

Performance enhancement of a thermoelectric generator using a 2D simulation and a physics-informed neural network for condition monitoring

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Motivation: Thermoelectric generators can be used to harvest usable electrical energy from waste heat. This energy provides energy to sensor nodes which enable condition monitoring of the system under consideration. A new method is proposed that combines finite element simulation with a physics-informed neural network (PINN). This makes it possible to separate the cost-intensive numerical simulation process from the end user query process. Thus, optimization of the design and energy harvester efficiency can be accelerated for specific use cases.

2D multiphysical numerical simulation

A thermoelectric generator (TEG) with an integrated heat sink – defined by 4 parameters - was modelled in COMSOL Multiphysics (see Figure 1). The surface on which the TEG is mounted has a temperature of 350 K, while the ambient temperature is 280 K. The inlet velocity of the air runs from left to right and is adjustable.

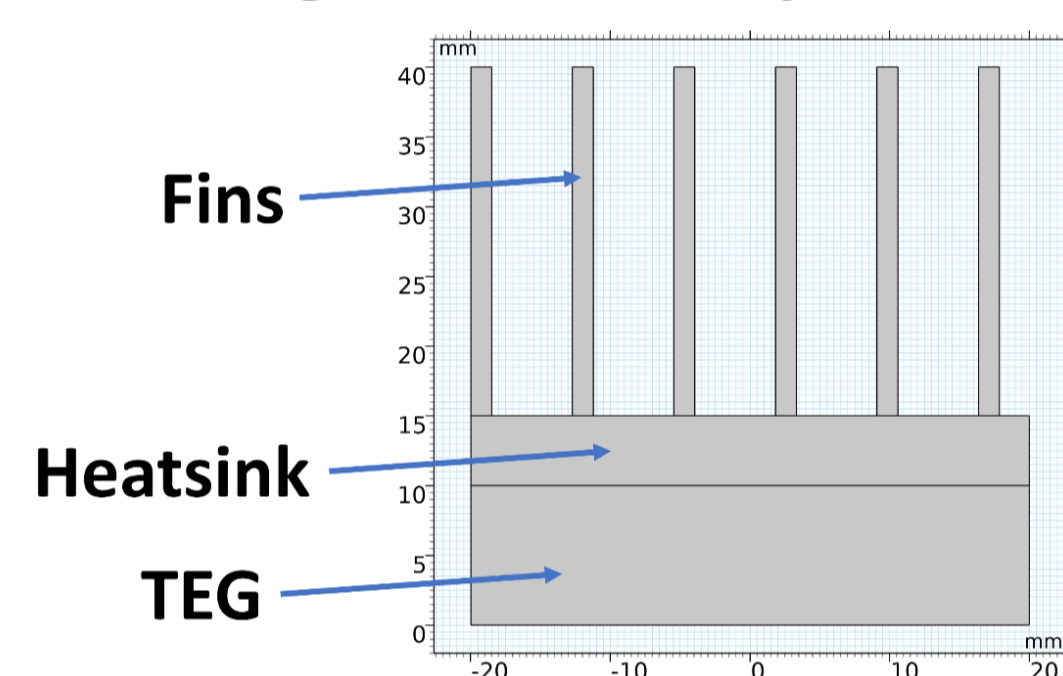


Figure 1: The geometry of the surface area of the heat sink influences the heat transfer rate and the fluid dynamics of the coolant.

The multiphysically coupled heat equation and Navier-Stokes equations are solved using COMSOL and the results are color-coded for display (Figure 2 and 3).

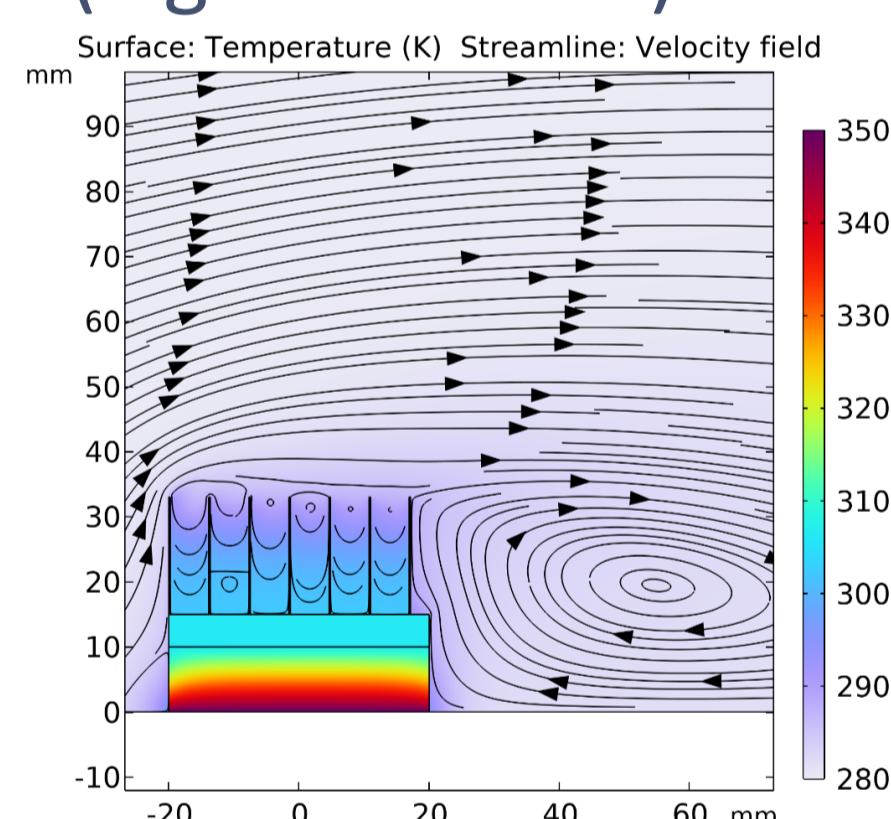


Figure 2: The velocity field around the TEG. Vortices occur behind the module due to turbulence.

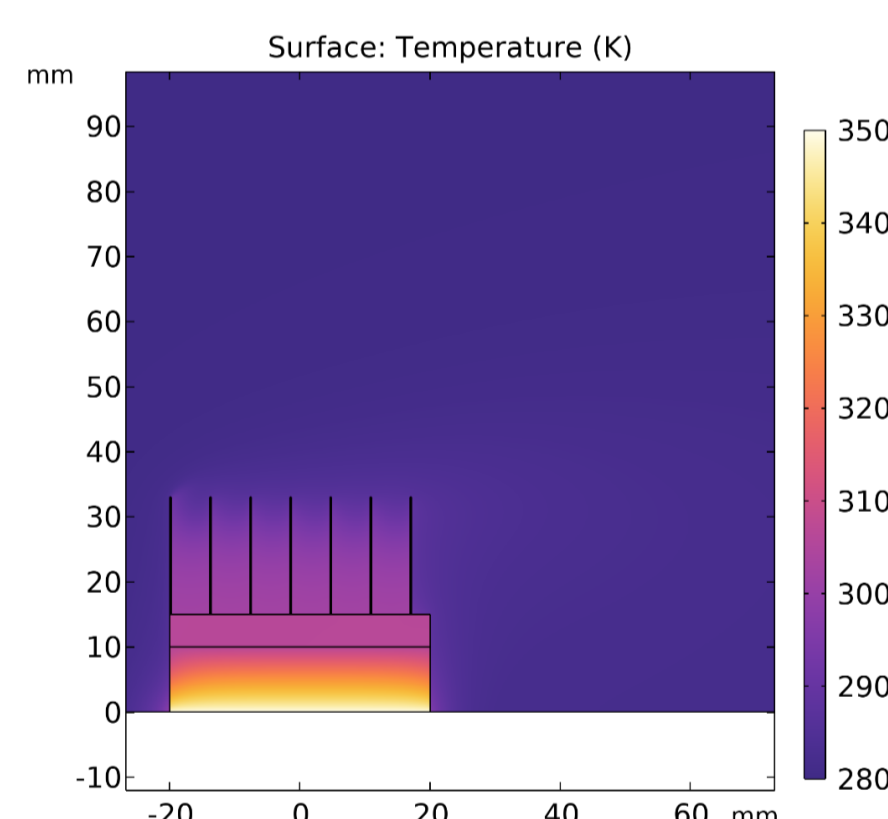


Figure 3: The temperature field around the TEG. The temperature gradient between the upper and lower side of the TEG is relevant for the heat flux.

The simulation shows the heating of the TEG with the heat sink due to heat conduction from the surface through the module and heat transfer via convection from the heat sink to the ambient air.

Physics-informed neural network

The 150 data sets obtained from the simulation are used to train and validate a neural network (see Figure 4).

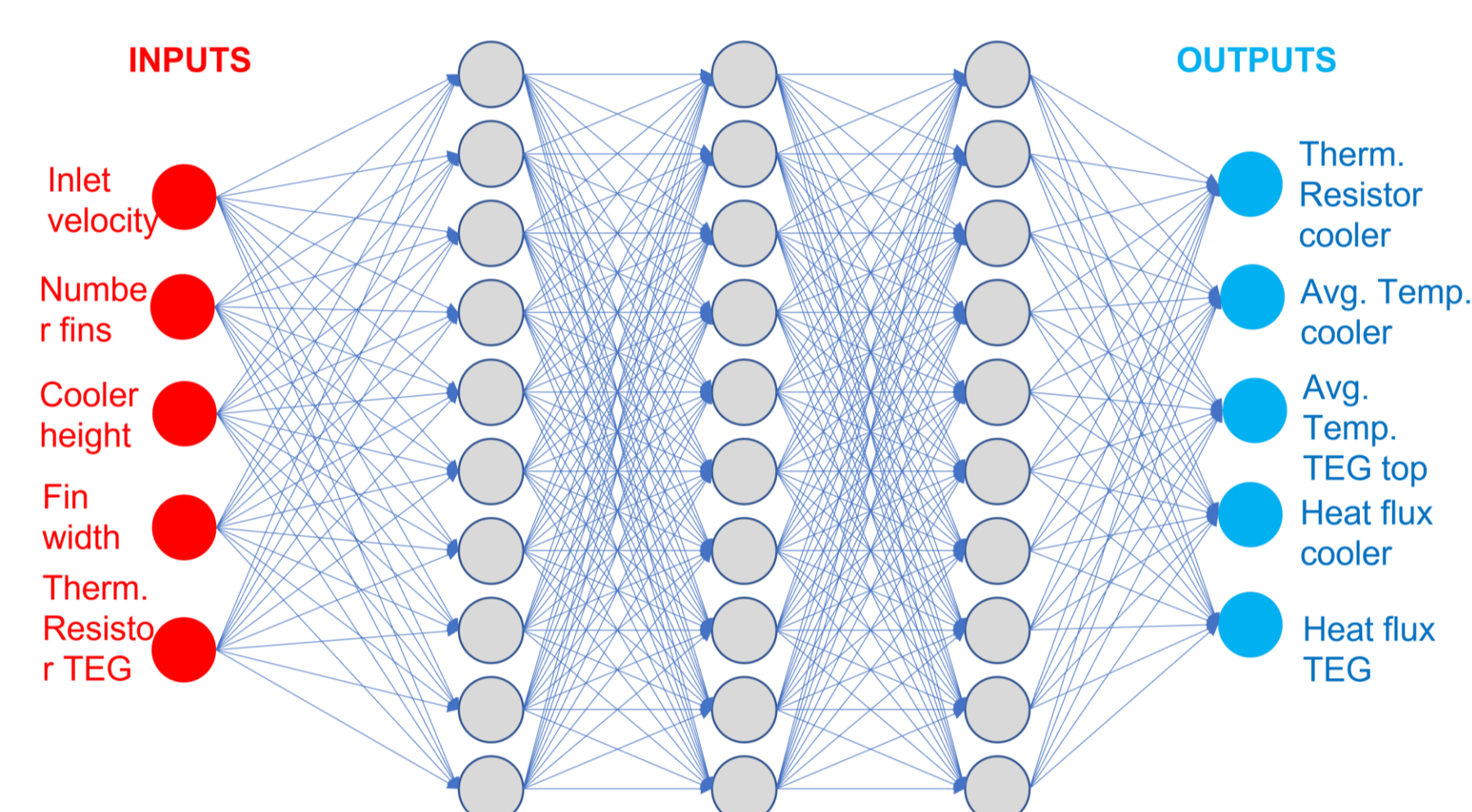


Figure 4: The neural network contains an input layer with 5 nodes, 3 hidden layer with 10 nodes each and an output layer with 5 nodes.

After the training and validation phase (method: Adam, number of epochs: 20000), the neural network can be used as a replacement for the FEM model. A crucial advantage is that the processing time for a result is significantly shorter than with simulation alone (seconds instead of minutes). A GUI in which the neural network is integrated can be implemented in COMSOL via the Application Builder. The results from the app and from the FEM simulation can be seen in Figure 5.

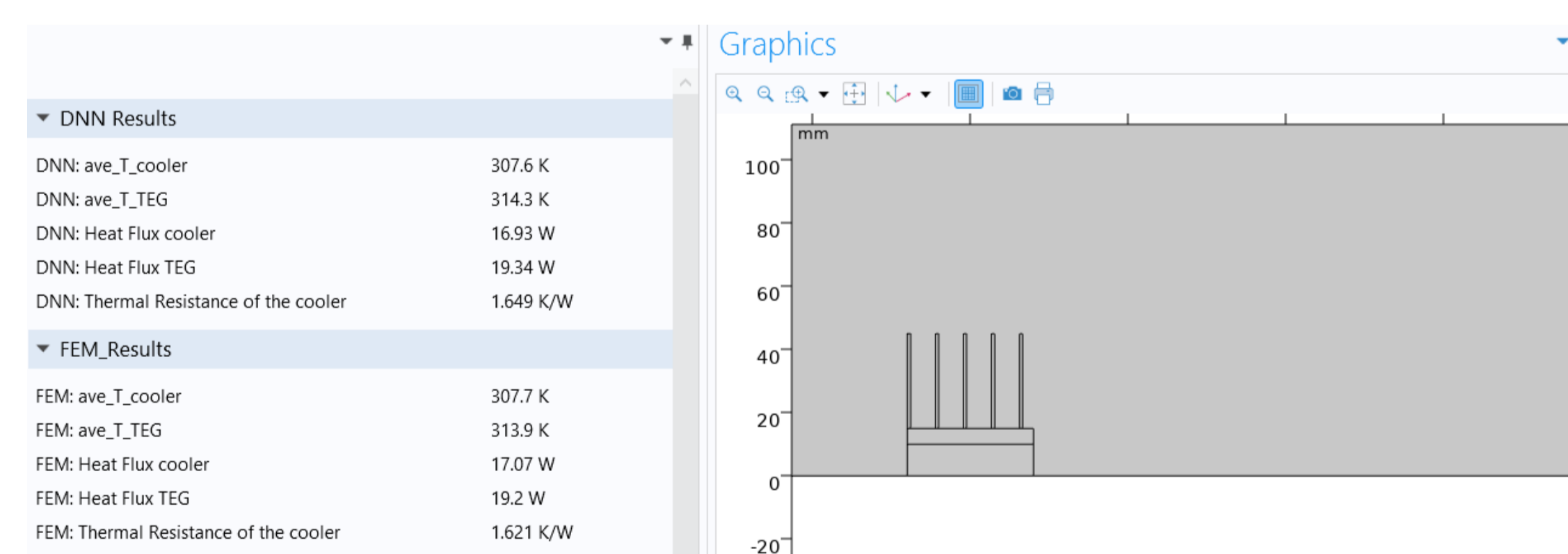


Figure 5: The screenshot of the app. The discrepancy in the values could be reduced by a larger amount of data.

Summary and conclusion

FEM simulations in combination with corresponding neural networks can be used to develop a digital twin. This imitates its real version and provides information about its behaviour much faster than the simulation alone. The two-dimensional case was only considered as proof-of-concept. The next step would be an extension to 3D with an even more significant processing time advantage for the PINN. This work was funded by the EU Chips Act project LoLiPoP-IoT (#101112286). In this work, a use case from the LoLiPoP-IoT project is considered, whereby motorized vehicles are equipped with TEGs. These are used to operate sensor nodes that monitor the status of the vehicle, e.g. the fill level of the fuel tank.

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