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Metaheuristic-Based Enhancement of Cooling Capacity in Miniaturized Thermoelectric Refrigeration Systems

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Abstract

Because of its small size, dependability, silent operation, and appropriateness for precise thermal management to electronic and portable cooling applications, miniaturized thermoelectric refrigeration systems have received a lot of attention. However, geometrical limitations, electrical losses, and difficulties with heat dissipation frequently limitations their cooling capacity. In order to better understand and improve the cooling performance of miniature refrigeration systems, this work offers a thorough model for mathematics of a single-stage thermocouple cooler (TEC). In order to accurately forecast system performance under limited operating conditions, the model integrates significant thermoelectric phenomena with pragmatism factors such electrical contact opposition and hot-side thermal immunity. Two metaheuristic optimization algorithms—Genetic Algorithm (GA) and simulator annealing (SA)—are used to maximize the cooling capacity, which is represented in terms of the rate of chilling (ROR). The thermoelectric elements' geometric design parameters and input current are taken take into account as choice variables by the optimization system. These methods are used to find the best design combinations that can improve cooling efficiency while preserving the small size needed for tiny workloads. The findings show that by discovering nearly ideal combinations of structural and operating factors, both metaheuristic techniques successfully boost TEC's cooling capability. When compared to traditional arrangements, the improved designs produce a significant boost in ROR. Additionally, the solutions derived from GA and SA show strong agreement, demonstrating the security and dependability of the optimization procedure. The GA offers several workable optimal solutions, providing more flexibility in practical design selection without sacrificing cooling effectiveness, even though both approaches achieve comparable performance improvements. The suggested metaheuristic-based optimization approach promotes the use of high-performance scaled thermoelectric refrigeration systems in cutting-edge thermal management technologies and offers an advantageous structure for their development.

Keywords: Single-stage thermoelectric cooler, rate of refrigeration, genetic algorithm, simulated annealing

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INTRODUCTION

The results demonstrate that both metaheuristic approaches effectively increase TEC's cooling capacity by discovering nearly optimal combinations of structural and operating parameters. The enhanced designs resulted in a notable increase in the ROR compared to the conventional configurations. Furthermore, there was a high degree of agreement between the solutions obtained via GA and SA, indicating the reliability and security of the optimization procedure. Although both approaches yield similar performance benefits, the GA offers several feasible

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ideal alternatives that allow for greater flexibility in practical form selection without compromising cooling efficacy. The proposed metaheuristic-based optimization method provides an advantageous framework for the development of high-performance scaled thermoelectric refrigeration systems and encourages their use in state-of-the-art thermal management technology [1–4].

Interest in miniature thermostatic refrigeration systems has increased owing to the rising need for small, energy-efficient cooling solutions. Despite their benefits, TECs have a coefficient of performance (COP) and a very small cooling capacity compared to standard refrigeration systems. These restrictions prevent their broader commercial use, especially in systems where excellent cooling performance is crucial in small spaces. Therefore, a major research issue is to increase the cooling capacity of tiny thermoelectric refrigeration systems while maintaining compact dimensions.

The figure of merit (Z=\alpha^2/RK), where (\alpha) is the Seebeck coefficient, (R) is the electrical resistance, and (K) is the thermal conductance, is frequently used to evaluate the performance of thermoelectric materials. To increase cooling effectiveness, several investigations have concentrated on creating sophisticated thermoelectric compounds with higher figures of merit [5–8]. To improve refrigeration performance, additional studies have investigated solar-powered thermoelectric cooling systems, optimum cooling configurations, and innovative thermoelectric module topologies [9–17].

Optimization-based methods have recently been emphasized as a feasible way to enhance the TEC performance without the need to produce new materials. Metaheuristic optimization techniques are especially useful for tackling intricate nonlinear design problems with several variables and constraints. Among these methods, the simulation of annealing (SA) and Genetic Algorithms (GA) have proven to be highly effective in finding near-optimal solutions while preventing early convergence compared to local optima.

To maximize the cooling capacity of a single-stage thermoelectric refrigeration system, which can be expressed by the rate of refrigeration (ROR), a computational model of the system was created in the current study, and GA and SA were used. In addition to considering economic factors such as thermal resistance and electrical contact resistance, the optimization framework considers both the geometry and operating design characteristics, such as the input current and thermoelectric element dimensions. The purpose of this study is to find the best design variety to improve the cooling performance of compact thermoelectric refrigeration systems with constrained spaces.

MATHEMATICAL MODELLING

Figure 1 shows the physical model of a single-stage thermoelectric cooler. One thermoelectric module, appropriate hot and cold side materials, and an outer hot side heat exchanger are featured [18–22].

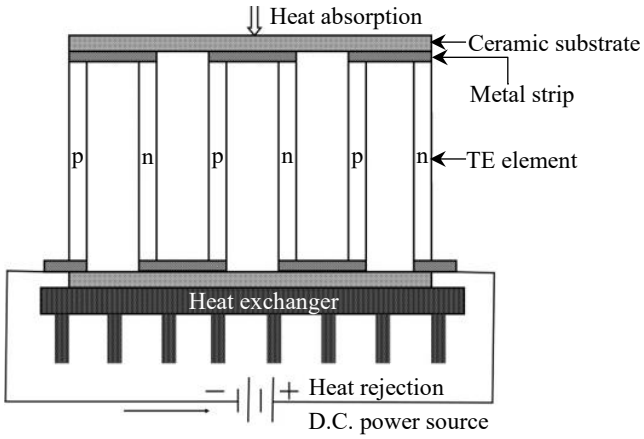


Figure 1. A single stage thermoelectric cooler.

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The basic thermoelectric correlations published in the literature [23, 24] serve as the foundation for this study. The Peltier effect, which causes heat to be absorbed or expelled at the junction of two different semiconductor materials when an electric current flows between them, is the primary process governing the operation of thermoelectric refrigeration systems. To create a temperature gradient between the cold and hot sides of the module, several p-type and n-type semiconductor elements are dynamically coupled in parallel and electrically connected in series in a standard thermoelectric cooler (TEC). Electrical resistance causes Joule heating after operation, with approximately half of the heat being directed toward either side of the thermoelectric module. To enable efficient thermal rejection, the hot side is connected to a heat sink via thermally conductive and electrically insulating materials, and the cold side is set up in thermal contact with the cooling load. Continuous heat transmission from the cooled area to the surrounding area is made possible by the alternating electrical connections of the p-type and n-type elements, which provide a complete electrical chain. Figure 1 shows the schematic layout of the miniaturized thermoelectric refrigeration system studied in this investigation. Mathematical modeling and subsequent metaheuristic optimization of cooling capacity using a genetic algorithm (GA) and simulated annealing (SA) approaches were performed on this setup.

The equations for heat balance at the two junctions of the module are:

$$Q_c = 2N\left[I\alpha T_c - \frac{kA(T_h - T_c)}{L} - \frac{1}{2}I^2\left(\frac{\rho L}{A} + \frac{2\xi}{A}\right)\right] \quad (1)$$

where Qc is the rate of heat absorption at the cold junction, commonly known as the rate of refrigeration (ROR), and Qh is the rate of heat rejection obtained from the hot junction. The Seebeck coefficient, electrical resistivity, thermal conductivity, and electrical contact resistance are the attributes of thermoelectric materials. L and A represent the length and cross-sectional area of the thermoelectric elements, respectively, and Th and Tc signify the hot and cold junction temperatures, respectively. where N is the total number of thermoelectric couplings in the module, and I is the input current. The thermal conduction and heat in joules are shown by the heat fluxes kA (Th −Tc)/L and ½ I2 (ρL/A+2rc/A), respectively. The Peltier heat at the hot junction is IαTh and that at the cold junction is IαTc.

Bismuth telluride is a thermoelectric element employed in this investigation. The mean temperatures (Tave) of the hot and cold sides dictate the properties of thermoelectric compounds. The equations for this temperature range were provided by Melcor [25] and are described as follows:

$$\alpha = (22224 + 930.6T_{ave} - 0.9905T_{ave}^2) \times 10^{-9} \quad (2)$$

$$\rho = (5112 + 163.4T_{ave} + 0.6279T_{ave}^2) \times 10^{-10} \quad (3)$$

$$k = (62605 - 277.7T_{ave} + 0.4131T_{ave}^2) \times 10^{-4} \quad (4)$$

To precisely assess the effect on the hot-junction temperature and overall cooling performance of the miniature thermoelectric refrigeration system, the thermal resistance metric of the hot-side heat exchanger was integrated into the mathematical model in this study. A more genuine evaluation of the system behavior and cooling capacity optimization is made possible by considering this useful thermal limitation. Therefore, the following connection is satisfied when determining the hot-junction value [25].

NUMERICAL OPTIMIZATION OF SINGLE STAGE TEC

$$N = \frac{S \times \text{packaging density}}{2A} \quad (5)$$

The usable cross-sectional area of the piezoelectric refrigeration system under consideration in this study was fixed at 25 mm² with a packing density of 0.8, enabling the use of 10–40 thermocouples. The input current was chosen as a design variable and was free to fluctuate between 0.1 and 3.0 A. An initial estimate of the hot-side temperature (T_h) is assumed to determine the system's working conditions, and the related thermoelectric material properties are measured using Eqs. (3)–(5). The revised value of T_h

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will be determined using Eqs. (1), (2), and (6). To ensure an accurate thermal solution, an iterative process was performed until the discrepancy between the estimated and assumed hot-side values converged to a negligible value.

Both operating and geometric design elements were used in the formulation of the optimization problem to improve the cooling capacity, as indicated by the rate of refrigeration (ROR). To determine the ideal design configuration, two metaheuristic optimization methods are used: genetic algorithm (GA) and Simulated Annealing (SA). These algorithms effectively search the design space and identify parameter pairings that satisfy the space limitations of miniature thermoelectric refrigeration systems while optimizing their thermal performance.

OPTIMIZATION RESULTS

Optimization Results Using GA

The real-coded evolutionary optimization strategy proposed by Deb and Agarwal, which uses the Simulated Binary Crossover (SBX) operator for a successful answer space search, is the foundation of the Genetic Algorithm (GA) used in this study [20]. The algorithm was written in C and used to tailor the cooling capacity of a miniature thermoelectric refrigeration system, which was measured using the rate of refrigeration (ROR). Through selection, crossover, and mutation techniques, the GA gradually improves the design variables while evaluating a population of potential solutions over several generations. In complicated and nonlinear design spaces, this population-based search approach enables the efficient discovery of near-optimal solutions. Table 1 displays the optimization parameters used for the GA implementation. The optimization process was performed five times independently to guarantee solution consistency and dependability because GA is intrinsically stochastic. The optimal design setup for increasing the cooling capacity of the thermoelectric refrigeration system was determined by identifying the best-performing solution from the available results.

The cooling capacity of the miniaturized thermoelectric refrigeration system was significantly increased by Genetic Algorithm (GA) optimization, which yielded a maximum rate of refrigeration (ROR) of 1.144869 W. The ideal solution was found at an input current of 2.360 A, thermoelectric (TE) element length of 0.542 mm, and TE element cross-sectional area of 1.0 mm^2. There is a clear and workable optimum for optimizing cooling performance, as the optimal TE element length falls well within the defined design range of 0.5–1.5 mm. However, the ideal sectional area was discovered near the upper limit of the acceptable design range, indicating that future research may be able to increase the cooling capacity by raising the upper limit of this parameter. Ten thermoelectric couples were identified as the ideal configuration throughout the optimization phase, and this design satisfied the space restrictions placed on the miniaturized system. These findings highlight the effectiveness of the GA-based metaheuristic method in locating the ideal geometric and operational parameters for increasing the cooling capacity of tiny thermoelectric refrigeration equipment (Figure 2).

The Genetic Algorithm (GA) was run on multiple occasions with various initial populations and parameter parameters to better investigate the features of the optimal landscape and evaluate the presence of multiple high-performance solutions. Three different optimal solution sets that created the same maximum rate of freezing (ROR) were identified. This result suggests that the cooling-capacity augmentation problem of miniaturized thermoelectric refrigeration systems has a multimodal optimization structure, meaning that numerous combinations of design factors can produce comparable optimal results.

Optima-1, Optima-2, and Optima-3 are the best-performing solution sets that correspond to the identified optima, as shown in Table 2. All configurations provided the same optimum ROR, offering flexibility in practical design and manufacturing considerations, even though the indices of some design factors varied among the three alternatives. One interesting finding is that, for all three optima, the ideal photovoltaic element length (L) remained at 0.542 mm. This consistency implies that the TE element length has a distinctive optimal value for the specified operating circumstances and space limits, making it a crucial design parameter that influences the cooling capacity.

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Table 1. Parameters settings for GA.

Population size	**20**
Crossover probability	0.80
Mutation probability	0.25
Termination criteria	1000 generations
Number of runs	5

Table 2. GA optimization results.

S.N.	**I (A)**	**L (mm)**	**A (mm^2)**	**N**	**Optimized ROR (watts)**	**Label**
1	2.361	0.543	1.1	11	1.244869	Optima -1
2	1.181	0.543	0.6	21	1.244869	Optima -2
3	0.945	0.543	0.5	26	1.244869	Optima -3

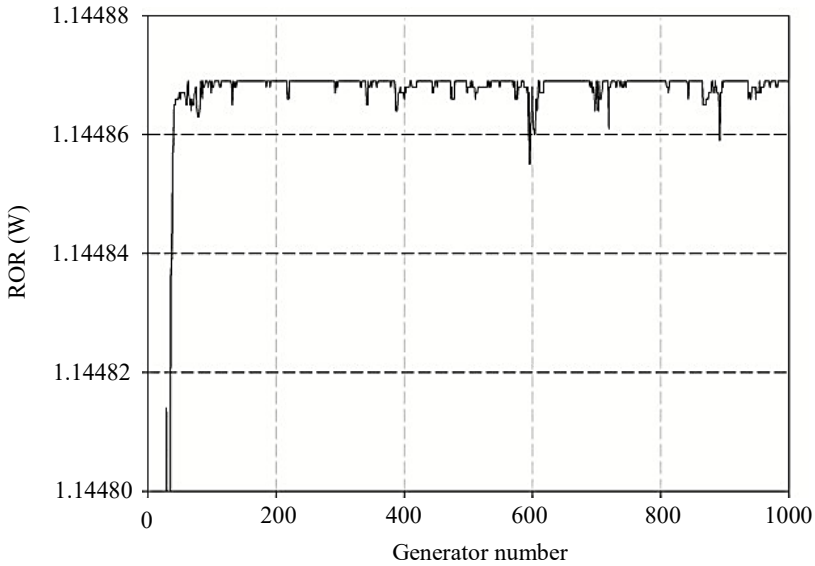


Figure 2. GA convergence curve of optimized ROR.

The GA-based metaheuristic approach can find alternative outstanding performance. design configurations is demonstrated by the existence of multiple equivalent optima, providing more flexibility in the design of miniature temperature-controlled refrigeration systems without compromising the cooling performance.

Optimization Results Using SA

This consistency implies that the TE element length has an exclusive optimal value for the specified operating conditions and space limits, making it a crucial design parameter that influences the cooling capacity. The GA-based metaheuristic modeling approach can find alternative outstanding performance. Designing configurations is demonstrated by the existence of multiple equivalent optima, providing a greater range of options in the design of miniature temperature-controlled refrigeration systems without sacrificing cooling capacity.

The annealing temperature and cooling schedule are the two main factors that control the optimization method. A comparatively high temperature at the start of the search allows for extensive exploration of the design space. The operating temperature is progressively lowered to comply with a predetermined cooling rate while optimizing, enabling the algorithm to concentrate on promising areas and converge into an ideal solution. The MATLAB® source code created by Yang served as the base for the SA implementation used in this study, which successfully handled nonlinear constrained standard optimization problems.

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Several simulations using multiple SA parameter choices were performed to assess the robustness of the optimization methodology. The ability of each arrangement to optimize the ROR was used to evaluate its performance. For the final optimization, the parameter combination that generated the optimum cooling performance was used. Table 3 provides an overview of the related SA settings that were utilized to tailor the miniature thermoelectric refrigeration equipment.

SA's maximum recorded ROR is 1.144869 watts. The way forward vector, designated Optima-1 in Table 2, was the same as that generated by the GA. As shown in Table 4, SA was able to obtain the single best peak despite running this simulation multiple times with different settings. The improved ROR value and associated optimal design parameters can be assured using these appropriate GA and SA values.

The optimization approach considers the input current (I), thermoelectric element length (L), and cross-sectional area (A) as independent design considerations. Conversely, when satisfying the geometric requirements of the miniaturized thermoelectric refrigeration framework, the number of thermoelectric couplings ((N)) is a dependent variable that is computed from the value of (A) using Eq. (8). The ideal value of the thermoelectric element length remained constant at 0.542 mm for all solutions produced using both Genetic Algorithm (GA) and Simulated Annealing (SA), according to the optimal results shown in Tables 2 and 4. The importance of (L) as a crucial design component controlling the system's cooling capacity is further supported by this consistency in the results.

To enable representation in graphics of the optimization landscape, (L) was fixed at 0.542 mm because the rate of chilling (ROR) is a function of the three independent variables (I), (L), and (A), and the optimal value of (L) is constant for all ideal solutions. Thus, using Eq. (1), a three-dimensional response surface was created, with (I), (A), and ROR displayed along the X-, Y-, and Z-axes, respectively, as shown in Figure 3. On this surface, the GA-identified optimal solutions were superimposed and designated as Optima-1, Optima-2, and Optima-3.

Optima-1 was correctly identified by both GA and SA, whereas Optima-2 and Optima-3 were only detected by GA, as shown by comparing the results in Tables 2 and 4. The availability of numerous identical optima validates the multimodal nature of the cooling-capacity optimization issue, even if all three solution vectors provide the same maximum ROR of 1.144869 W. GA's superior exploration capabilities and efficacy in managing multimodal search spaces have been demonstrated by its ability to locate all three ideal regions. However, SA converged to only one of the optimal solutions despite multiple simulations using various parameter values. In turn, GA demonstrated a greater potential to identify several globally optimal design configurations and preserve the same degree of cooling performance for the current metaheuristic-based improvement in cooling capacity in miniaturized thermoelectric refrigeration equipment (Figure 3).

Table 3. Parameters used for the simulated annealing optimization process.

Initial temperature	**1.1**
Final temperature	$1e^{-10}$
Cooling factor	0.81
Boltzmann constant	1.1
Number of iterations per temperature level	500

Table 4. SA optimization result.

S.N.	**I (A)**	**L (mm)**	**A (mm^2)**	**N**	**Optimized ROR (watts)**	**Label**
1	2.365	0.543	1.0	10	1.145869	Optima-1

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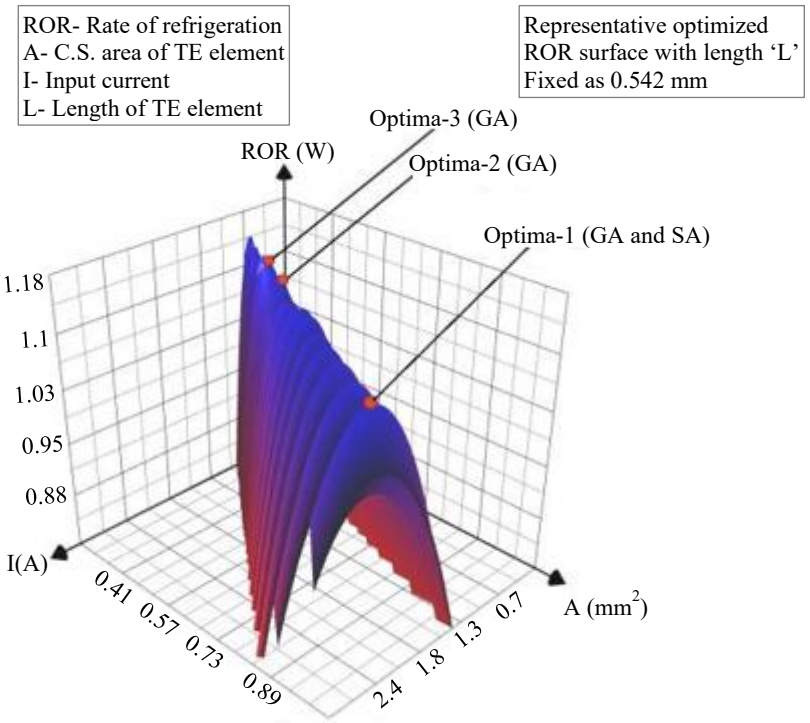


Figure 3. Multiple optima labeled at the *ROR* surface with thermoelectric element length L = 0.542 mm.

CONCLUSION

Miniature thermoelectric refrigeration systems have become an ideal cooling solution because of their small size, security, environmental friendliness, and capacity to provide precise temperature control without the use of hazardous refrigerants. However, their comparatively modest cooling capacity often discourages their widespread use. Therefore, it is crucial from a practical standpoint to find the best design of a variety that improves cooling performance in locations with space limitations.

In this study, two metaheuristic methods—Genetic Algorithm (GA) and simulated annealing (SA)—were used to create and optimize a mathematical model of a single-stage thermoelectric refrigeration system. Maximizing the rate of cooling (ROR), a crucial measure of cooling capacity, was the optimization goal. The results showed that the geometric features and operating current of the thermoelectric elements both have a major impact on the system performance and can be efficiently tuned to increase the cooling capacity.

High-performance design solutions were successfully found using both methods of optimization. However, by finding several ideal design configurations that had the same maximum ROR, the comparison research showed that the GA had a higher exploration capability. The multimodal character of the optimization problem was validated by the availability of three different optima. More design flexibility without sacrificing cooling performance was made possible by the GA's successful discovery of all suggested optimal regions, whereas the SA was only able to find one of the global optima.

The results of this study provide a useful basis for improving the cooling capacity of miniature thermoelectric refrigeration systems using metaheuristics. Designers can optimize refrigeration performance while overcoming space constraints using an optimum mix of input current and thermal element geometry. To further increase the effectiveness and cooling capacity of compact thermoelectric systems for refrigeration, the developed optimization framework can be expanded in subsequent studies by applying alternative optimization algorithms, multi-objective optimization strategies, or advanced thermoelectric supplies.

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