters. At about 2.5 m from the flat panel (point 30) variations due to the operation of the device become negligible. This kind of information is particularly relevant when designing GHEs, since one has typically to reduce the mutual interference among the devices.

During the heating operation mode the GHE is cooling the ground. The more significant this effect is, the larger the perturbation induced in the environment, and the operation of the device itself may be compromised. Propagation of the uncertainty and GSA may assist the design of the devices, giving also the chance to control this phenomenon. For the present case study, inappropriate temperature perturbations are not detected at the selected points during the simulated year.

5. Final remarks

Results obtained via GSA allow to understand the role played by key soil and climate parameters in heat conduction processes in the presence of a flat-panel GHE. This is relevant to reduce the uncertainty in the estimation of the soil thermal field, affecting in turn the design of the exchangers in real applications. The way to do this consists in improving measurements of the influential parameters at the most sensitive space-time locations. In the present case study, we analyzed a basic configuration and we found that the variability associated with climate parameters plays the most relevant role. Importance of heat conductivity increases with depth. The kind of analysis proposed here for a simplified configuration, including a single device, becomes more relevant when designing complex real installations. In particular, this methodology allows to estimate accurately the perturbations induced in the ground by the exchangers. This is crucial to (i) maximize the efficiency of the devices and (ii) keep the installation compliant with the environment and subsurface natural processes.

References

[1] Kavanough SP, Rafferty K. Ground-source heat pumps design of geothermal systems for commercial and institutional buildings, ASHRAE, 1997.

[2] Rybach L, Eugster WJ. Sustainability aspects of geothermal heat pumps. In: Proceedings, 27th Workshop on Geothermal Reservoir Engineering, Stanford, CA, 2002.

[3] Bottarelli M, Gabrielli L. Payback period for a ground source heat pump system. Int J of Heat and Technology 2011; 29:145-150.

[4] Chiasson AD. Modeling Horizontal Ground Heat Exchangers in Geothermal Heat Pump Systems. In: Proceedings of COMSOL conference, 2010.

[5] Bozzoli F, Pagliarini G, Rainieri S, Schiavi L. Estimation of soil and grout thermal properties through a TSPEP (two-step parameter estimation procedure) applied to TRT (thermal response test) data. Energy 2011; 36(2):839-846.

[6] Wagner V, Clauser C. Evaluating thermal response tests using parameter estimation for thermal conductivity and thermal capacity. J Geophys Eng 2005, 2(4):349-356.

[7] Wagner V, Bayer P, Kübert M, Blum P. Numerical sensitivity study of thermal response tests. Renew Energ 2012, 41:245-253.

[8] de Vries DA. Thermal properties of soils. In: Physics of Plant Environments, W. R. van Wijk, 1963.

[9] Campbell GS, Jungbauer JD, Bidlake WR, Hungerford RD. Predicting the effect of temperature on soil thermal conductivity. Soil Sci 1994, 158(5):307-313.

[10] Sobol IM. Sensitivity estimates for nonlinear mathematical models. Math Modeling Comput 1993, 1:407-414.

[11] Sobol IM. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Math Comput Simulation 2001, 55:271-280.

[12] Wiener N. The homogeneous chaos. Am J. Math. 1938, 60:897-936.

[13] Ghanem RG, Spanos PD. Stochastic finite elements-a spectral approach. Berlin: Springer, 1991.

[14] Sudret B. Global sensitivity analysis using polynomial chaos expansions. Reliab Eng Syst Safety 2008, 93:964-979.

[15] Ciriello V, Guadagnini A, Di Federico V, Edery Y, Berkowitz B. Comparative analysis of formulations for conservative transport in porous media through sensitivity-based parameter calibration. Water Resour Res 2013, 49(9):5206-5220.

[16] Ciriello V, Di Federico V, Riva M, Cadini F, De Sanctis J, Zio E, Guadagnini A. Polynomial chaos expansion for global sensitivity analysis applied to a model of radionuclide migration in a randomly heterogeneous aquifer. Stoch Env Res Risk A 2013, 27(4):945-954.

[17] Ciriello V, Di Federico V. Analysis of a benchmark solution for non-Newtonian radial displacement in porous media. Int J Nonlinear Mech 2013, 52:46-57.

[18] Bottarelli M, Di Federico V. Numerical comparison between two advanced HGHEs. Int J of Low-Carbon Technologies 2012, 7:75-81.

[19] UNI11466: Heat pump geothermal systems - Design and sizing requirements, Italian Authority of Techincal Regulation, UNI 11466:2012, 2012.

[20] Xiu D, Karniadakis GE. The Wiener-Askey polynomial chaos for stochastic differential equations. J Sci Comput 2002, 24(2):619-644.

[21] Webster M, Tatang MA, McRae GJ. Application of the probabilistic collocation method for an uncertainty analysis of a simple ocean model. Technical report MIT series no. 4, Massachusetts Institute of Technology, 1996.