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Assessment of Transient Extractable Power from Puga Geothermal Field using Neural Network Model

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ABSTRACT

Three-dimensional conceptual model of Puga geothermal reservoir, which is developed using the available resistivity data is presented and the appropriate zones for the extraction of entrapped thermal energy are demarcated. Subsequently, the dynamic response of reservoir under doublet extraction scheme is simulated under various operational conditions by considering coupled fluid flow and heat transfer processes involved during the operation phase of the geothermal reservoir. Each operating condition is a combination of distinct well spacing, injection temperature, injection/extraction rate and injection depth. Subsequently, the transient temperature of thermal water that can be extracted over the lifetime of reservoir is estimated by solving the coupled governing equations, which is further used to be determine the extractable power. The heuristic knowledge between well spacing, injection/extraction rate, injection depth, extractable temperature and time is used to train and develop a feed forward neural network model which can further be used to predict the transient extractable temperature for any desired operating condition. The extractable temperature estimated using developed network model is observed to be satisfactory as the mean percentage average deviation is less than 0.5 %. The developed neural networks model, helps to estimate the extractable power from Puga geothermal reservoir for different operational conditions without performing simulation studies for intermittent conditions.

1. INTRODUCTION

The consumption of energy has been growing rapidly in India. Coal, lignite, natural gas, petroleum and renewable sources are being used conventionally to meet the required demand. From the breakup of primary commercial energy resources discussed by Lakshmi, (2017), it is evident that the coal is the major contributor for the generation of electricity. Energy generation through the combustion of coal has an adverse impact on environment (Jha and Puppala, 2017). Considering the foreseen energy demand, dependency of the country on fuel imports, environmental issues and insecurity into account, there is a massive need to alter the present energy breakup by emphasizing the growth of renewable energy. Studies of Jha and Puppala, (2017), ratified that the thrust on development of geothermal energy could be a promising option to alter the present energy breakup and to minimize the negative impact caused by the ignition of fossil fuels to generate electricity.

Geothermal energy is the heat that is stored within the earth’s crust and is considered as an inexhaustible source of energy in a human time scale. It is clean, renewable and sustainable source of energy. Radioactive decay of Thorium(232Th), Potassium(40K) and Uranium(238U,235U) is one of major reasons of this enormous heat (Barbier, 2002). Geothermal gradient at a location is a measure to estimate the heat that could be encountered in the deeper zones. Although this heat energy is spread all over the world beneath the feet, the amount of available geothermal energy at any field, is location specific and the areas with promising geothermal gradients are referred as geothermal fields. These locations are suitable for the installation of geothermal power plants. The Geysers, Cerro Prieto, Larderello, Olkaria, Sarulla, Tiwi, Hellisheidi, Navy, Darajat and Malitbog are few of the eminent geothermal plants with installed capacity ranging between 1517 MW-233MW. The installed capacities of the aforementioned geothermal plants along with few other prominent geothermal plants are shown in Figure 1. From Figure 1, it is evident that the share of United States of America is relatively higher with a potential of 1972 MW, and is followed by Indonesia and Philippines. In contrast to the global scenario, it is observed that there is no operational geothermal power plant in India (Chandrasekharam and Chandrasekharun 2015; Puppala and Jha 2018). However, the geo-scientific studies conducted by National Geographic Research Institute (NGRI) have ratified that Puga, Chhumathang, Manikaran, Tattapani, Tapoban and Unhavre Khed are the most promising locations for the exploitation of geothermal energy on an industrial scale.

The entrapped heat within the geothermal reservoir is generally extracted using borewells which are drilled up to a depth 3000-7000 meters. Depending on the number of borewells and their functioning, the production schemes can broadly be classified into single well systems and multiple well systems. In single well systems, water is extracted continuously from deeper zones and the temperature of extracted water depends on the difference in temperature at bottom of extraction well and ambient temperature. Continuous supply of water at a constant temperature can be extracted in this system till the pressure in the reservoir diminishes and alters the production rate. In contrast to single well systems, the extracted water is re-injected into the reservoir to maintain the reservoir pressure in case of multi well systems. This surmounts the problem of water subsidence, as observed in single well systems. It is also concluded that developing the doublet production scheme facilitates the natural regain of lost heat in the deeper zones (Gringarten, 1978). However, it has to be noted that, a zone is created around an injection well with a temperature equal to the re-injected fluid, and this zone propagates toward the extraction well with time. This movement of front reduces the extraction temperature and is refereed as thermal breakthrough.

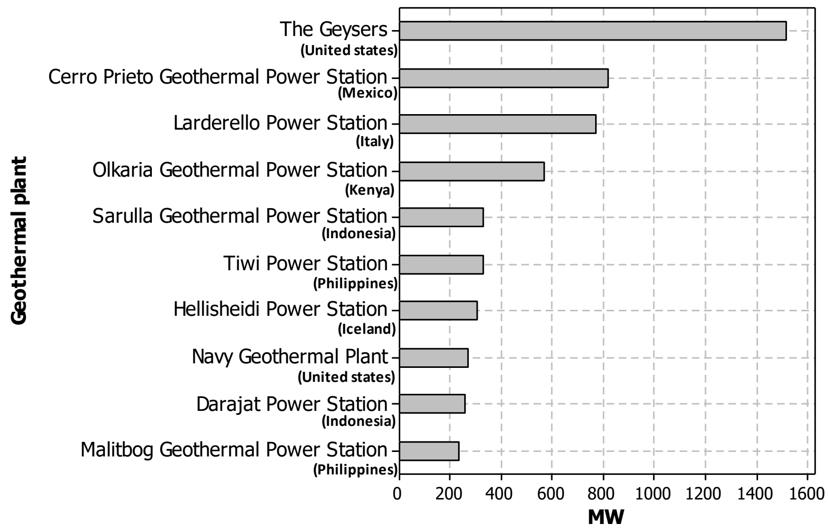

Figure 1: Prominent geothermal plants in world and its production capacity

Although, it has been observed in the literature that single well systems can be adopted to extract the thermal fluid at a constant temperature, the recovery factor of this production scheme is observed to be less than the doublet production scheme. Studies carried out by Gringarten (1978) showed that re-injection of extracted thermal fluids into the reservoir will enhance heat recovery factor and production potential. Depending on the number of multiple borewells used in exploiting the reservoir and its layout, extraction schemes are classified into doublet, triplet, quadruplet and quintuplet systems. Success and lifetime of a geothermal plant under a chosen extraction scheme is often associated with available thermal energy. Under these prevailing conditions, prior to industrial exploitation, there is a great need to conduct geo-scientific studies and perform simulation studies to estimate the possible potential that can be drawn from a geothermal reservoir. Heat flow, areal analogy, volumetric methods, lumped parameter models, decline curve analysis, numerical reservoir simulation are few of the different available techniques to estimate the potential of a geothermal reservoir, prior to installation. Among these techniques, volumetric analysis has been used widely to estimate the potential (Muffler and Cataldi, 1978). Although it has been widely used, the estimations obtained are considered to be preliminary estimate, since it does not evaluate the fraction of energy that can be extracted. Simulation studies are typically performed to estimate the temperature of thermal water that can be extracted from the reservoir.

Attempts on developing conceptual models of a geothermal reservoir in India are meagre due to the lack of geothermal information base of India. As discussed in the aforementioned sections, wide range of field investigations are conducted in India and identified Puga, Chhumathang, Manikaran, Tattapani, Tapoban and Unhavre Khed as most promising locations for the exploitation of geothermal energy on an industrial scale. Studies of Puppala and Jha (2018**)** identified that Puga geothermal field is the most significant geothermal field among the explored fields, to exploit entrapped heat energy. Although it is identified as the promising geothermal field by various researchers, no developmental activities have been conducted for the industrial exploitation of geothermal energy. The exploratory studies conducted at Puga are limited to shallow depths. This impaired the development of conceptual model for deep geothermal reservoir and assessment of extractable power potential.

The status of geothermal exploitation and developmental activities in India is in contrast with global scenario. Various geothermal fields have been explored through various field investigations and the obtained information is unified to develop conceptual models. Dubti geothermal field (Battistelli et al., 2002), Momotombo reservoir, Nicaragua (Enrique and Porras, 2008), Ngatamariki geothermal reservoir, New Zealand (Chambefort et al., 2016), Sabalan geothermal field, Iran (Seyedrahimi-Niaraq et al., 2017), Sibayak geothermal reservoir (Atmojo et al., 2000), Ohaaki geothermal system in New Zealand (Mroczek et al., 2016) and Los Humeros geothermal field (Arellano et al., 2003) are few of the conceptual models developed in the recent times. The developed conceptual models are further used to study the dynamic response of reservoir under exploitation using simulation studies. Simulation studies of Podhale geothermal reservoir (Bujakowski, Tomaszewska, and Miecznik, 2016), Habanero geothermal reservoir (Llanos, Zarrouk, and Hogarth, 2015), Mofete geothermal field (Carlino et al., 2016), Groß Sch¨onebeck reservoir (Jacquey et al., 2016) and Khankala deposit (Farkhutdinov et al., 2016) are few of the examples.

From the aforementioned simulation studies, it is noted that the dynamic response of considered reservoir is studied under a particular extraction scheme and operating condition. Although simulation studies help to study the dynamic response of reservoir under a set of operational conditions and to estimate the extractable temperature, it does not enable modeler to correlate the change that would occur in extractable temperature with the change in operational conditions. Therefore, modeling the relation between input parameters and output parameters would help to predict the extractable power for any operating conditions without performing simulation studies. The art of identifying and modelling complex process with the help of input-output data have been the subject of investigation and has attracted many researchers. In this regard, soft computing techniques such as fuzzy logics, artificial neural networks and evolutionary algorithms have been used to model these complex relations.

Artificial neural networks have been widely used in forecasting and decision modelling problems. These are the mathematical models that mimic the functioning of biological neurons. Based on the neural network architecture, neural network models have been classified into feedforward and feed backward networks. Development of Neural Network Models, typically involves 3 different stages which includes collection of input and output data, training and validation of network and testing of developed neural network (Keçebaş, Yabanova, and Yumurtacı, 2012). The architecture of neural network model and the steps involved are well known from literature (Zhang, Eddy Patuwo, and Y. Hu, 1998; Bayram, 2001).Thermal data obtained from the heating system of Afyonkarahisar geothermal district is used to determine the exergy and the data set is used to train the neural network and later to predict the exergy for broad range of operating conditions (Keçebaş, Yabanova, and Yumurtacı 2012). Neural networks are also used in the selection of the optimum bit selection (Yılmaz, Demircioglu, and Akin, 2002). The heuristic knowledge between bottom hole temperatures and shut in times and transient temperature gradients in geothermal wells is captured using a neural network model (Bassam et al., 2010). The relevance of using ANN in estimating the performance of vertical ground coupled heat pump have been discussed by Esen and Inalli, (2009). The philosophy of ANN is used in developing a new geothermometer where Na and K values obtained from the thermal waters are treated as input signals and the geothermometric values are considered as output signals (Bayram. 2001). A similar attempt has been made by (Serpen, 2009) and (Can, 2002) in developing a neural network model for Na-K geothermometer. Farshad, Garber, and Lorde, (2000) developed a neural network model to predict the temperature of flowing fluid at any considered depth in a flowing oil well.

In view of the aforementioned studies, neural network model is developed to determine the transient extraction temperature from Puga geothermal reservoir using the data obtained from series of simulation studies. The operational parameters used in establishing doublet extraction scheme are considered as the input parameters. A detailed insight of operational parameters is given in the subsequent sections. The extractable temperature is considered as an out parameter, which is further used to determine the extractable power. The architecture of the neural network model, its properties and the steps involved in developing the network model are also discussed in the subsequent sections.

2. CONCEPTUAL MODEL OF PUGA GEOTHERMAL FIELD

Puga geothermal field comes under Himalayan geothermal province and is located at a distance of 1600 Km from New Delhi. It Lies in the southeast part of Ladakh and frames a piece of the Himalayan geothermal belt. The geographical location of this geothermal field is shown in Figure 2. This valley extends from Sumdo village and Polokongka La which are situated in east and west directions respectively. Geothermal activity at this region is evident in the form of numerous hot springs with surface temperatures up to 84^{o}C. Minor hot water seepages are also noticed in this region (Jawaharlal, 2002)

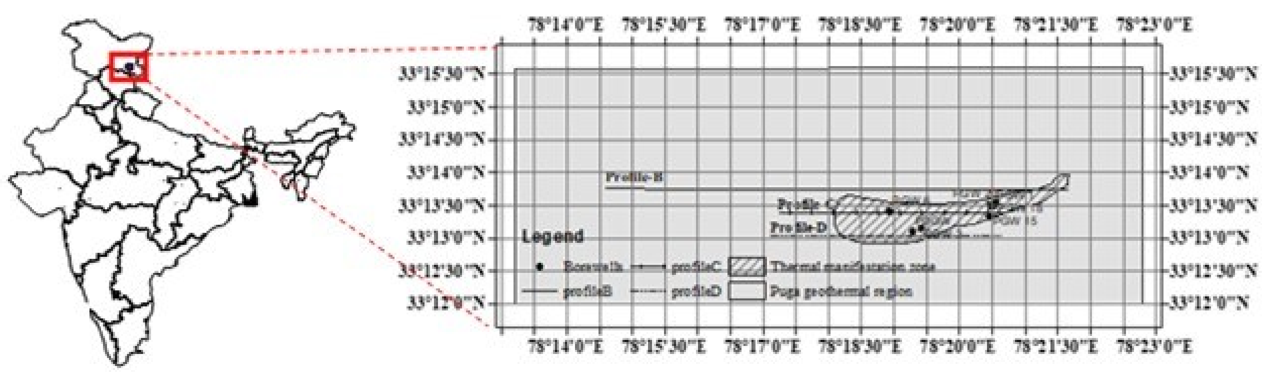

Figure 2: Geographical location of Puga geothermal field, India

Wide range of geo-scientific studies including magnetic, gravity, refraction, seismic refraction and resistivity surveys have been conducted in this region to delineate thermal manifestation zone (Harinarayana et al., 2006). The areal extent of thermal manifestation zone is shown in Figure 2. The valley region is explored through borewells which are drilled at 34 discrete locations with depths ranging from 28.5 m to 384.7 m (Jawaharlal, 2002). Few of the well locations are shown in Figure 2. Among the 34 borewells, artesian condition is noticed at 17 borewells and a maximum temperature of 140 ^{o}C is noticed (Jawaharlal, 2002). The cumulative discharge from these 17 borewells is observed to be 83 l/s. In addition to physical exploration, heat flow studies conducted at this region is observed to vary between 180 mW/m^2 to 540 mW/m^2 (Ravishanker, 1991). From the available data, it is observed that the findings of the aforementioned studies are confined to shallow depths. These limited findings, impaired the knowledge on subsurface geology, state of volcanic activity and 2D or 3D temperature fields. The geoelectric response of the valley region is mapped with the help of magnetotelluric studies along various sections by (Harinarayana et al. 2006, 2004; Azeez and Harinarayana, 2007). From the resistivity fields, it can be interpreted that heat source is towards eastern side of the valley and approximately at a depth of 2 km from thermal manifestation zone (Azeez and Harinarayana, 2007).

A conceptual model extending in N-S direction with sectional dimensions of 7300 m x 1500 m have been developed and temperature, pressure distributions have been studied (Absar et al., 1996). The findings of the study conducted by Absar et al., (1996), identified that temperature increased up to a depth of 500 m and then a decreasing trend is reported. Conceptualizing the reservoir as two-dimensional domain and considering its orientation along N-S direction limited the applications of the findings. Following this remarkable work, few additional conceptual models have been developed by considering the findings of field works conducted at Puga geothermal reservoir (Jha and Puppala, 2018). Besides the conceptual model developed by Absar et al., (1996), Jha and Puppala, (2018) conceptualized Puga geothermal region as a reservoir domain along E-W direction. This conceptual model stretches to a length of 3270 along E-W direction and to a depth of 3200 m. Considering the region as a homogenous field along N-S south direction, adopting the synthesized thermo-hydro-geological fields in E-W direction and mapping the initial temperature of reservoir using a constant thermal gradient limited the model in terms of precision. Owing to these drawbacks, a methodology has been developed by Jha and Puppala, to characterize 2D thermo-hydro-geological fields with block heterogeneity up to a depth of 6000 m (Jha and Puppala, 2018b). Although this model surmounts the drawbacks of earlier models, the mapped variation is confined only along a section. In this regard, all the limitations of 2D models developed by Absar et al., (1996); Jha and Puppala, (2018a), (2018b); Gupta et al., 1979 has been overcome in this study through the development of 3D conceptual model. The steps involved are expounded in the subsequent sections.

3. METHODOLOGY

This study is intended to develop a Neural network model to predict the transient extractable temperature that can be generated from Puga geothermal reservoir under various operating conditions. Initially, considering the developed three-dimensional conceptual model, the dynamic behavior of Puga geothermal reservoir due to exploitation using doublet extractions scheme is simulated. It has to be noted that the simulation of dynamic reservoir response under exploitation is a multi-disciplinary subject involving the study of fluid flow, mechanical deformation, chemical transport and heat transfer. However, in this study, fluid flow and heat transfer processes involved during the operation phase of geothermal reservoir are considered. The simulation studies are performed for various operating conditions by varying the configurations of doublet extraction scheme. Various operational conditions are synthesized by varying well spacing, injection/extraction rate, injection depth and injection temperature and sensitivity of these parameters to extraction temperature is studied. Subsequently, the relation between operational parameters and extractable temperature is modelled using feed forward neural networks. The different phases and steps involved in modelling a network model are shown in Figure 3.

From Figure 3, it can be inferred that the modelling can be divided into three phases. The first phase involves developing the conceptual model of Puga geothermal reservoir and synthesis of various operational conditions by varying well spacing, injection/extraction rate, injection depth and injection temperature. Later, the extractable temperature from the reservoir is computed using simulation studies by solving the coupled fluid transfer and heat transport equations, which is further used to determine the extractable power. The governing equation of fluid flow and heat transport equations, the initial boundary conditions used in solving them are discussed in the subsequent sections. Later, the heuristic knowledge between the operational parameters and extractable power is modelled using neural network. The architecture of neural network models and its properties are presented in the subsequent sections.

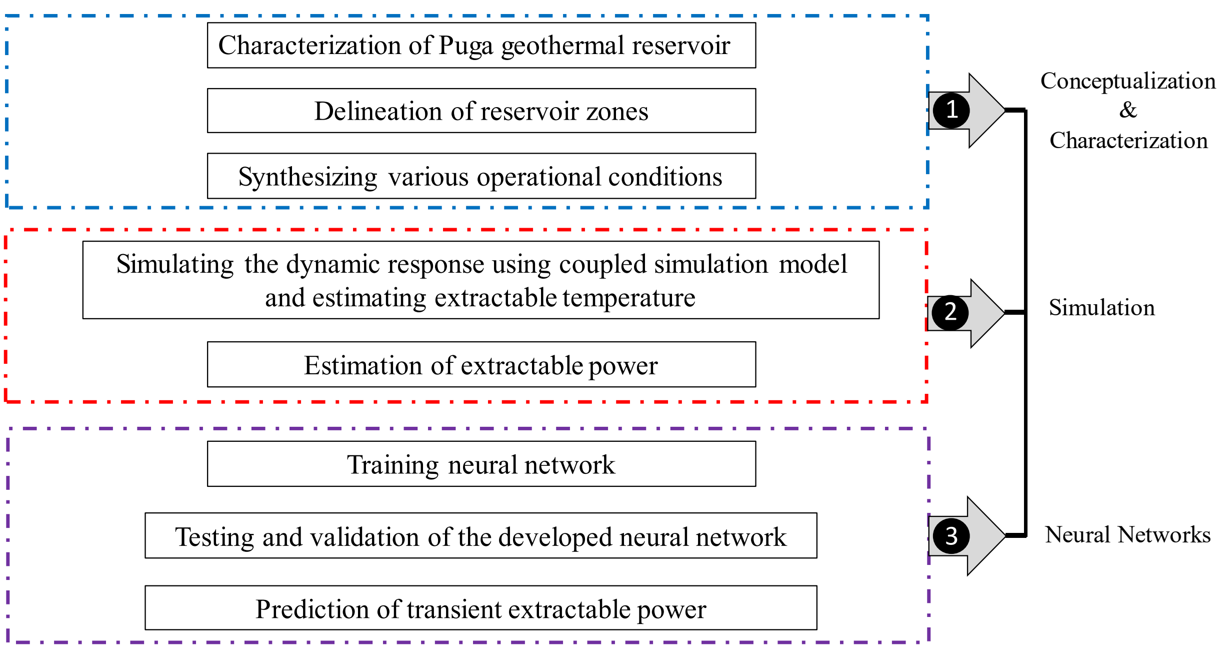

Figure 3: Steps involved in the prediction of extractable power generation

3.1. Conceptual model of Puga geothermal field, India (Phase-1)

The methodology developed by Jha and Puppala, (2018), is integrated with kriging interpolation technique to estimate the 3D variation of reservoir fields, which include porosity, thermal conductivity, specific heat, density, radioactive heat capacity and permeability up to a depth of 4000 meters. The resistivity data used in developing three-dimensional model is adopted from literature (Harinarayana et al., 2006). Subsequent to the characterization, K-means algorithm is used to group the blocks by considering the optimal number of blocks, which is decided based on the pseudo F-statistics. The thermo-hydro-geological properties of each group are discussed in the subsequent sections.

3.2. Simulation studies to estimate the transient extractable temperature (Phase-2)

As discussed in the aforementioned sections, simulation of dynamic reservoir response under exploitation is a multi-disciplinary subject involving the study of fluid flow, mechanical deformation, chemical transport and heat transfer. However, in this study only fluid flow and heat transfer processes involved during the operation phase of geothermal reservoir.

The governing equations of fluid flow and heat transfer processes can mathematically be represented as Equation (1) and Equation (2) respectively.

Governing equation of fluid flow

$$\frac{\partial}{\partial t}\left(\phi_r \rho_{gf}\right) + \nabla.\rho_{gf}\left[\frac{k_r}{\mu_{gf}}\left(-\nabla P_{gf} + \rho_{gf} g \nabla z\right)\right] = 0 \tag{1}$$

Governing equation of heat transfer

$$\rho_s c_{p,s}\frac{\partial T}{\partial t} + \nabla.\left(\rho_{gf}\boldsymbol{v}c_{p,gf}T - \lambda\nabla T\right) = 0 \tag{2}$$

Where, $\nabla.$ is divergent vector, ρ_{gf} is the density of the geothermal fluid, v is the Darcy velocity and ϕ_r is the porosity of the geothermal reservoir, k_r is intrinsic permeability of the matrix, μ_{gf} is the dynamic viscosity of geothermal fluid, P_{gf} is fluid pressure, g is the acceleration due to gravity and z is depth from the surface. λ is the effective thermal conductivity of geothermal fluid and solid medium which can be expressed as $\phi_s \lambda_s + (1-\phi_s)\lambda_{gf}$.

From Equation (1) and (2), it can be inferred that both the equations are coupled with velocity term. These coupled equations are solved to determine the possible extraction temperature.

3.2.1. Initial and boundary conditions

Cold water is injected for 50 m injection length through an injection well. In simulating the reservoir dynamics, heat diffusion is taken into account through the surrounding layers. To further explain this fact, consider region 1 lying between 200 m and 350 m from the surface. If the heat transport and fluid flow process is considered only within 50 m thickness of injection length with top and bottom boundary as insulated, then it may not represent a realistic situation. Keeping this in view, the process is simulated for 1000 m of reservoir thickness with top and bottom boundaries as insulated (for detailed explanation, refer section 4).

Extraction rate is maintained equal to injection rate for all reservoir configurations to ensure mass balance. This infers that there is no surplus water in the operation phase of reservoir. Furthermore, the top and base of computational domain is considered as thermally insulated due to the variation of thermal properties among the reservoir rock and the surrounding rocks (cap rock and bed rock). The extreme faces perpendicular to the top and bottom faces are considered as an open boundary in context to the heat flow whereas these boundaries are assigned with a constant hydraulic head for fluid flow boundary conditions. This depicts the fact that the ground water flow is neglected. The temperature of injected water is maintained at 293 °K throughout the operation phase (for base case) of reservoir by neglecting the seasonal temperature variation. The mathematical description of boundary conditions is presented below.

3.2.1.1. Boundary conditions to solve fluid flow equation

In solving the governing equation of fluid flow, the following boundary conditions are adopted.

Injection well: Since cold water is injected at a constant rate through the injection well. This can be mathematically represented using Equation 3.

$$Q(t)\text{injection} = Q \text{ m}^3/\text{s}; \text{ for } 0 < t < 30 \text{ years} \tag{3}$$

Production well/extraction well: Thermal water which is in equilibrium with the temperature of reservoir is extracted through production well. This phenomenon can be represented using Equation 4

$$Q(t)\text{production} = Q \text{ m}^3/\text{s}; \text{ for } 0 < t < 30 \text{ years} \tag{4}$$

Top surface, bottom surface: Advection is more dominant in x-direction and is expected that the injected cold water doesn't reach the top and the bottom surface, which leads to the assumption of no water losses from the reservoir domain., which can be represented using Equation 5

$Q=0\ m^3/s$ for $0 < t < 30$ (5)

Side boundaries: A Dirichlet boundary condition of hydraulic head is considered. A zero-hydraulic gradient is assigned to model which depicts the absence of ground water flow which can mathematically represented as Equation 6.

$P(t) = \rho_L g(H_0 - D)\ i.e. -\frac{\partial H}{\partial x}$ for $0 < t < 30$ years (6)

3.2.1.2. Boundary conditions to solve heat transfer equation

Fluid flow and heat transfer equations are coupled using velocity term. The boundary conditions adopted in solving heat transfer equation are discussed below.

Injection well: The temperature of injected cold water is assumed to be constant through the operation period of reservoir. This can mathematically be expressed using Equation 7.

$Ti(t)= T_{inj}$ K for $0 < t < 30$ years (7)

Production well: The temperature of extracted thermal water at various intervals of time is evaluated by solving the coupled equations. This is given as Equation 8.

$T_o(t)$ =? for $0 < t < 30$years (8)

Top surface, bottom surface: Heat transfer is more dominant in terms of advection than in conduction. Since advection is more dominant in x and y direction, it is assumed that the losses from top and bottom are zero. In this regard, the top and bottom boundaries are considered as insulated boundary conditions. This can mathematically be expressed as Equation 9.

$-n.q(t)=0$ (9)

Side boundaries: An open boundary condition is assigned for the sides of reservoir which enables the interaction with surroundings. Open boundary condition can be mathematically expressed as Equation 10.

$T(t)= T_{int}(t)$ if $n.\ v<0$; $-n.\ q(t)=0$, if $n.\ v>0$ for $0 < t < 30$ (10)

3.3. Prediction of extractable power using neural network model (Phase-3)

The different steps involved in developing a neural network model is well known from literature (Keçebaş, Yabanova, and Yumurtacı 2012). Whilst a detail description of Artificial Neural Network (ANN) is beyond the scope of this paper, a brief over view of ANN in context to the present study is presented in this section. The prediction of extractable temperature using ANN can be categorized into three different stages which includes defining the architecture of network model, training and testing of developed model and validation of model. Typically, the developed network model consists of an input layer, output layer and multiple hidden layers. These hidden layers are sandwiched between the input layer which contains the operational parameters and time; the output which contains the extractable temperature. The schematic representation of this architecture is shown in Figure 4. Wide range of operational scenarios with minimum and maximum limits as shown in Figure 4, are synthesized and the coupled governing equations as presented in section 4, are solved, to obtain the extractable transient temperature of thermal water. The obtained temperature is further used to evaluate the extractable power as discussed in section 4.

Neural network fitting tool in Matlab (Howard and Mark, 2002) is used to develop the network model. A two-layer feed-forward network with sigmoid hidden neurons and nonlinear output neurons is used to fit the heuristic knowledge between the input parameters (operational parameter) and output parameters (extractable temperature). Owing to literature, (Keçebaş, Yabanova, and Yumurtacı 2012) Levenberg-Marquardt backpropagation algorithm which is considered to be fastest and accurate algorithm is used in this study to train the network. Since it is difficult to determine the optimal number of hidden neurons to be used in the hidden layer, an iterative study is performed in this study, till the performance criteria is met. The limits of input parameters are evident from Figure 4. As discussed above, different operational scenarios are synthesized by varying well spacing, injection/extraction rate, injection temperature and injection depth. Later, the extractable temperature for 30 years at 0.1-year time step is estimated by solving the coupled heat transport and fluid flow equation. Consequently, 96688 data samples obtained from simulation studies. Among this, 67682 (70% of available sample) samples are used for training; 14503 (15% of available sample) samples are used for validation and the rest 14503 (15% of available sample) data samples are used for testing.

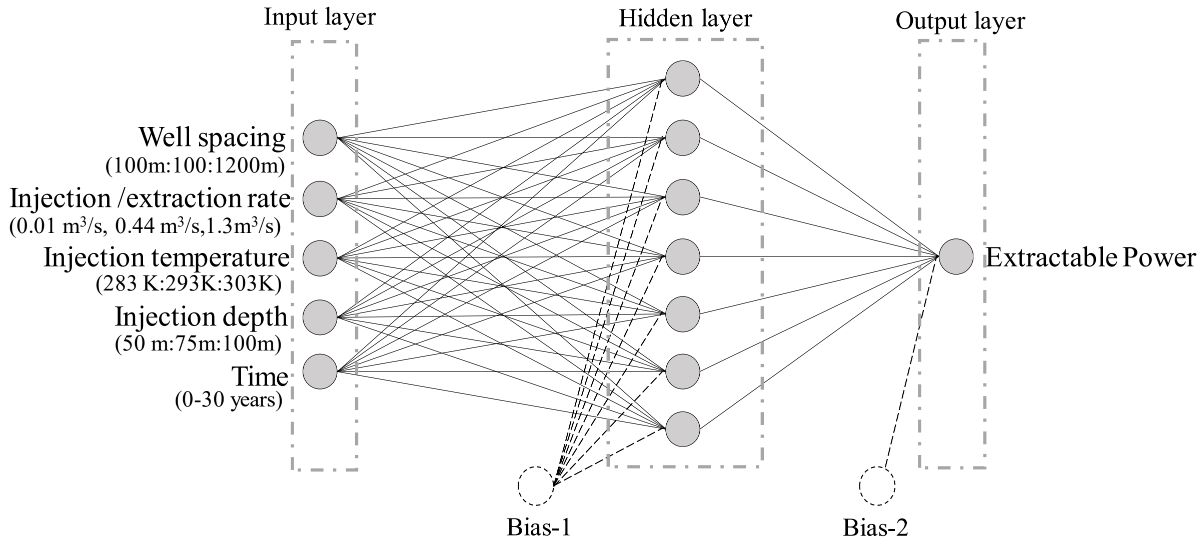

Figure 4. Architecture of Neural network model

4. RESULTS AND DISCUSSIONS

As per the methodology mentioned in the aforementioned section, the imagery of resistivity fields corresponding to Profile B, C and D are classified using Interactive supervised classification. The equivalent resistivity of a block is evaluated using shifting window algorithm (Jha and Puppala 2018) with block size 100 x 50 m. Later, ordinary kriging interpolation technique (Jha and Puppala 2017b), is used to estimate 3D resistivity field, which is used further to estimate the reservoir fields. It is observed that the reservoir fields are not varying widely along N-S direction, to ease the computation, the total blocks are now grouped into 15 clusters (Optimal number of groups as per pseudo-F statistic) using k-means algorithm. The estimated reservoir fields as per the classified groups are shown in Figure 5 and the spatial distribution of groups is presented in Figure 6.

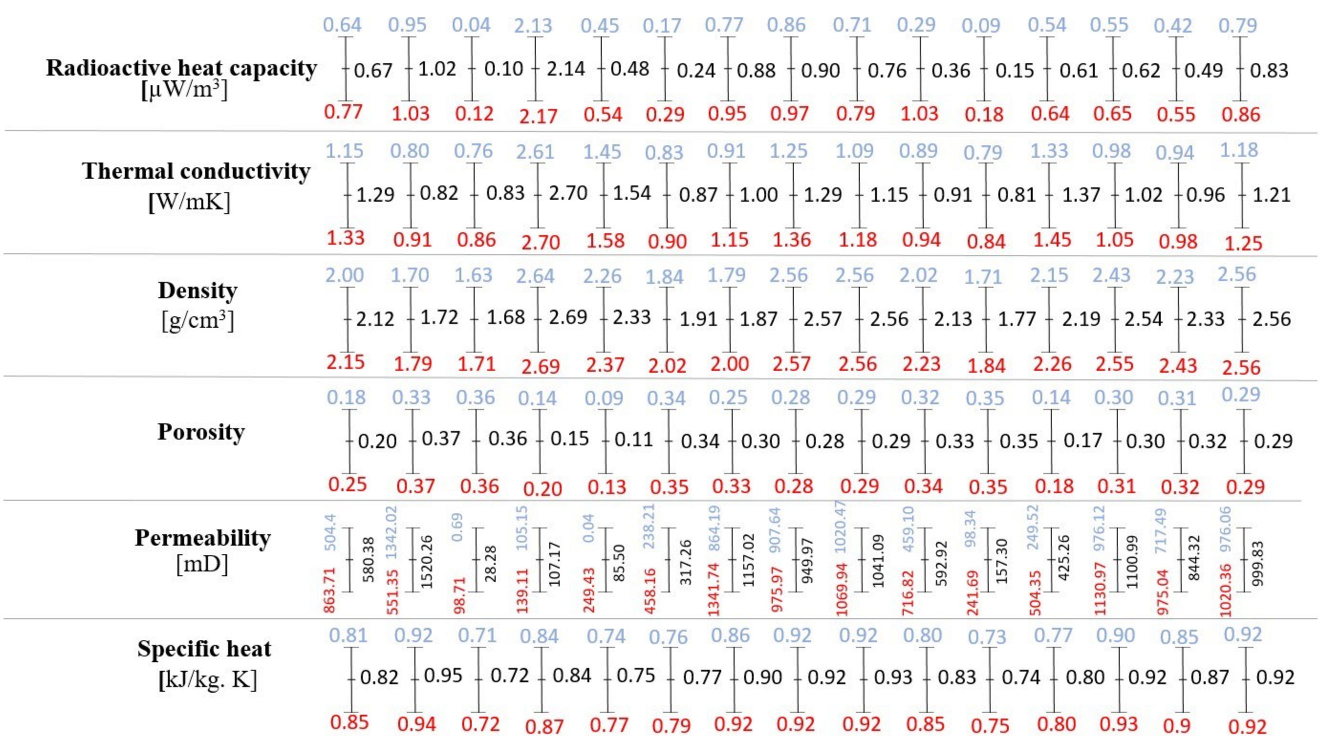

Figure 5. Thermo-hydro-geological properties of each clustered group

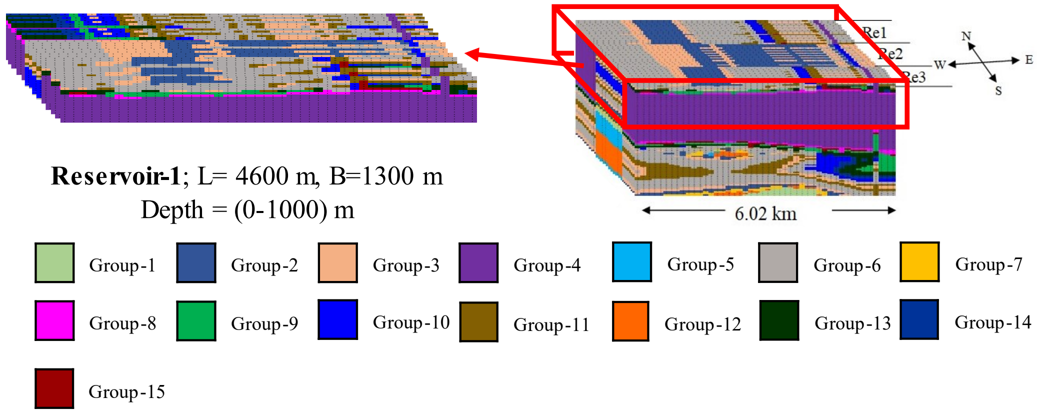

Figure 6. Spatial distribution of classified groups in reservoir-1

From the findings of cluster analysis, it is observed that group 4 is the predominant lithology within 3000 meters of depth, whereas the lithology of Re2 region, up to 3000 meters is varying widely. Permeability of group 4 is relatively less than that of Re2. This will help to decelerate the rate of flow in N-S direction, relative to flow in E-W direction. Since the response of magnetotelluric studies indicate the heat source is extending along E-W direction and also the low resistive zones are identified along Profile-C, it can be inferred that the more amount of heat can be extracted in the Re2 compared to Re1 and Re3. To avail the advantage of this structural formation, Re2 is considered as the favorable region for the extraction of thermal water. By giving a special emphasis on rock distribution of Re2, the appropriate depths at which water can be extracted is identified. Consequently, 200m-350m; 650m-800m; 1350m-1550m and 1750m-2050m from the surface are observed to be appropriate depths. The extractable power potential from region 1 is emphasized in this paper. Since the effect of injection in region 1 will not be significant over the entire 4000 m of depth, the dynamic response of reservoir due to injection and extraction of thermal water in Region 1 is studied by considering the depth of domain as 1000 m instead of considering 4000 m. This helps to reduce computational effort involved in simulation studies. The injection depth is maintained symmetrical to the 275 m depth.

The coupled governing equations i.e. Equation 1 and Equation 2, are solved numerically using COMSOL Multiphysics for various operational scenarios, which are synthesized by considering all the possible combinations of limits shown in Figure 4. The transient extraction temperature for one of the operating conditions is shown in Figure 7(a). The temperature vs time results, shown in Figure 7, are further used in evaluating extractable power from each reservoir using Eq 11 and the plots are shown in Figure 7(b).

$$P = \dot{m} \cdot c_p \cdot (T_{ext} - T_{ref}) \tag{11}$$

The equivalent data for other operating conditions is obtained using simulation studies and is not displayed in this manuscript. In all the simulated conditions, with the continuous injection of cold water, hot water is simultaneously extracted from the extraction well. Consequently, from the extraction temperature vs time plots, it is observed that the extraction temperature decreased with time. This could be inferred with the fact that, with the injection of cold water, a region with low temperature, whose temperature is equal to injection temperature is formed and this region extends and propagates towards the extraction well with time. It is observed that the time after which the injected cold water plume reaches the extraction well depends on injection rate and well spacing and injection depth.

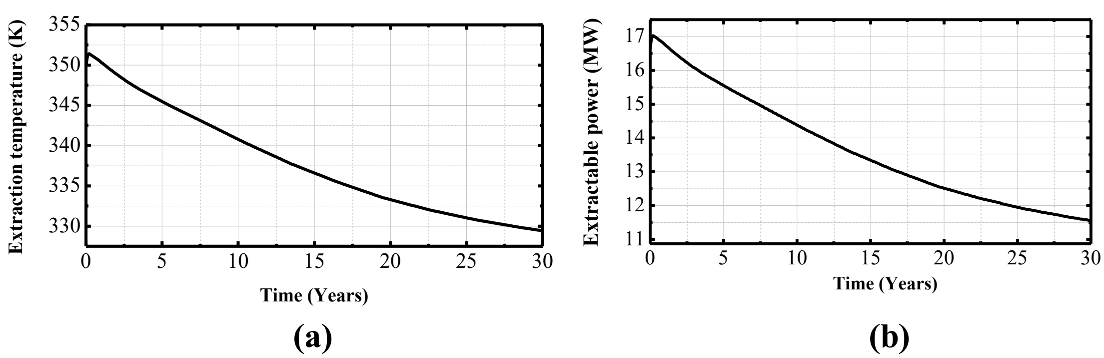

Figure 7. Transient extraction temperature for (d=800 m; T=283K; v=50 m; Q=0.44m^3/s)

The transient extraction temperature estimated in case of all the synthesized scenarios are used to train the network using Matlab neural network tool box. The performance of the developed network model is measured in terms of Coefficient of multiple determination and mean square error and the measured stats are shown in Table 1.

Table 1. Performance of the developed neural network model

Neural Network Model Phase	Performance parameters	
	R^2	MSE
Training	0.96	1.66
Validation	0.96	1.60
Testing	0.96	1.61

4.1. Comparison of temperature fields

The developed feed forward neural network is used to predict the transient temperature fields for an intermittent operational conditions, which is different from the conditions synthesized. Further the extractable temperature is predicted for the same conditions using simulation studies. The comparative plots are shown in Figure 8.

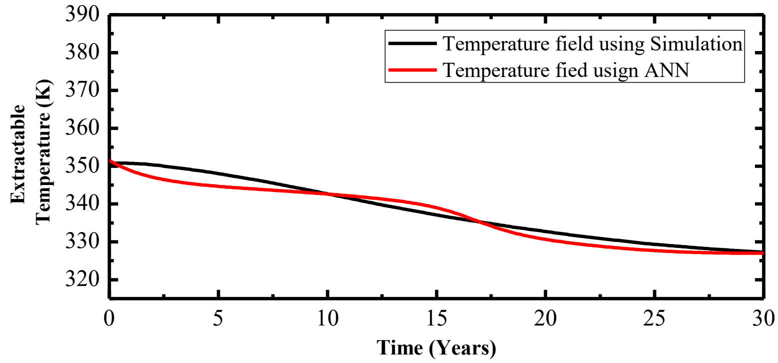

Figure 8. Comparison of temperature fields using simulation and feed forward neural network

The consistency of the predicted temperature fields using neural network is measured in terms of mean average percentage error (MAPD), which can be evaluated using the mathematical relation shown as Eq 12.

$$MAPD = \left|\frac{T_{simulation} - T_{ANN}}{T_{simulation}}\right| \times 100 \tag{12}$$

The maximum deviation between the simulated and predicted temperature fields is found to be 1.07% whereas predicted temperature field matched with the simulated fields at few intervals of time period. Nearly for about 75% of the operation period, the deviation is observed to be less than 0.63%, from which it can be conceived that the developed feed forward neural network gives satisfactory results. The mean average percentage deviation is found to be 0.50%, which is reasonable. Subsequent to the prediction of extractable temperature, the power that can be generated throughout the reservoir operation period is estimated using Equation (11) as shown in Figure 9. For comparison propose, the power estimated using the temperature plots obtained through simulation studies is also shown in Figure 9. From the plots shown, it can be inferred that estimated power is underestimated for 22.7 years (0.2-9.9 years and 17-30 years) whereas it is over estimated for 7.3 years (0-0.2 years, and 9.9-17 years).

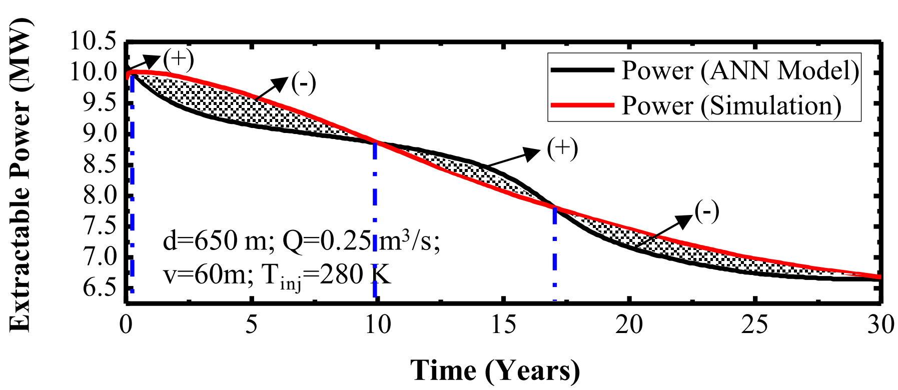

Figure 9. Predicted transient power usign neural networks

From the transient power predictions and the observed mean average percentage deviation, it can be ratified that the developed neural network gives satisfactory results and the predictions are in line with the simulation studies. Further the developed neural network helps to estimate the probable extractable power without performing simulation which generally involves huge computational effort.

6. CONCLUSION

Geothermal exploitation on industrial scale is still at nascent stage and is just confined to direct heat applications in India. Due to the limited geothermal information base, studies on conceptualizing geothermal reservoirs are meagre. Using the available resistivity data, and integrating with kriging interpolation technique, this study presents a three-dimensional conceptual model of Puga geothermal reservoir. Variation of Thermal conductivity, specific heat, density, radioactive heat capacity, permeability and porosity within the region is mapped, which is further used to identify appropriate zones for the injection and extraction of thermal water are identified by considering the structural formation. Consequently, 200m-350m; 650m-800m; 1350m-1550m and 1750m-2050m from the surface are observed to be appropriate depths. The power that can be extracted from the shallow depths is emphasized in this study. Since it is a common practice, to simulate the dynamic response of reservoir before exploitation, various operational scenarios have been synthesized and the transient extractable temperature is evaluated by solving the couple heat transport and fluid flow equations. Each of the operational scenarios are distinguished by varying well spacing, injection temperature, injection depth and injection/extraction rate. Subsequent to the estimation of transient extractable temperature, the heuristic knowledge between the aforementioned operational parameters and transient extractable temperature is used to train the network. The predictions made, for a chosen operational condition is found to be in line with the results obtained from simulation studies and the results are satisfactory since the mean average percentage deviation is found to be 0.50%.

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