Machine learning-enabled optimization of multi-pair thermoelectric coolers under dynamic operating conditions

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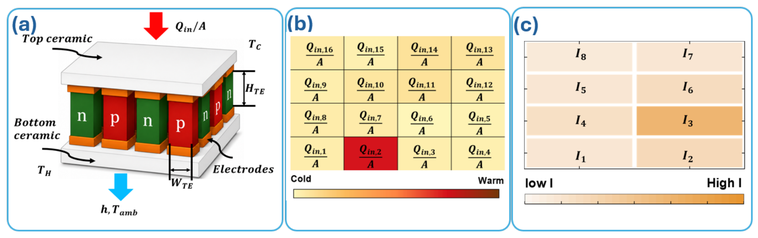
1. Introduction

- Thermoelectric cooler enables electricity-to-heat conversion and provide compact cooling solutions for electronics and renewable systems[1].
- Conventional design tools ensure the model performance depends on the geometry, materials, and operating conditions.
- ANNs provide fast, accurate prediction of TE device performance[2][3].
- Multi-objective Genetic Algorithms (GAs) could efficiently balance multiple conflicting parameters and control the current focus on colling hotspot.

2. ANN Thermoelectric Cooler Model

i. Physical model

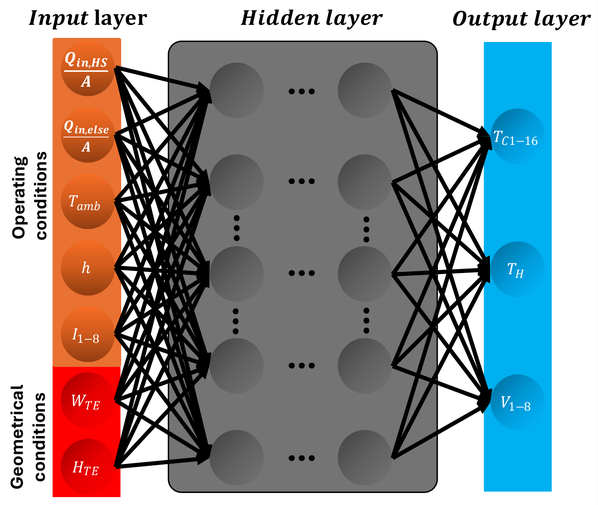
- ❑ Multi-pair TEC (8 pairs in total).
- ❑ $Bi_{2-x}Sb_xTe_3$ for p-type material and $Bi_2Te_{3-x}Se_x$ for n-type material.



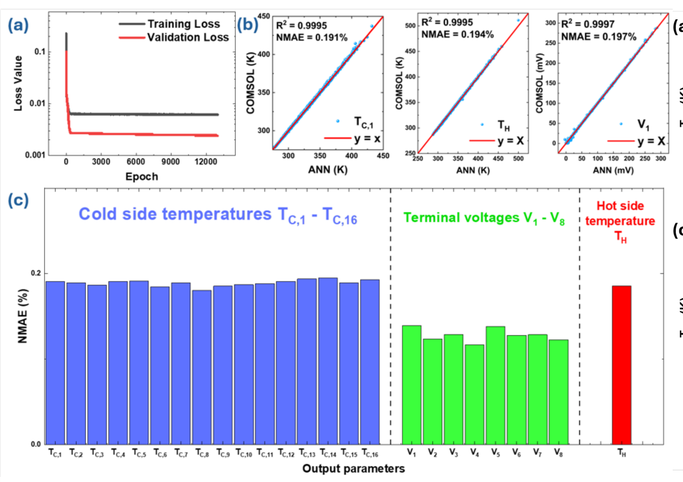
- ❑Temperature dependent Seebeck, electrical and thermal resistivity [4]
- ❑Non-uniform with one hotspot input power density
- ❑Independent current control system, $I_1 - I_8$.

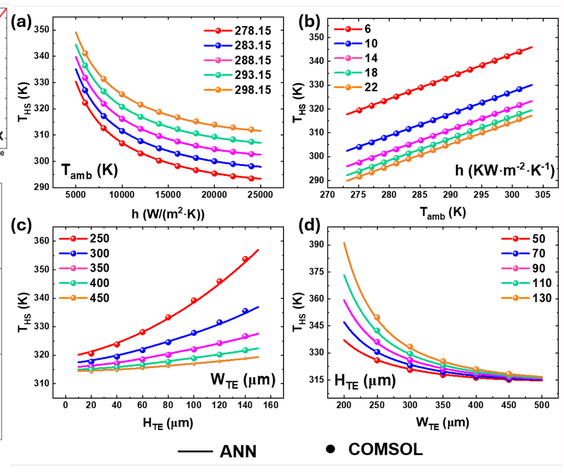
ii. ANN configuration and training

- 26,000 parameter sets simulated in COMSOL as training dataset
- Geometrical parameters
  - Leg width (W_{TE})
  - Leg height (H_{TE})
- Operating conditions
  - Hotspot input power density ($Q_{in,HS}/A$)
  - Other input power density ($Q_{in,else}/A$)
  - Ambient temperature (T_{amb})
  - Convection (h)
  - Current (I_{1-8})
- Temperature at cooling side (T_{C1-16})
- Temperature at heat dissipation side (T_H)
- Voltage of each TEC pair (V_{1-8})



iii. Performance evaluation





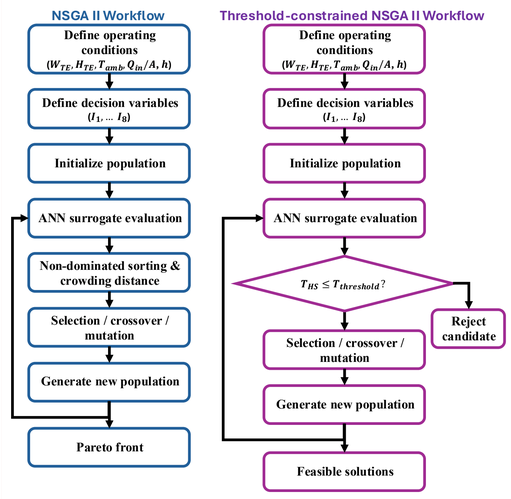
- Mean NMAE of 0.17% across 25 outputs, with maximum NMAE of 0.195%.
- Together with $R^2 > 0.999$ across all outputs.
- High efficiency – About 1,050,000 times faster compared with COMSOL model *(0.27s only if predicting 4720 data by ANN model, while for COMSOL model, approximately 180s for each data)*

4. Conclusion

- Artificial neural networks (ANNs) served as a forward modeler of the multi-pair TEC trained on 3D COMSOL simulation, with NMAE < 0.2%.
- ANN model could significantly reduced operation time, achieves 1,050,000 times (forward) and 480,000 times (optimization) speedup over FEM.
- Coupling with multi-objectives optimization algorithm, ANN can balance the conflicting factors (i.e. hotspot temperature and electric power) for TEC.
- Independent control current configuration has lower electric power costs than the uniform configuration, but costs more electric power at hotspot.
- ANN model coupling with the optimization algorithm could be applied to multiple optimization scenarios, for instance, on-chip cooling.

3. TEC Optimization by Genetic Algorithms

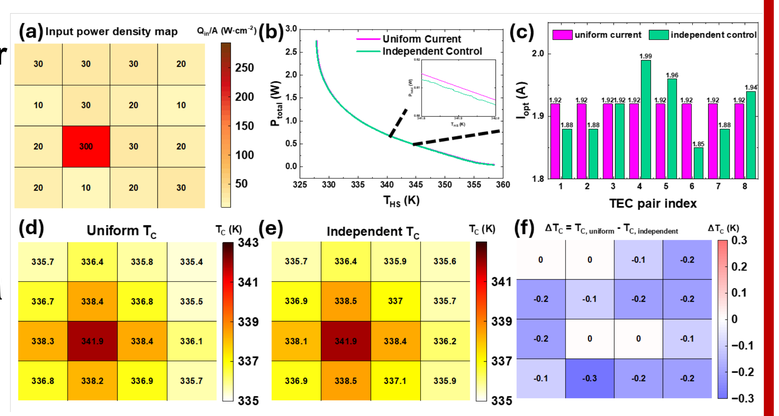
i. Flow chart for genetic algorithms

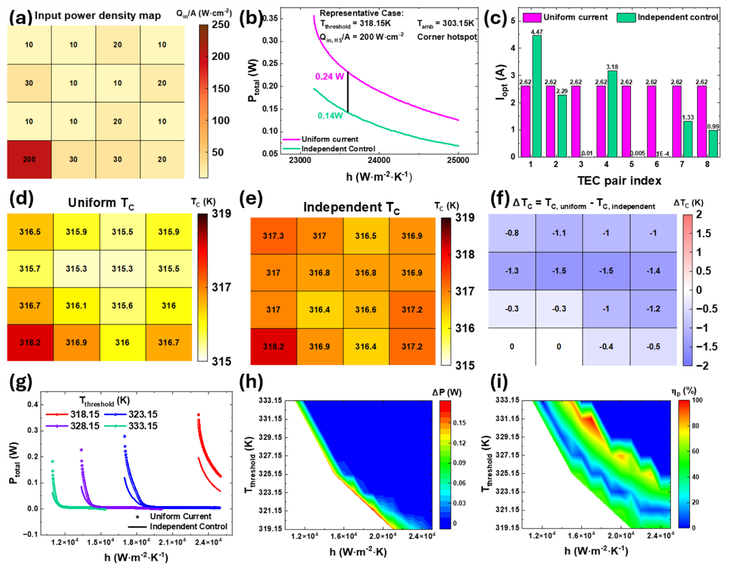


- ANN assist multi-objectives genetic algorithm.
- Optimization based on uniform and independent current configuration.
- Balance two conflict factors, P_{total} and T_{HS}, lower both the P_{total} and T_{HS} to ideal value
- Balance the two conflict factor, P_{total} and h (T_{amb}), when define a $T_{threshold}$ to hotspot.

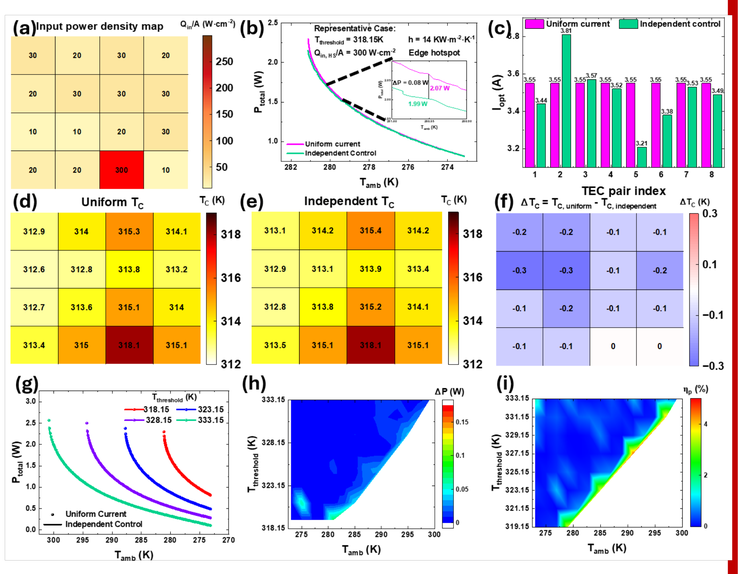
ii. Results

- Independent case has lower P_{total} than uniform case for same T_{HS}.
- Independent configuration has higher I at higher Q_{in}/A area while lower I at other area.

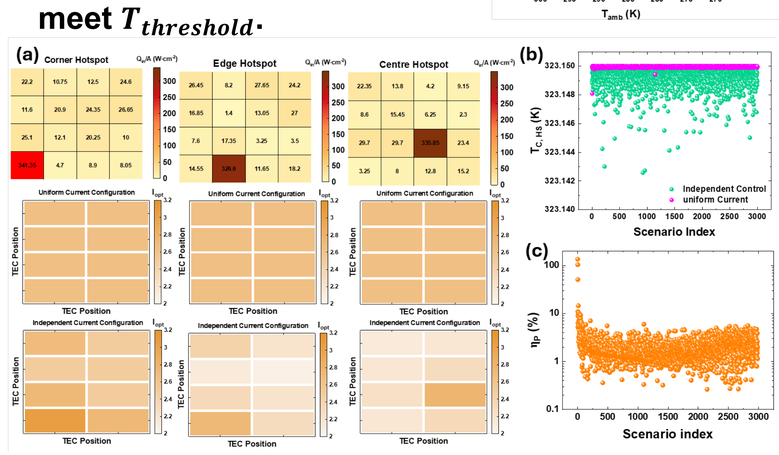




- Balance T_{HS} and h with $T_{threshold}$.
- Independent case's P_{total} lower than uniform case.
- Higher h, lower ΔP.
- Lower h may cause fail to meet $T_{threshold}$.
- Input current focuses on hotspot area for independent conditions.



- Independent case costs less electric power in total than uniform case.
- $I_{hotspot}$ is higher than other areas for independent case.
- Lower $T_{threshold}$, higher ΔP.
- higher T_{amb}, higher power saving rate.
- Higher T_{amb} may cause fail to meet $T_{threshold}$.



- I optimization across 3,000 cases with independent and uniform configuration.
- 172s for 3,000 optimizations (57ms/case).

- Independent case has better cooling performance compared to the uniform case with less total electric power.

Reference

[1] D.Zhao and G.Tan A review of thermoelectric cooling: Materials, modeling and applications. *Applied Thermal Engineering 2014;66:15-24.*

[2] Y. Zhu, D. W. Newbrook, P. Dai, H. Kees, and R. Huang Artificial neural network enabled accurate geometrical design and optimisation of thermoelectric generator. *Applied Energy 2022;305:117800.*

[3] Yang, H., Zhu, Y., Chong, H. M. H., & Huang, R. (2026). Accurate and efficient design and optimization of thermoelectric cooler via machine learning technologies. *Applied Thermal Engineering, 285, 129224*

[4] Mao J, Zhu H, Ding Z, Liu Z, Gamage GA, Chen G, et al. High thermoelectric cooling performance of n-type Mg_3Bi_2 -based materials. *Science 2019;365:495–8.*

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