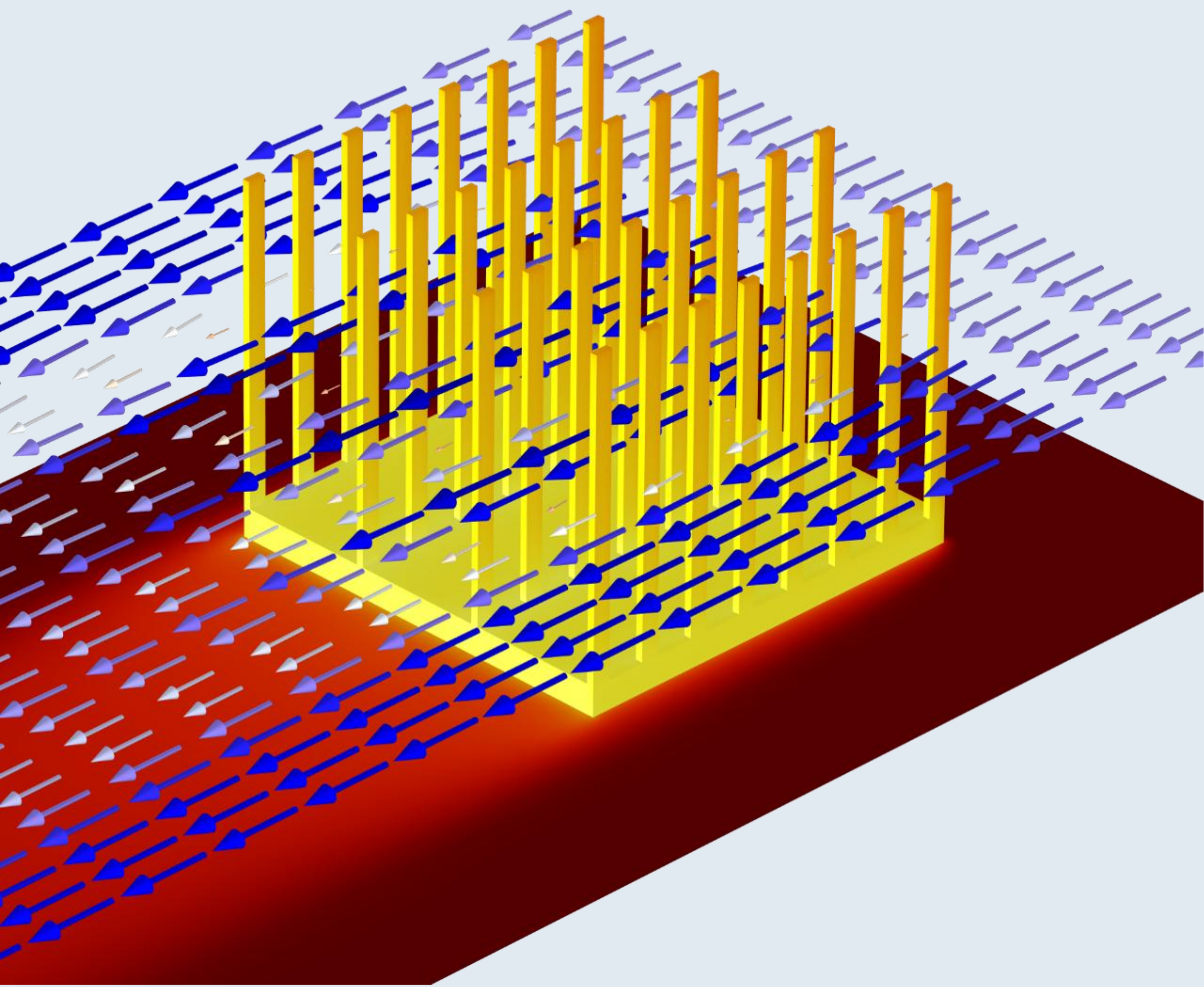




Surrogate Models Trained with Limited Data Sets for a Thermoelectric Energy Harvester

This work compares the performance of three machine learning-based surrogate models. The training data size for each model is limited.

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1. Introduction

Energy from the environment can be reclaimed through the use of energy harvesters. By eliminating the need for a wired power supply and regular battery replacement, autonomous wireless sensor networks become possible. This reduces both logistical and financial costs. How well the ambient energy can be converted depends on the environmental conditions. Thermoelectric generators (TEGs), for example, utilize temperature differences—such as those caused by industrial waste heat—and convert them into electrical energy using the Seebeck effect. This means that a

sufficiently large temperature gradient results in a high energy yield. To develop efficient thermoelectric energy harvesting systems (TEHs), device parameters must be adapted to the respective environmental conditions. Computer-aided “digital twins” are frequently used for this purpose since simulation-based parameter studies reduce the costs of prototype manufacturing. However, FEM models are computationally costly, so optimizations and sensitivity analyses can take a long time; surrogate models promise to be faster and acceptably accurate at the same time.

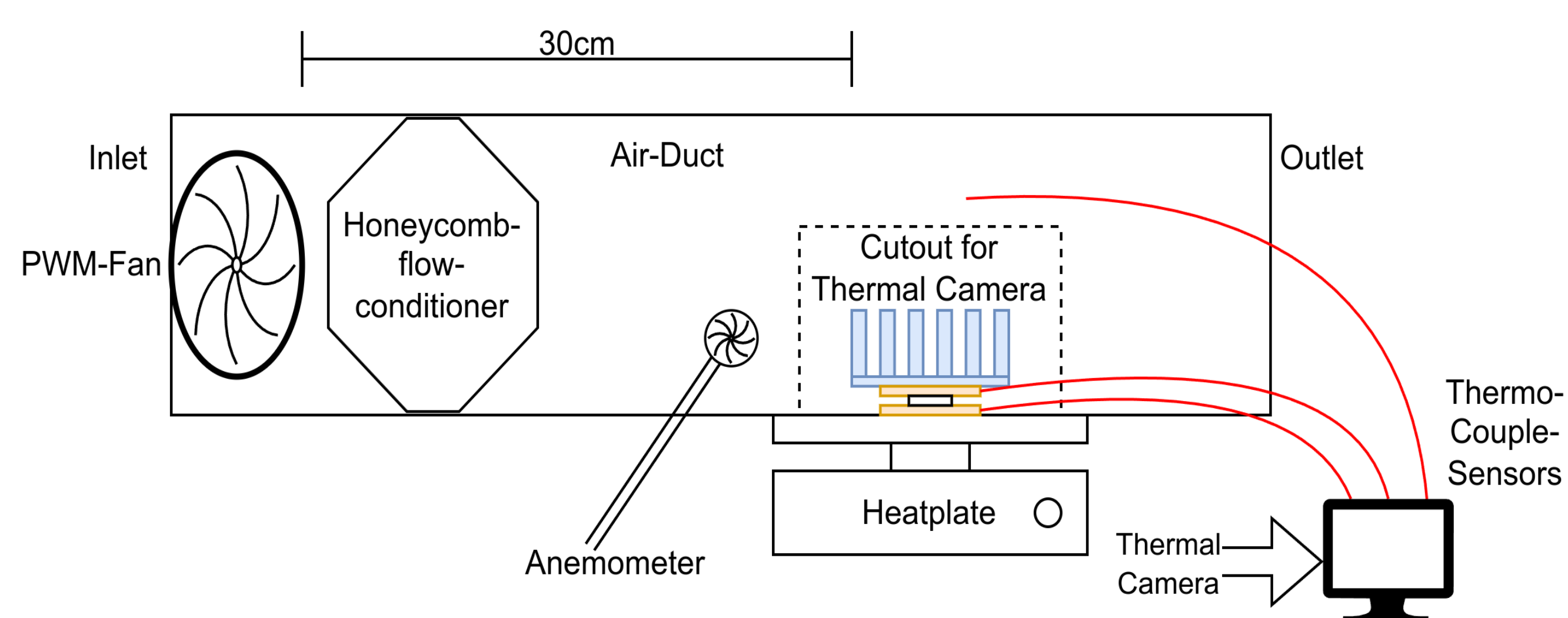


FIGURE 1: Sketch of the measurement setup. A fan creates an airflow, which is conditioned and measured before the device under test.

3. Multiphysics Simulation

In the COMSOL finite element model, the TEG with a heat sink is simulated using a phenomenological black-box approach that accounts for coupled thermoelectric effects (Joule heating, the Seebeck effect, heat conduction, and charge transport), as well as material properties such as thermal conductivity, the Seebeck coefficient, electrical resistance, and heat capacity. A coaxial heat sink with a finned base plate improves convective cooling; thermal radiation is neglected. After model development, training data is generated through iterative forward evaluation using Latin hypercube sampling (LHS), which offers more uniform coverage of the input space with fewer samples compared to standard Monte Carlo methods—particularly advantageous for high-dimensional tasks and uncertainty quantification. The setup yielded 1,000 training samples and 32 validation samples for 16 input and 8 output parameters.

2. Experiments and Surrogate Modeling

Various temperatures T_{hot} were set on the underside of the TEG using a resistive heating plate. At the same time, the ambient air temperature T_{amb} and the temperature between the heat sink and the TEG $T_{TEG,top}$ were measured using thermocouples. Subsequently, two temperature gradients are determined from the three measured variables: $\Delta T_{tot} = T_{hot} - T_{amb}$ and $\Delta T_{TEG} = T_{hot} - T_{TEG,top}$. The resulting air velocity v_{in} is measured with a handheld anemometer.

Three different surrogate models were created using machine learning techniques: Deep Neural Networks (DNN), Polynomial Chaos Expansion (PCE), and Gaussian Process Regression (GPR). The training data was generated using a finite element model (FEM).

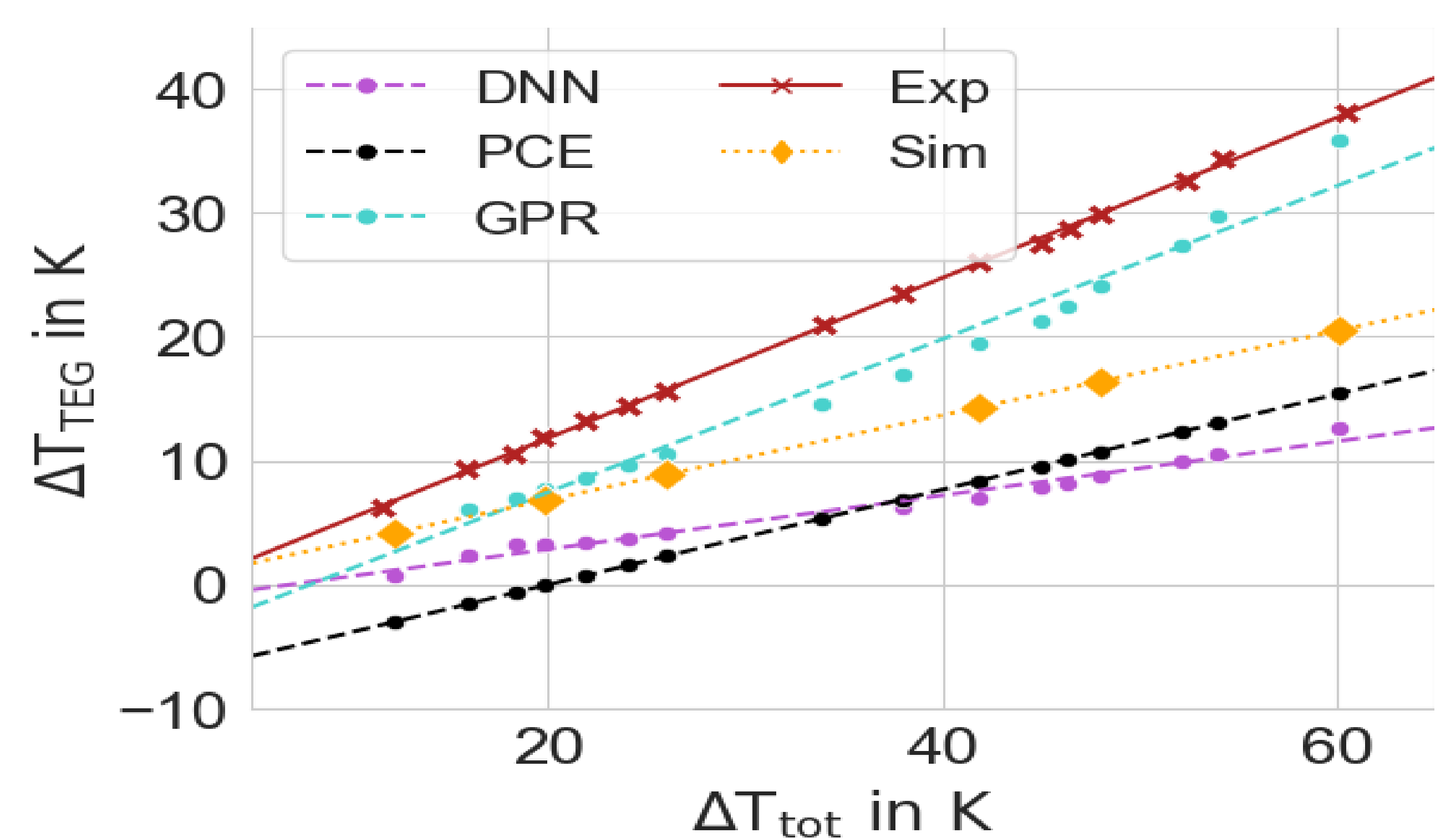


FIGURE 2: All graphs exhibit similar characteristics. First, they all follow a linear trend, and second, all these straight lines have a positive slope of the same order of magnitude.

REFERENCES

Vambolt, E., Pöpel, N., Wiecek, J., Moazamigoudarzi, M., Rothmayr, J., & Lohbreier, J. (2026). Machine learning-based surrogate models trained with limited datasets for a thermoelectric energy harvester. *Energy and AI*, 25, 100812. <https://doi.org/10.1016/j.egyai.2026.100812>

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