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Machine Learning-Based Power Density Prediction for Binary Cycle Geothermal Power Generation in Japan

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ABSTRACT

The objective of this work is to apply effective machine learning (ML) techniques in introduction potential estimation for binary cycle geothermal power generation in Japan. I utilized the dataset of the Renewable Energy Potential System (REPOS) web geographic information systems (GIS), which has been managed by the Ministry of the Environment, Government of Japan (MOE) since 2020. The REPOS database provides introduction potentials of renewable energy resources all over Japan. The database includes geothermal reserves, introduction potentials, and vertical temperature profiles at hot spring wells and geothermal wells. The resource estimation is based on the U.S. Geological Survey (USGS) volumetric methodology. The introduction potential has been estimated by a three-dimensional smoothed temperature model, featuring large scale hydrothermal system such as heat convection and conduction. Therefore, it might be less affected by pressurized hot water in faulted and fractured geothermal reservoirs at major flash steam power plants in Japan. Moreover, it is also adjusting to local land use restrictions. As a result, there is a significant discrepancy between estimated introduction capacity and installed capacity in the area close to existing geothermal power plants or active volcanoes. In this study, I focused on the investigation of the introduction potentials for binary cycle power generation. The introduction potential estimates were investigated in terms of power density. A feedforward neural network (NN) algorithm was applied for the power density prediction. The ML approach covers the shortcomings of dataset concerning lower reservoir temperature than 200 °C in Japan. The preliminary results show that the behavior of predicted power density and average reservoir temperature gives us a useful information to optimize capacity for binary cycle system and manage the influence on hot spring resources in Japan. Moreover, I applied a recurrent neural network (RNN) method with Long Short-Term Memory (LSTM) networks for prospective temperature modeling. The purpose of the RNN approach was deeper temperature prediction to mitigate geological risks for depletion of hot spring resources and geothermal production. The ML based prediction approach allows us to precisely evaluate geothermal resources using shallow borehole data without drilling additional deep wells. These data-driven ML techniques will be powerful and cost-effective tools to accelerate introduction of binary cycle system in Japan.

1. INTRODUCTION

Increasing the amount of geothermal electric capacities has been encouraged since 2011 in Japan. MOE has developed the REPOS web GIS on exploitation of renewable energy of solar power, solar heat, wind power, hydropower, geothermal power, and ground source heat pump because of the recent energy transition policy. This interactive web mapping should be useful for startup company and local governments to create synergies, associated with geothermal energy in commercials. Geothermal reserves and introduction potentials of the REPOS web GIS were evaluated by the USGS volumetric methodology (Brook et al., 1979). This manner requires many reservoir parameters such as reservoir area, reservoir depth, reservoir thickness, reservoir temperature, thermal recovery factor, conversion efficiency and others. Garg and Combs (2011) described that the reservoir parameter estimation would be difficult tasks and highly dependent on the stage of development of a geothermal system. More subsurface information is necessary for application to volumetric method to mitigate uncertainty in these reservoir parameters. Therefore, alternative methods have been proposed (e.g., power density, decline analyses and reservoir simulation) in previous studies.

The goal of this study is to develop an effective utilization of the REPOS web GIS to exploit geothermal developments for small and medium scale power generation. At first, I investigated these introduction potentials in terms of power density. Wilmarth & Stimac (2015) have shown that power density can be explained as a function of temperature and categorized by tectonic setting of fault-based, arcs, rifts, and others. Figure 1 shows the power density and average reservoir temperature data derived from 66 operating geothermal fields in the world. These geothermal plants have more than 10 MW net output and 5 years of production history. When focusing on Japanese geothermal fields, the dataset includes 11 flash steam power plants producing steam/hot water from deep reservoirs. On the other hand, there is a lack of information associated with lower temperature reservoirs because fewer deep wells are targeting binary cycle system due to drilling costs. Under this situation, ML approach would be a powerful and cost-effective solution to predict key reservoir parameters. In this paper, I present two supervised ML models with the aim of examining candidates for small and medium scale binary cycle systems. One is a simple multi-layer neural network to predict power density where there is a lack of information about lower reservoir temperature than 200 °C. The other is a recurrent neural network to prospective temperature modeling using shallow borehole data.

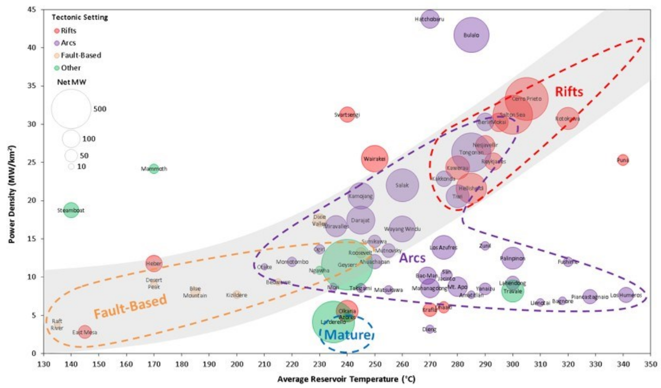

Figure 1: Power density and average reservoir temperature in the world (Wilmarth & Stimac, 2015).

2. REPOS DATABASE

The REPOS web GIS displays the interactive mapping of geothermal energy resources, introduction potentials and geothermal temperature in Japan. Each grid cell of 500 m x 500 m covers all Japan area. The vertical increments of temperature-depth profile are given at every 50 m level from surface. The spatially dense three-dimensional geothermal dataset is referencing the previous study of the Geothermal Potential Map in Japan (Muraoka et al., 2008). This mesh size was set to 1 km by 1 km and the digitized dataset has been published by Geological Survey of Japan, National Institute of Advanced Industrial Science and Technology in 2009. Reducing grid size from 1km to 500 m has a great advantage to consider introduction of small to medium scale binary cycle systems, while the applied three-dimensional temperature model has been significantly smoothed due to limited availability of dataset. The gridding has been conducted by means of minimum curvature method. The key parameters of reservoir temperature and reservoir thickness were calculated with concepts of activity index associated with temperature depth curve fitting. Hayashi (1982) proposed the activity index to mitigate uncertainty in deep reservoir parameters where no well data was available. The other parameters were reference temperature of 15°C, thermal recovery factor of 25%, conversion efficiency of 40%.

A key point of the REPOS mapping is that geographical conditions have effect on the estimates of introduction potentials. For instance, laws and regulations in national parks, distance from residence and developed areas, and local policy in land use have been accounted in the estimates. In addition, contribution of existing production wells in geothermal power plants has been discounted from the estimates of introduction potentials. These definitions and settings would cause a significant discrepancy between actual installed capacity and predicted introduction capacity. Figure 2 shows a comparison between the installed capacity and the predicted capacity in the REPOS web GIS database. The blue-colored bars and orange-colored bars display the introduction potentials of binary-cycle system with the reservoir temperature ranging from 53 °C to 120 °C and from 120 °C to 150 °C, respectively. In addition, the grey-colored bars display the flash steam introduction potentials for reservoir temperature over 150 °C in the graph. An alternative concept such as power density would enable us to increase intuitive understanding of the introduction potentials in geothermal resources derived from the REPOS database.

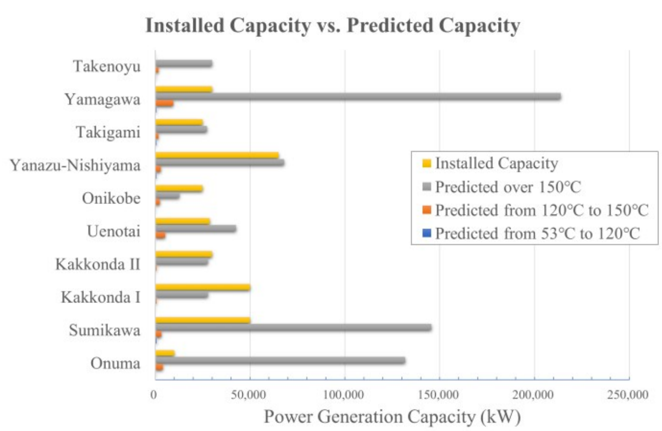

Figure 2: Comparison between installed capacity and predicted capacity provided from the REPOS web GIS.

3. POWER DENSITY PREDICTION

3.1 Feedforward Machine Learning Modeling

A feedforward neural network (FNN) algorithm was applied for power density prediction. The model architecture is a multilayer perceptron (MLP). The model is a fully connected in encoder part, consists of an input layer, hidden multi-layers and an output layer.

Figure 3 shows a schematic diagram of the FNN architecture. It has five hidden layers with different number of nodes. The total number of parameters is 13,057. The activation function is rectified linear unit (ReLU). The input layer was explained by 15 features collected at 12 geothermal plant locations in the model. Table 1 shows the input and output parameters in the modeling. All feature parameters were standardized by Z-transform in Scikit-learn module. Figure 4 shows a validation test result using the loss values of training and validation data (80% training, 20% validation). The error was calculated by mean squared error. The loss values of training and validation data illustrated sufficiently convergence at the end of 80 epochs.

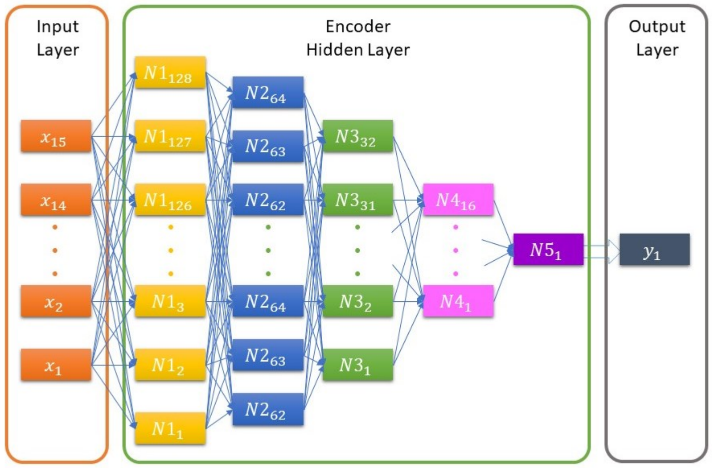

Figure 3: Schematic diagram of the feedforward NN architecture.

Table 1: Target object and features in the NN modeling.

Item	Parameters	Unit	Source
Target object	Power density	MW/km^2	Wilmarth & Stimac (2015)
Feature 1	Latitude	degrees	REPOS Web GIS (2020)
Feature 2	Longitude	degrees	
Feature 3	Elevation	meters	
Feature 4	Top reservoir depth	meters	
Feature 5	Bottom reservoir depth	meters	
Feature 6	Fluid type	steam or water	Wilmarth & Stimac (2015), REPOS Web GIS (2020), AIST (2009)
Feature 7	Installed power generation system	flash steam or binary cycle	
Feature 8	Average reservoir temperature	°C	
Feature 9	Flash system potentials over 200 °C	kW/km^2	REPOS Web GIS (2020)
Feature 10	Flash system potentials over 180 °C	kW/km^2	
Feature 11	Flash system potentials over 150 °C	kW/km^2	
Feature 12	Binary system potentials from 120 °C to 150°C	kW/km^2	
Feature 13	Binary system potentials from 80 °C to 120 °C	kW/km^2	
Feature 14	Binary system potentials from 53 °C to 120 °C	kW/km^2	
Feature 15	Precipitation	mm/year	JMA Website

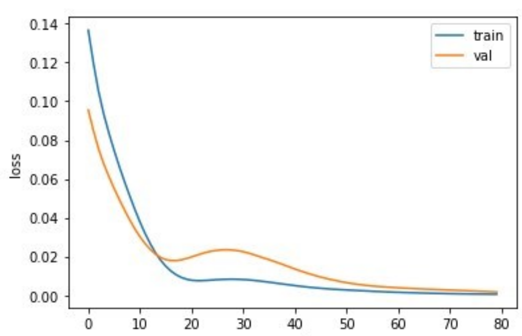

Figure 4: Loss curves of the training and validation data.

3.2 Predicted Power Density

Figure 5 (a) shows the predicted power density data at 18 locations in Japan. The applied model was shown in Figure 3. Figure 5 (b) is an overlay graph on the power density and average reservoir temperature in the world, adapted from Wilmarth & Stimac (2015). The predicted power density data are shown within the grey-colored area when ranging from 130 °C to 180 °C. It would be categorized in the same area of the fault-based tectonic settings. The behavior of distribution supplies an insight into candidates for introduction of binary cycle generation system in Japan. The others would be categorized in the geological setting of the island arcs when reservoir temperature is higher than approximately 200 °C. There is an outlier found at the predicted power density of 31 MW/km^2 and its average reservoir temperature of 200 °C. The outlier was obtained at the Sugawara binary cycle power station with the installed capacity of 5 MW, in contrast to typical brand-new binary power plants installed with medium or micro running capacities less than 1 MW. Because the location of the largest binary power plant is next to a major flash steam power plant, the heat source might be coincided in part with deeper and higher temperature reservoir for the flash steam generator. It implies that quantifying uncertainty of average reservoir temperature will be a key element when considering introduction potential from the point view of power density as a function of reservoir temperature.

(a)

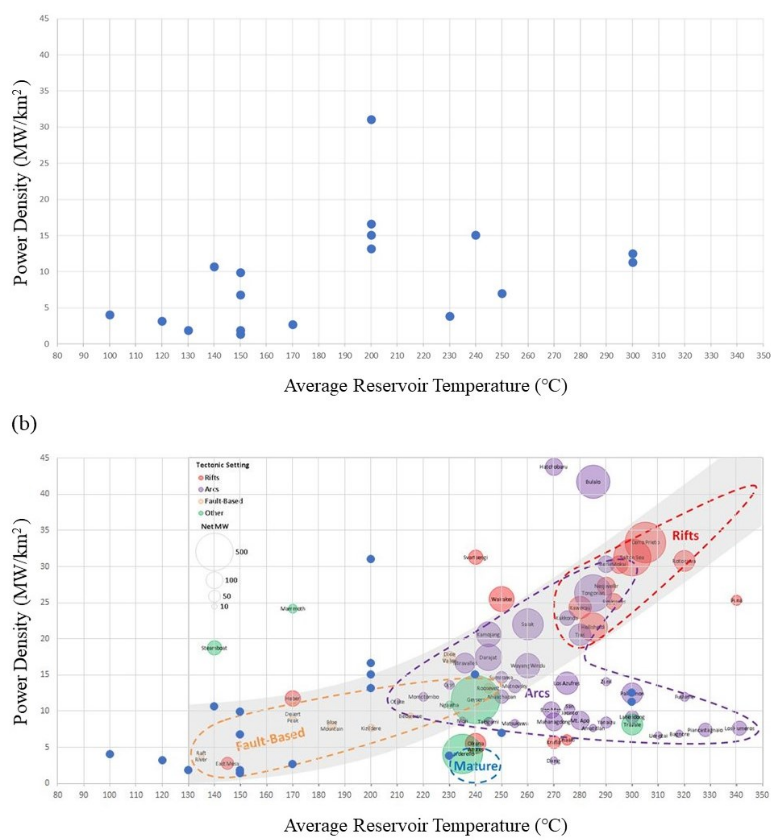

Figure 5: Power density and average reservoir temperature; (a) the predicted power density data of 18 locations in Japan, and (b) an overlay graph on the power density in the world, adapted from Wilmarth & Stimac (2015).

4. TEMPERATURE-DEPTH PROFILE PREDICTION

4.1 LSTM Based RNN Modeling

A RNN modeling was selected as a solution in forecasting temperature-depth profile to mitigate uncertainty in average reservoir temperature estimation. The RNN approach was implemented using Keras module in TensorFlow. The architecture was built with LSTM neural networks, proposed by Hochreiter & Schmidhuber (1997). LSTM methods have often been used in time series predictive modeling for geothermal reservoir characterization and downhole data management (e.g., Gudmundsdottir & Horne, 2020; Beckers et al., 2021). In this study, a LSTM architecture known as sequence-to-sequence (Seq2Seq), was implemented to forecast temperature at 400 m deeper from a data point in depth series. Figure 6 shows a schematic diagram of the LSTM based RNN architecture. The input and output series are temperature depth profiles instead of conventional time series. Table 2 gives a list of hyperparameters in the four models. Hyperparameter tuning is an essential aspect to performance and accuracy in deep learning. I conducted a preliminary tuning in focusing on the number of epochs and the number of hidden layers in the LSTM algorithm. The other hyperparameters of batch size, input steps and output steps were constant for its simplicity. After the input sequences were selected from 12 wells which were utilized in the power density prediction, two preprocessing steps have been conducted prior to training. One is incremental downscaling from original 50 m to 25 m with the aim of increasing the length of data series. The input steps and output steps are set to 24, which is equal to 600 m length in depth domain. The other preprocessing is standardization to use balanced parameters of target series and two feature series including observed temperature and temperature changes. Because the dataset includes a lot of shallow well data, total depth of typical shallow production wells is less than 500 m within hot spring fields. Therefore, I merged the two sequences of all well data into those of one well. Then the dataset was split into train and validation data series (80% training, 20% validation). Figure 7 shows the comparisons between the observed temperature and the predicted temperature using validation data. The results of the four models show the difficulty in higher temperature prediction than 260 °C. In addition, it should be noted that it is necessary to add more training data including lower temperature than 180 °C.

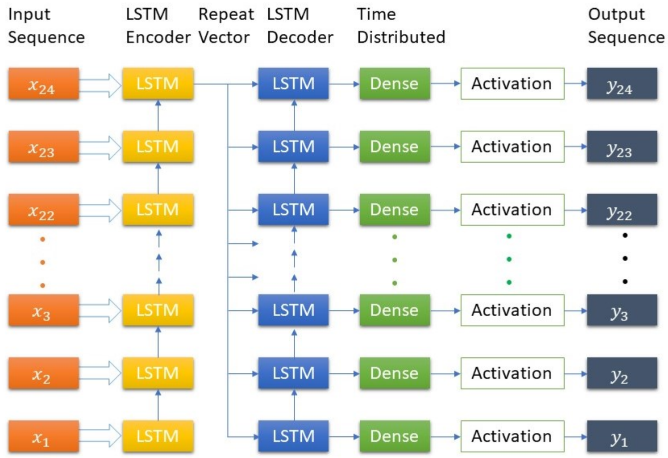

Figure 6: Schematic diagram of the LSTM based RNN architecture in the training.

Table 2: Hyperparameters in the RNN training.

Model Name	Epochs	Hidden Layers	Batch Size	Input/Output Steps
Model A	80	30	24	24
Model B	80	24	24	24
Model C	40	24	24	24
Model D	20	24	24	24

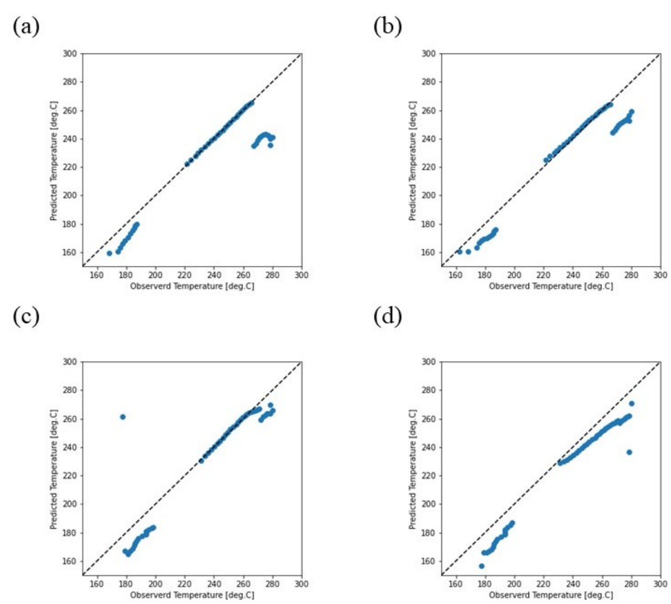

Figure 7: Comparisons between observed and predicted temperature in the RNN validation using four models shown in Table 2; (a) Model A, (b) Model B, (c) Model C, and (d) Model D.

4.2 Predictive Temperature Profile

Figure 8 shows the results for three shallow wells with total depth of approximately 600 m from ground level. Red dashed line shows predictive temperature profile. Each predicted temperature profile starts at 500 m in depth. The black solid line and the blue dashed line show interpolated and extrapolated temperature profiles in the REPOS web GIS, respectively. Figure 8 (a) displays the results of better curve fitting in Model A and Model B, compared to Model C and Model D. It shows that the larger number of epochs increasing accuracy of the prediction. Figure 8 (b) displays that Model A and Model B have a good match with the observed data. However, the prediction of Model C depicts unstable temperature profiles even though the number of epochs is larger than that of Model D. It implies that outliers in the validation test may cause the error as shown in Figure 7 (c). In contrast, Figure 8 (c) shows that all models could not match with the observed data. This shallow well has lower temperature profile than other two wells. It is necessary to add the typical curves of lower temperature reservoirs than 100 °C to improve the accuracy of the ML prediction.

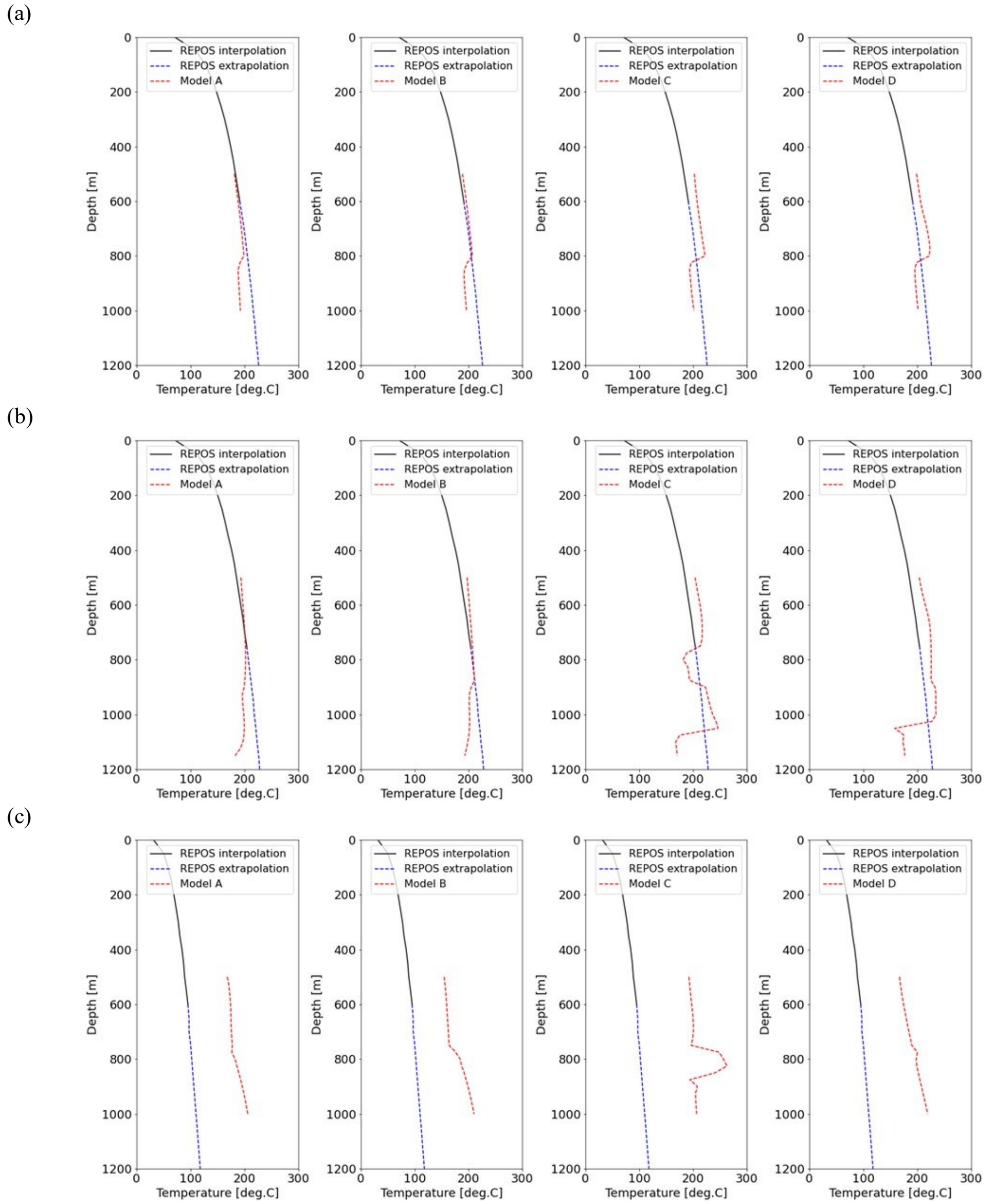

Figure 8: Comparisons between the REPOS data and predictive temperature-depth profiles in three shallow wells. The applied RNN models are shown in Table 2.

5. DISCUSSION AND CONCLUSION

This preliminary study showed the two ML approaches in power density and temperature prediction focusing on lower temperature reservoirs in Japan. The implemented NN architectures were for the purpose of effective use of introduction potentials provided from the REPOS web GIS. It showed that these ML approaches can overcome the shortcomings in dataset associated with the candidates of binary cycle system introduction in Japan. The feedforward NN model might be shallow learning but effective to predict the relationship between power density and wide range of average reservoir temperatures. In the preliminary results, most of the predicted power density estimates were categorized in fault-types tectonic settings when reservoir temperature was less than 200 °C in this dataset. However, the achievement of this approach totally depends on the accuracy in average reservoir temperature estimation. The second RNN model has been developed for improving reservoir temperature estimation. The LSTM architecture, known as Seq2Seq would be a solution to mitigate the uncertainty in average reservoir temperature estimation using shallower wells than the bottom of geothermal reservoirs. From the comparison of prediction results of the four models, the ML prediction approach worked well as a better curve fitting method to the observed temperature profiles for binary system with small and medium scale capacity. On the other hand, it was found that this training of the RNN model did not include enough observed data to deploy for prediction of lower reservoir temperature than 100 °C. It needs to add more training data especially for small capacity power generation. Future work is to improve the accuracy of the data driven prediction by managing supervised data and application of different RNN algorithms.

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