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Geological Stratification Effects on the Prediction Accuracy of Neural Networks for Energy-Pile Heat Exchange#

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ABSTRACT

Energy piles integrate building foundations with ground heat exchangers to harvest shallow geothermal energy, providing low-carbon heating and cooling. Subsurface geological conditions—particularly vertically stratified soil layers with contrasting thermal properties—can influence the heat-exchange performance of piles; yet their impact on the accuracy of neural-network predictions remains underexplored. This study quantifies how geological layering affects predictive performance by employing a hybrid spatio-temporal neural network that captures both spatial and temporal characteristics of a pile's thermal field. The model maintains high predictive accuracy even in layered soils. These findings indicate that, in the absence of groundwater flow or other perturbations, geological layering alone exerts a limited effect on neural-network-based prediction accuracy of energy-pile performance.

Keywords: geothermal, energy pile, stratified soil, heat-exchange prediction.

1. INTRODUCTION

Building operations account for approximately one-third of global final energy consumption and generate about 28 % of energy-related CO_2 emissions [1]. More than half of that energy is devoted to space heating, domestic hot water, and cooling, making the buildings sector a prime target for decarbonization efforts.

Ground-source heat pumps (GSHPs) exploit the nearly constant temperature of shallow geothermal reservoirs, yielding coefficients of performance far above those of air-source heat pumps and greatly reducing weather-dependent variability [2]. By circulating a working fluid through buried heat exchangers, GSHP systems can operate efficiently year-round with minimal seasonal fluctuations [3].

Energy piles embed GSHP heat-exchange pipes directly within foundation piles, thereby combining structural support and thermal exchange in a single element. This integration reduces land take and installation costs relative to conventional vertical borehole heat exchangers [4]. However, the heat-exchange efficiency of an energy pile depends strongly on subsurface conditions: soil thermal properties, groundwater flow dynamics, and geological stratification can all perturb the local temperature field around the pile and thus its thermal performance [5].

Accurate short-term prediction of the pile heat exchange performance is critical for real-time control strategies of GSHP systems. Traditional statistical time-series models and shallow-learning methods often struggle to capture the coupled spatial and temporal variability of the soil temperature field—especially under non-stationary conditions such as transient heating or cooling loads. Hybrid deep-learning architectures that combine convolutional layers (for spatial feature extraction) with recurrent layers (for temporal dependencies) have demonstrated robustness in analogous spatio-temporal forecasting tasks [6].

While the impact of groundwater flow on energy-pile thermal recovery and effective ground conductivity has been quantified in detail [5], the influence of vertical geological layering on data-driven prediction accuracy remains largely unexplored. Yet many urban and peri-urban sites feature complex stratigraphy that could alter subsurface thermal regimes.

The present study therefore quantifies the effect of vertical soil stratification on the short-term heat-exchange performance of energy piles and evaluates

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whether a spatio-temporal deep-learning model can maintain high prediction accuracy under such heterogeneity.

2. METHODS

2.1 Experimental Setup

A laboratory-scale experiment was conducted in a 2.45m × 2.45m × 2.0m steel soil tank, fully insulated to minimize heat loss to the surroundings. The tank was filled with saturated sand, and two identical prefabricated concrete piles (diameter 0.15m, length 1.5m) were embedded at a 2m spacing in a square arrangement. Each pile contained a cross-connected U-tube of 9.5mm inner diameter through which water circulated. The pile and tank were instrumented with temperature sensors (inside the pile outlets and in the surrounding soil), and the circulating water flow rate and inlet temperature were controlled. In a typical test, 45 °C hot water was circulated at 0.08 m^3/h through a pile while the surrounding sand was initially started at about 17.7 °C.

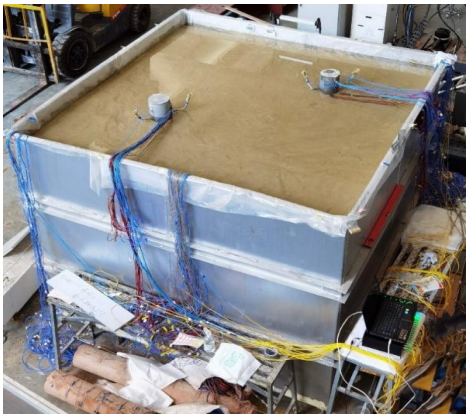

Fig. 1 Energy pile experiment

2.2 Numerical Simulation and Validation

A three-dimensional finite-element model was built in COMSOL Multiphysics replicating the experimental geometry and boundary conditions. The soil domain measured 3.5 m×3.5 m×3.0 m, ensuring a semi-infinite approximation around the pile (see Figure 2).

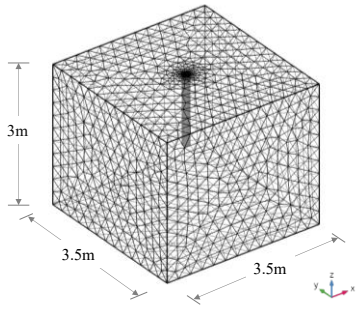

Fig.2 COMSOL mesh of the energy pile

Thermophysical parameters are summarized in Table 1. The simulation ran for 140 h, and the simulated outlet-temperature time series was compared against experimental measurements. Good agreement—within 0.2 °C on average and capturing the stabilization near 43.5–44 °C—validated the numerical model's reliability (see Figure 3).

Table 1 Key thermophysical parameters

Parameter	Unit	Value
Concrete density	kg/m^3	2342.7
Concrete specific heat	J/(kg·K)	944.7
Concrete thermal conductivity	W/(m·K)	1.89
Soil density	kg/m^3	1900
Soil specific heat	J/(kg·K)	1155
Soil thermal conductivity	W/(m·K)	2.7

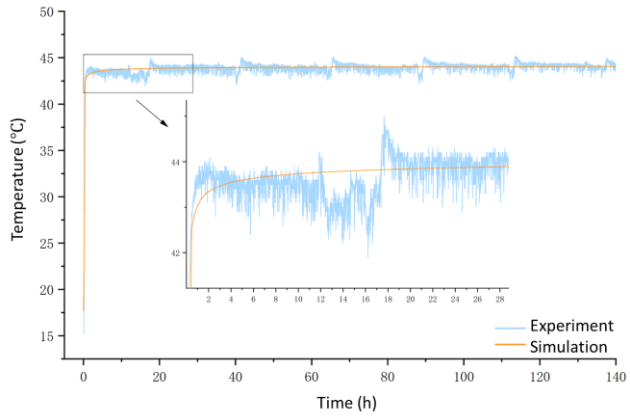

Fig.3 Outlet water temperature for the energy pile: experiment vs. simulation under 45 °C heating

2.3 Stratified soil model

To analyze geological-layering effects, a three-layer soil profile inspired by borehole data from Wuhan was imposed:

- 0–5 m: clay (λ = 1.2 W/m·°C; α = 5.28×10^{-7} m^2/s)
- 5–20 m: gravelly sand (λ = 1.9 W/m·°C; α = 7.87×10^{-7} m^2/s)
- 20–50 m: sandstone (λ = 3.0 W/m·°C; α = 1.33×10^{-6} m^2/s)

The upper, middle and lower thirds of the pile were embedded in clay, gravelly sand and sandstone, respectively. While all other geometric, boundary, and initial conditions matched the homogeneous case. The validated COMSOL simulation generated stable thermal-field data, sampled at 30-minute intervals.

2.4 Data Preparation and Feature Selection

Fourteen time-series features were fed to the network: the inlet water temperature, the outlet temperature, and the readings from twelve soil-temperature sensors arranged around the pile (sensor locations in Figure 4). All channels were sampled every 30 min, producing 672 time stamps for the 14-day simulation period.

The data were split chronologically: the first 70 % of samples trained the model, and the remaining 30 % assessed its performance. A sliding-window strategy was applied: for every prediction step the model ingested the two most recent observations of each feature (i.e., the preceding 60 min) and output the forecasted outlet temperature 30 min ahead.

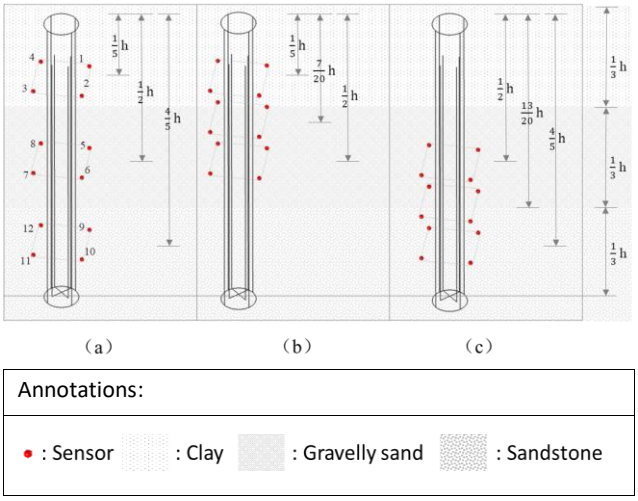

Fig.4 Different sensor arrangement schemes under geological stratification: (a) scheme 3-1; (b) scheme 3-2; (c) scheme 3-3

2.5 Neural-network architecture

A hybrid CNN-LSTM network was chosen to predict the pile outlet temperature from measured data. The input features consisted of time-series sensor readings from the pile inlet, outlet, and multiple soil-temperature sensors. These inputs have *both* temporal correlations (they evolve over time) and spatial correlations (sensors at different locations sample the temperature field). CNNs are effective at extracting spatial patterns, while LSTMs capture temporal dependencies. Therefore, our network first applies a stack of convolutional layers to the multichannel input (viewed as an "image" over sensors), followed by pooling and flattening, then passes the result through an LSTM layer. The LSTM output is finally mapped to a single output (predicted outlet temperature). The CNN-LSTM architecture is as follows: two Conv2D layers (128 and 32 filters with 2×3 kernels), each followed by max-pooling, then a Flatten and RepeatVector, then an LSTM with 100 units, and a Dense output neuron. The network was trained for 100 epochs with a batch size of 32.

3. RESULTS AND DISCUSSION

3.1 Prediction performance under stratification

Three sensor-placement schemes (schemes 3-1, 3-2, and 3-3) were evaluated, differing only in the positions of the 12 soil sensors around the pile (Figure 4). Each scheme's trained model was run ten times to assess variability. Table 2 summarizes the mean performance metrics on the test set.

Table 2 Averaged prediction performance across ten runs for three sensor configurations

Scheme	RMSE	MAE	MAPE	R^2
3-1	0.291	0.232	2.544	91.247%
3-2	0.290	0.222	2.407	90.993%
3-3	0.297	0.244	2.670	90.999%

All three schemes achieved R^2 exceeding 90.9%, with differences under 0.5 percentage points. RMSE and MAE also remained tightly grouped (0.29 – 0.30°C and 0.22 – 0.24°C, respectively). Figure 5 presents box plots of the ten runs' RMSE, showing minimal variability and no scheme-dependent bias.

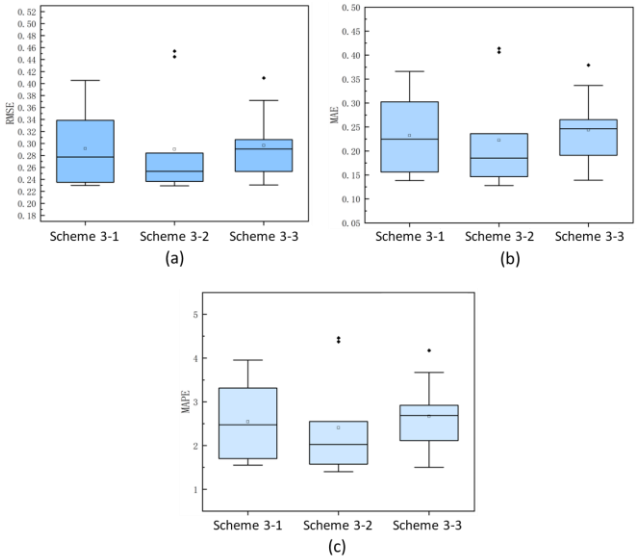

Fig.5 Box plots of prediction accuracy under different sensor arrangement schemes

3.2 Thermal-Field Analysis

To explain the model's robust accuracy despite stratification, temperature isosurfaces were extracted from the COMSOL model at t = 269 h (Figure 6). The stratified layers induce slight discontinuities in the thermal gradient at layer interfaces, but the overall deviation in the soil temperature field around the pile is minor (≤ 0.5 °C). This limited perturbation preserves the spatio-temporal patterns that the neural network learned in the homogeneous case, accounting for the negligible drop in prediction accuracy.

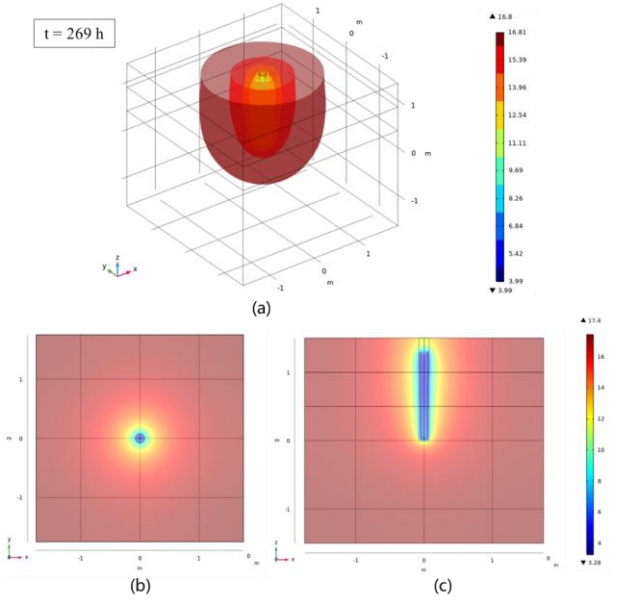

Fig.6 Temperature isosurfaces around the pile at 269 h under stratified soil conditions

The results demonstrate that vertical geological layering, in the absence of convective groundwater flow or other disturbances, has a limited impact on short-term prediction accuracy of neural-network-based models for energy-pile outlet temperature. The thermal conductivity contrasts among clay, gravelly sand, and sandstone layers (1.2–3.0 W/m·K) create only subtle variations in the local temperature field under steady heating. As a result, the convolutional filters trained to recognize spatial patterns remain effective in stratified media.

4. CONCLUSIONS

This study quantified the effect of vertical geological layering on the prediction accuracy of a hybrid neural-network model for energy-pile outlet temperature. Using a validated laboratory experiment and numerical simulation with a three-layer soil profile (clay – gravelly sand – sandstone), this study generated spatio-temporal datasets that were used to train a convolutional – recurrent network. Across three distinct sensor-placement schemes, differences among schemes were under 0.5 percentage points. Thermal-field analysis revealed that stratification induced only minor perturbations in the soil temperature field, explaining the model's resilience. The findings suggest that, in the absence of significant groundwater flow, geological layering alone does not substantially degrade the accuracy of data-driven predictions for energy-pile performance, and that sensor arrangements may be flexibly designed without loss of fidelity.

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