Semiconductor Optoelectronics, *Vol. 42 No. 1 (2023), 986-1004*
https://bdtgd.cn/

Semiconductor Optoelectronics
ISSN: 1001-5868

DESIGN OF OPTIMAL FIN SELECTION IN THERMOELECTRIC GENERATOR DEVICE BY MULTI-OBJECTIVE FUNCTION USING GMAO

Ajitha Mary C[1], Dr. Ritesh Yadav[2]
[1,2]Department of Physics, Dr. A.P.J. Abdul Kalam University, Indore (M.P.), India-452016

Abstract: Globally, numerous scientists have focused on utilizing Waste Heat Recovery (WHR) technology in various applications. To recover those heat energies, the Thermoelectric Generator (TEG) is very helpful. However, enhancement is required in the TEG material for attaining an efficient conversion. Thus, an optimal fin design for the TEG device for enhanced heat exchange is proposed in this paper. By selecting the optimal fin by the Gaussian Mutated Aquila Optimization (GMAO) considering a multi-objective function, the TEG device is designed initially. The fin's input parameters like spacing betwixt two different fins, the fin's thickness, length, and angle are optimized for the design. Utilizing the proposed Polynomial Structure-centric Maximum Power Point Tracking (PS-MPPT) technique, the power output is maximized after the Buck DC-DC converter is utilized for the conversion here. After that, in the electrical storage super capacitor (or) battery, the attained load is stored. Then, regarding conversion efficiency, fitness vs iteration, power output, along with pressure loss, the proposed optimal fin-centered TEG design's performance is evaluated with the prevailing approaches. Moreover, for the proposed MPPT technique, the power outcome's maximization is assessed. The experiments exhibited that the proposed mechanism outperforms the prevailing frameworks.

Keywords: *Thermoelectric Generator (TEG) device, Gaussian Mutated Aquila Optimization (GMAO), Buck DC-DC converter, Polynomial Structure based Maximum Power Point Tracking (PS-MPPT), and Maximize power.*

1. INTRODUCTION

The Thermoelectric (TE), which can convert thermal energy into electricity directly without moving components or gas or fluid emission, making them reliable along with compact when analogized with other energy conversion approaches, is a solid-state device (H. Lv et al., 2021). TEG and Thermoelectric Cooler (TEC) are the major devices included in the TE. With a better temperature control ability, efficient heat transfers and dissipation could be provided by the TEC as an active cooling approach for electronic devices. Grounded on the Seebeck effect, electric power is produced by a TEG. Seebeck effect is a phenomenon where electromotive force is produced by temperature gradients in which the merits like compact volume, higher reliability, zero emissions, and long work life are afforded (M. He et al., 2020). The TEG is made a promising WHR technology with these benefits since it does not depend on conventional fossil fuel energy; also, the waste heat is converted into electricity directly. For recovering several waste energy resources like exhaust gas, human body heat, geothermal energy, along with solar energy, the TEG can be applied flexibly (Ge et al., 2021). Moreover, it has numerous benefits like no chemical reaction, no pollution, long-term reliability, no moving parts, no noise, maintenance-free, along with easier adjustment of device or equipment size. Thus, as of the academic along with industrial communities, more attention has been attracted toward them (S. Lv et al., 2020). TEGs comprise TE modules that are placed betwixt two heat exchangers. For power generation, the TEGs are endowed with higher potential by intriguing features like a longer reliable lifespan, maintenance-free, along with no scaling together with moving parts. Generally, arrays of N-P semiconductor chips are included in a TEG. These are electrically connected in series and thermally connected in parallel; also, they are covered by ceramic substrates (Wang et al., 2021). But, the TEGs' power generation efficacy relies on their arrangement, system-level components, along with material (Kumar et al., 2019). To enhance the electrical energy, conversion enhancement is required for the TEG. On the materials' enrichment covering several TE materials like skutterudite, half-Heusler, bismuth telluride, lead telluride, oxides, together with other alloys, there were massive efforts (W. Li et al., 2020). For several applications, optimizing the TEGs design is essential rather than enhancement of the TE materials' intrinsic efficacy (Yang et al., 2021). The development of numerical models investigating the efficient use of TEG systems centers mainly on operating temperatures, optimizing geometric dimensions, various materials in TEG construction, and design optimization of hot along with cold side heat exchangers. Moreover, the TEG system design concentrates on the energetic efficiency of conductive and convective system sorts (Burnete et al., 2021). Every single technology has its merits as well as demerits; however, lower heat-to-electricity conversion efficacy is the main limitation of the TEG device. Numerous device-level challenges avert TEG devices as of being wielded in real applications despite the challenges offered by TE materials (Huang et al., 2018). To overcome this issue, this proposed technique optimizes the fin design utilizing GMAO with multi-objectives as the fin is a significant component in the energy generation of the TEG device.

1.1 Problem Definition

To maximize power generation, prevailing approaches provide various solutions; however, those approaches have some issues, which are enlisted further,

- For the TEG design and development, most of the research works consider only a single objective.
- The TEG may produce the minimum amount of power if temperature variation and pressure loss are present.
- For the TEG design and development, prevailing approaches only consider limited geometrics.
- High-energy approaches are open to production errors.
- The prevailing numerical simulation approaches represent a complex TE process.

By considering the entire drawback, which was addressed above, the work aims in providing an optimal fin design for TEG design by considering multi-objectives for enhancing the energy conversion efficiency.

The balance part of the technique is organized as: section 2 elucidates the related works; the proposed technique is explicated in section 3; section 4 exhibits the results along with the discussions; lastly, the paper is winded up with future work in section 5.

2. RELATED WORK

(Zoui et al., 2022) developed a cost-efficient, compact, along with robust design that is easy for incorporating into gas/liquid TE energy recovery schemes. Utilizing a numerical technique advanced with ANSYS-Fluent, the module properties like heat exchanger performance, resin properties, and contact resistance were examined. Thus, at a fin spacing (2-3 mm) along with a height (11-13 mm) at the operation condition described, the exchanger thermal efficiency was detected. Simulations along with testing outcomes revealed that the parameters affected module efficiencies like contact resistance together with resin layer effects. Only single-fin geometry was considered so it was not effective.

(Kim et al., 2019) introduced a Thermal Interface Material (TIM) with higher thermal conductivity along with temperature resistance as the key for mitigating the whole thermal resistance of the TEG module's heat path flow operating under higher temperatures. A TIM that had stable heat conduction behaviour at higher temperatures was generated in amalgamation with a polyimide matrix along with a multi-dimensional filler compound. Regarding energy conversion efficacy, a maximum enhancement was displayed by the TEG with TIM, which was 73.2 and 20.9% over the cases without a TIM and with a graphite TIM for similar temperature differences across the TEG, correspondingly. It was not fully proven with all the temperature conditions.

(X. Li et al., 2019) proffered the optimization of TE modules' number along with distribution pattern in an automotive exhaust TEG. Initially, 17 independent factors were evaluated. Also, by utilizing the Plackett-Burman design, the vital parameters were screened. Secondly, for evaluating the sensitivity of 6 selected factors, an experiment, which was developed with a central composite design, was performed; also, via the response surface approach, a surrogate technique was constructed. After that, with a multi-objective genetic framework, conflicts in '2' objectives were established. The outcomes elucidated that the system generated maximum power efficiently. But, the entire TEM system's electrical performance became inferior.

(Garud et al., 2021) examined an electro-thermo-structural coupled numerical technique for analogizing the TEG's structural, electrical, along with thermal performances for the hot heat exchanger's '6' various internal fin structures. For the hot heat exchanger with high net power output along with TEG's overall efficacy, the optimum fin internal structures were recommended. For validating the coupled evaluation's accuracy along with reliability, experiments were performed on the heat exchanger with straight fins. Within the errors of 1.5, 6, 3, and 5.45%, the coupled model predicted the hot gas outlet temperature, coolant outlet temperature, power output, and stress, correspondingly. However, it was not considered a significant structure so it was not efficient.

(Wu et al., 2021) intended to mount the temperature difference betwixt the hot and cold ends of TEG and enrich the temperature distribution uniformity, thus enriching the TEG's output power. The simulation model accuracy was verified by conducting experiments. The genetic algorithm was easily fallen into the local optimum problem so it was not reliable.

(Luo et al., 2020) established an optimization approach for TE module structures in which the TE legs' length was recognized by their specific temperature differences. The outcomes exhibited that the TEG system's temperature distributions along with voltage distributions with precise accuracy were determined by the fluid-thermal-electric multi-physics approach. Moreover, higher performance will be provided by the optimization approach if a higher number of TE legs were included in the TE module. The TE modules' output wielded for fluid WHR was enriched by the optimization approach. The approach did not consider several significant factors like the mass flow rate along with the hot fluid's specific heat, together with the effect of these parameters, so it was not reliable.

(Xiao et al., 2022) combined a TE assembly into a residential heating boiler for converting a portion of combustion heat to electricity while meeting space and/or water heating needs. A prototype where currently advanced TE modules were merged into a gas-fired boiler was established. In the experimental environment, the gathering of eight modules was the optimal choice. The assembly's power output enclosed '4' modules. These are augmented by 70% as of 7.85 to13.5 W owing to the fin's installation on the hot end. The combustion-side heat transfer's enrichment was more compound.

(Sheikh et al., 2021) developed the efficacy of an exhaust TEG grounded on changes in the baffle distribution of the heat exchanger. Here, in '3' various groups like A, B, along with C, nine sorts of heat exchangers were modelled in '3' dimensions and studied utilizing Computational Fluid Dynamics (CFD) analysis with several baffle arrangements for attaining electrical energy as of the vehicle exhaust. The outcome revealed that in the entire model, the pressure drop was in the permissible range; also, the gas flow velocity in group A was alike that was studied in other approaches. But, the power generated was 7.25%, which was high. Only three dimensions were considered.

(Deng et al., 2021) established a terrestrial Radioisotope TEG (tRTG) by employing the finite element evaluation. The electric heater along with a fin-shaped radiator was replaced by an octagonal cylinder-shaped. Therefore, the processes were built; also, for having a high surface temperature along with better temperature uniformity, the heater was presented. Moreover, at its optimal heat-sinking capacity, the heat could be dissipated by the fin-shaped radiator. Lastly, for optimizing the TE converters' geometry within a specific region, the finite element evaluation was executed. Thus, an enriched output power attained by the tRTG was 10.5 W, which mounted by 26.5%. On output performance, contact resistance had a massive influence.

(G. N. Li et al., 2021) developed a Heat Collector and Spreader (HCS) where various parameters like heat spreader thickness, thermal conductivity, and fin distribution were optimized for enriching the Self-powering and Self-aspirating Combustion Powered TEG (SSCP-TEG) performance. A portable prototype was provided by the study grounded on self-aspirating, combustion-powered TEG, self-powering, along with self-aspirating; it also contributed to emergency management technology. The temperature condition was varied, which may affect the system's performance.

(Aljaghtham & Celik, 2020) examined the feasibility of employing TEGs regarding oil pans for recovering the waste heat generated in internal combustion engines. For simulating the conversion of heat into electricity accurately by considering joule heating, turbulent air cooling, TE, along with heat conduction, a multi-physics simulation mechanism was developed. Under various oil pan geometries along with driving conditions, the total number of TE modules together with dimensions was optimized for maximizing the TE power. The simulations display that under a 76 ^{0}C temperature difference betwixt the hot and cold sides, the maximum power density attained with the multi-step oil pan geometry was 5.77 kW m^{-2}. It was difficult for complex shapes.

(W. He et al., 2019) suggested a general plate-type TEGs' performance optimization in vehicle exhaust power generation schemes. In the numerical computation, a commercial-type TE material was utilized. Also, all sorts of work conditions with various exhaust parameters along with cooler heat processes were enclosed here. The entire optimal features were evaluated when peak net power was attained. Here, the air-cooling along with water-cooling techniques was considered. However, it was not considered an important feature.

(Tang et al., 2019) recommended an H-type finned elliptical tube heat exchanger with longitudinal vortex generators. The model is integrated with the finite volume technique initially. Then, the design parameters like the longitudinal vortex generators' height, position, length, together with angle, along with the objective functions, namely Nusselt number and friction factor were established. Finally, by comprehensively analogizing, the optimal combination was determined.

(Elghool et al., 2020) conducted an analytical and statistical study on fin materials, fin height, fin space, along with optimum geometry parameters' effect on the TEG's performance. Moreover, the optimum geometry of the Heat Pipe Heat Sink (HP-HS) is determined by the study. The outcomes displayed an enhancement in TEG performance when analogized with the literature.

(Manikandan et al., 2020) developed a technique for enriching the TEC's thermal performance by amalgamating it with Phase-Change Material (PCM). For maintaining a constant along with a relatively lower temperature, the PCM was combined at the TEC's hot side. The outcomes revealed that in TEC's hot together with cold side, a vital reduction was there with the PCM's usage.

3. PROPOSED GMAO-BASED OPTIMAL FIN DESIGN IN TEG DEVICE

TE, which handles the conversion of unused heat energy into electrical power and vice versa, is an attractive technology. The merits like silence in operation, compact systems without moving parts, being reliable, and environmentally friendly are shared by the TE conversion techniques. The fin in the ceramic layer is the significant one for maximizing energy production. Thus, by considering multi-objective functions, an optimal fin in TEG is designed by this approach. Initially, the TEG fin is selected optimally; also, the buck DC-DC conversion is executed. The PS-MPPT approach is utilized for maximizing the energy; also, in the electrical storage super capacitor (or) battery, the load is stored. Figure 1 displays the block diagram for the proposed framework.

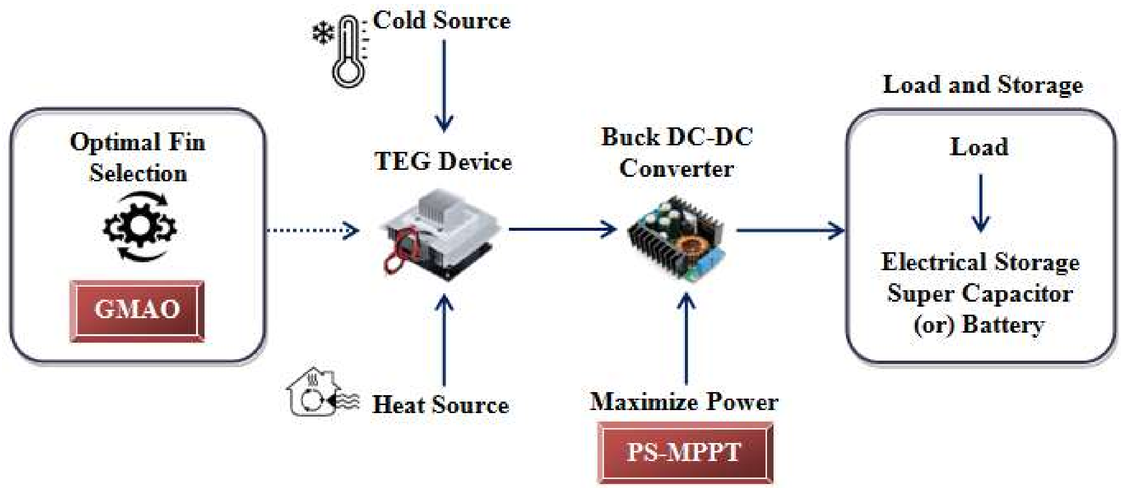

Figure 1: Block diagram for the proposed methodology

3.1 Optimal TEG Device

The TEG device encloses p-type and n-type semiconductor materials. These are organized electrically in series and thermally in parallel. Also, it has a hot along with cold surface. Hence, the '2' dissimilar (semiconductors) materials are connected with a metal conductor and sandwiched betwixt two ceramic layers at various temperatures, which causes an open circuit electromotive force. In TEG, the heat exchange's main function is the fin. The heat transfer area along with the temperature of the TE module's hot side can be mounted by the fin for attaining high output power. By optimizing the fin distribution, the heat exchanger's temperature uniformity was enhanced here for maximizing the electric power. Here, by utilizing the GMAO approach, the fin's input parameters like spacing betwixt two different fins $P(f)$, the fins' thickness $T(f)$, the fin's length $E(f)$, along with the angle of the fin $A(f)$ are optimized.

Aquila Optimization (AO) is a swarm intelligence-centric system. For various sorts of prey, there are '4' hunting behaviours of Aquila. For various prey, the hunting strategies can be switched by the Aquila. Also, for attacking the prey, it utilizes its fast speed united with sturdy feet along with claws. The approach performed well; however, the algorithm may fall into the local optimum issue in rare cases. To overcome this issue, this technique utilizes the Gaussian mutation, which will increase the local searching capability so that it does not easily fall into the local optimum problem. Initially, the population, that is, the input design parameters of the fin is initialized for the candidate solution. After that, the fitness is evaluated. Here, the multi-objective function is considered fitness. Therefore, the multi-objective function is the amalgamation of maximizing electric power output, maximizing the electric conversion efficiency, and minimizing the pressure loss. Hence, the objective function is signified as A_a. After that, the optimization process is explicated in further steps.

Step 1: Expanded exploration

The prey's location is recognized by the Aquila; then, the best hunting area is selected by high soar with the vertical stoop. Here. For determining the search space's area, the AO broadly explores as of higher soar. Hence, the behaviour is mathematically represented as,

$$H_m(l+1) = H_e(l) \times \left(1 - \frac{l}{Q_l}\right) + H_r(l) - H_e(l) * \chi \tag{1}$$

Wherein, at iteration $l+1$, the position of m^{th} individuals is depicted as $H_m(l+1)$, at the current iteration, the best location is indicated as $H_e(l)$, within an interval of 0 and 1, the random number in Gaussian distribution is specified as χ, the maximum allowed iteration number is signified as Q_l, and $H_r(l)$ notates the mean positions of all individuals at the current iteration:

$$H_r(l) = \frac{1}{PO} \sum_{m=1}^{PO} H_m(l) \tag{2}$$

Where, the number of population is exemplified as PO.

Step 2: Narrowed Exploration

Here, at a higher level of altitude, the prey is found. During this position, Aquila would circle in the clouds, get into position, and prepare for attacking the prey. The formulation of this step is given as,

$$H_m(l+1) = H_e(l) \times \omega + H_p(l) + (d - h) \times \chi \tag{3}$$

Here, $H_p(l)$ exhibits a random position; also, ω derives the levy flights:

$$\omega = b \times \frac{t \times \tau}{|\rho|^{\frac{1}{\gamma}}} \tag{4}$$

$$\tau = \frac{\Gamma(1+\gamma)\times \sin\left(\frac{\pi\gamma}{2}\right)}{\Gamma\left(\frac{1+\gamma}{2}\right)\times \gamma \times 2^{\frac{\gamma-1}{2}}} \tag{5}$$

Here, the constant values are denoted as b and γ, in addition, t, ρ are random numbers betwixt 0 and 1, d and h are utilized for presenting the spiral shape in the search, which can be computed as,

$$h = \chi \times \sin(\theta) \tag{6}$$

$$d = \chi \times \cos(\theta) \tag{7}$$

$$\chi = \varepsilon + W \times Y_1 \tag{8}$$

$$\theta = -\psi \times Y_1 + \frac{3\pi}{2} \tag{9}$$

Where, the constant number is denoted as W, the number of search cycles is specified as ε, the integer number is illustrated as Y_1, and the fixed constant number is demonstrated as ψ. After that, the Gaussian mutation process is executed, which is expressed as,

$$G_m = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(H_e(l) - H_m(l))^2}{2\sigma^2}\right) \tag{10}$$

Wherein, the Gaussian mutated output is exemplified as G_m, and the standard deviation values of the population are indicated as σ.

Step 3: Expanded exploitation

Aquila descends vertically for performing a preliminary attack for probing the prey's response as the prey's area is precisely specified. Here, to attack along with approach the prey, the selected area is exploited by the AO. The position update $H_m(l+1)$ formula of Aquila in this step is defined as:

$$H_m(l+1) = \alpha \times [H_e(l) - H_r(l)] + \varphi \times [(B_b - O_b) \times \chi + O_b] \tag{11}$$

Where, B_b and O_b specifies the upper and lower bound values.

Step 4: Narrowed exploitation

Here, as per their stochastic movements, the prey over the land is attacked by the Aquila when it got close to the prey. This technique is named walks and grabbing prey. Lastly, in the last location, the prey is attacked by the AO here. Therefore, the behaviour is mathematically expressed as,

$$H_m(l+1) = J_c \times H_e(l) - (V_1 \times H(l) \times \varepsilon) - V_2 \times \omega + \varepsilon \times V_1 \tag{12}$$

Where, J_c illustrates the quality factor, which is computed as,

$$J_c = l^{\frac{2\varepsilon - 1}{(1-Q_l)^2}} \tag{13}$$

Where, V_1 and V_2 specify the variations of motion, which are derived as,

$$V_1 = 2\varepsilon - 1 \tag{14}$$

$$V_2 = 2\left(1 - \frac{l}{Q_l}\right) \tag{15}$$

Utilizing the AO, the optimal input parameters of the TEG device are selected. The pseudocode for the algorithm is given as,

Input: Input parameters of the fin
Output: Optimal fins for TEG

Begin
- **Initialize** population H_m, iteration l and maximum iteration Q_l
- **Calculate** fitness function A_a
- **Set** iteration $l = 1$
- **While** $(l \le Q_l)$ **do**
  - **Recognize** the location of the prey by $H_m(l+1)$ in expanded exploration
  - **Update** position with the help of a random position $H_p(t)$
  - **Update** the position in expanded exploitation by, $H_m(l+1) = \alpha \times [H_e(l) - H_r(l)] + \varphi \times [(B_b - O_b) \times \chi + O_b]$
  - **Attack** the prey at narrowed exploitation by considering the variation of motion V_1 and V_2
- **End while**
- **Calculate** fitness A_a
- **Set** $l = l + 1$
- **Return** optimal fin parameters

End

3.2 Buck DC-DC Converters

Here, by the buck DC-DC converter, the attained energy is converted. DC voltage's one level is converted into another by the DC-DC converters. Here, the buck DC-DC converter is wielded. A buck converter (step-down converter), which steps down voltage (while stepping up current) as of its input (supply) to its output (load), is a DC-to-DC power converter. It is a class of Switched-Mode Power Supply (SMPS) that typically contains a minimum of '2' semiconductors. An inductor (I), a capacitor (CA), a power semiconductor switch (SS_1), and a diode (DD) are the basic components utilized in the converter. It has two operations, namely closed and opened. The input power is passed to the load via I when the switch SS_1 is closed at a time $t = 0$. It makes the diode reverse biased and energy is increased, which is represented as,

$$\frac{di_I}{dt} = \frac{u_I}{I} = \frac{u_{in} - u_o}{I}, t \in [0, D_c] \tag{16}$$

Where, the duty cycle is symbolized as D_c , the inductor voltage is specified as u_I , u_{in} and u_o indicates the voltage input and output. The inductor I is charging during reverse-biased operation. After that, the inductor is discharging and I_L decreases at the rate of,

$$\frac{di_I}{dt} = \frac{u_I}{I} = \frac{-u_o}{I}, t \in [D_c, T] \tag{17}$$

Here, T specifies the end of the commutation cycle. Finally, the output voltage's average value is expressed as,

$$u_o = \frac{1}{T}\int_0^T u_o(t)dt = \frac{1}{T}\int_0^{D_c} u_{in}(t)dt = Du_{in} \tag{18}$$

Hence,

$$u_o = Du_{in} \tag{19}$$

Duty cycle (X_c) is given as,

$$X_c = \frac{t_{on}}{t_{on} + t_{off}} \tag{20}$$

For continuous conduction mode, the inductance's required minimum value is represented as,

$$I = \frac{u_o(1 - DD)}{2\lambda_o f_{X_c}} \tag{21}$$

Where, λ_o expresses the initial input voltage. Considering the output ripple voltage, the capacitor value can be computed, which can be represented as,

$$CA = \frac{i_o}{4\Delta U f_{X_c}} \tag{22}$$

Where, the output current is indicated as i_o, the duty cycle's switching frequency is specified as f_{X_c}, whereas, the output voltage ripple is indicated as ΔU .

3.3 MPPT algorithm

This technique utilizes the PS-MPPT algorithm for maximizing the energy. As conditions vary, for maximizing the energy extraction, a mechanism utilized with variable power sources is named Maximum Power Point Tracking (MPPT). For numerous systems like wind turbines, thermos-photovoltaics, photovoltaic solar systems, along with optical power transmission, this model is generally wielded. The system observes the difference in power before and after perturbation. This technique observes only one power being generated before. So that the oscillation has occurred during the power generation, which will make a time delay in power generation. Thus, for avoiding this issue, the methodology considers the polynomial structure grounded on previous power generation to include all previously power-generated output. Therefore, the proposed electricity maximization process is indicated as the PS-MPPT algorithm. The steps for the PS-MPPT are given further,

Step 1: Firstly, the voltage $L(j)$and current $R(j)$of the converted energy are measured.

Step 2: After that, the power $W(j)$is computed by the product of $L(j)$and $R(j)$, which is expressed as,

$$W(j) = L(j) * R(j) \tag{23}$$

Step 3: Then, the condition $(W(j) > E(j))$ is checked, here, $E(j)$ describes the polynomial structure of the previous power outcome, which is derived as,

$$E(j) = W(j-1)y^{j-1} + W(j-2)y^{j-2} + ... + W(1)y + W(0) \tag{24}$$

Where, y^{j-1}, y^{j-2} and y are the coefficients and all these coefficients are real numbers.

Step 4: If the step 3 condition is true, then $(L(j) > Z(j))$ is checked, wherein $Z(j)$ defines the polynomial structure of the previous voltage outcome. If this $(L(j) > Z(j))$ condition is satisfied then the duty cycle is mounted; then, $(L(j) = Z(j))$ and $(W(j) = E(j))$ are considered, else the duty cycle is decreased, then $(L(j) = Z(j))$ and $(W(j) = E(j))$ are considered.

Step 5: If the step 3 condition is not true, then $(L(j) > Z(j))$ is checked. If this $(L(j) > Z(j))$ condition is satisfied then the duty cycle is decreased; then, $(L(j) = Z(j))$ and $(W(j) = E(j))$ are considered, else duty cycle is increased, then $(L(j) = Z(j))$ and $(W(j) = E(j))$ is considered.

The pseudocode for the PS-MPPT is exposed as follows,

Input: Input parameters of the fin
Output: Optimal fins for TEG

Begin
    Initialize power $W(j)$, voltage $L(j)$ and current $R(j)$
    Calculate power
    If $(W(j) > E(j))$ {
        If $(L(j) > Z(j))$ {
            Increase the duty cycle
            Fix $(L(j) = Z(j))$ and $(W(j) = E(j))$
        } **else** {
            Decrease the duty cycle
            Fix $(L(j) = Z(j))$ and $(W(j) = E(j))$
        } **end If**
        } **else** {
            If $(L(j) > Z(j))$ {
            Decrease the duty cycle
            Fix $(L(j) = Z(j))$ and $(W(j) = E(j))$
        } **else** {
            Increase the duty cycle
            Fix $(L(j) = Z(j))$ and $(W(j) = E(j))$
        } **end If**
    Return Maximum energy
End

3.4 Load and Storage

Afterward, the attained load is stored in the electrical storage super capacitor (or) battery for further processes.

4. RESULT AND DISCUSSION

Here, the proposed technique's performance is evaluated. In the working platform of MATLAB, the proposed approach is employed.

4.1 Performance Analysis of Optimal TEG device design

Here, regarding conversion efficiency, fitness versus iteration analysis, power, along with pressure drop, the proposed GMAO-centric TEG device design's performance is analyzed with the prevailing frameworks like Salp Swarm Optimization (SSO), Seagull Optimization (SO), AO, together with Whale Swarm Optimization (WSO) approaches.

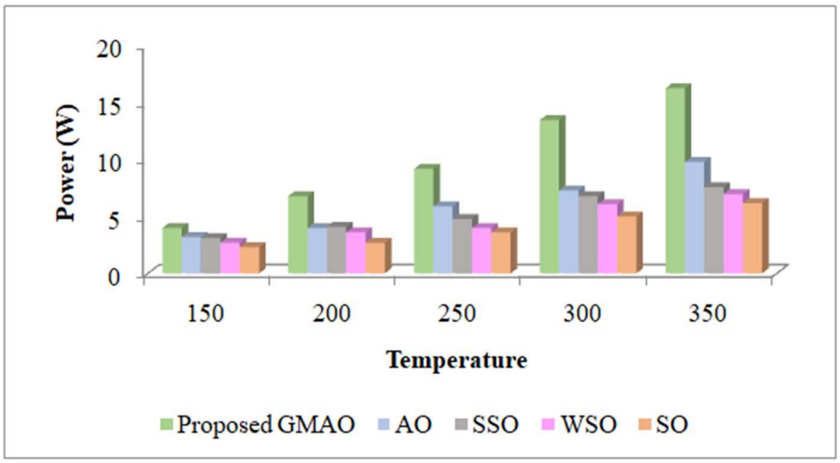

Figure 2: Graphical plot for the power output analysis

The graphical representation of the power output for the proposed GMAO with the previous models is depicted in figure 2. Concerning the temperature variation, that is, 150 to 350 ^{0}C, the performance is assessed. When the temperature level is 350 ^{0}C, the power output given by the proposed based TEG device is higher, which is 16.3W power. At the same temperature level, lower power outputs are given by the prevailing models, which are 9.8 W for AO, 7.6W for SSO, 6.98W for WSO, along with 6.2W for SO, correspondingly. Here, the GMAO-centered optimal fin selection in TEG gives a better outcome. Grounded on the remaining temperature levels also, the proposed one attains superior outcomes.

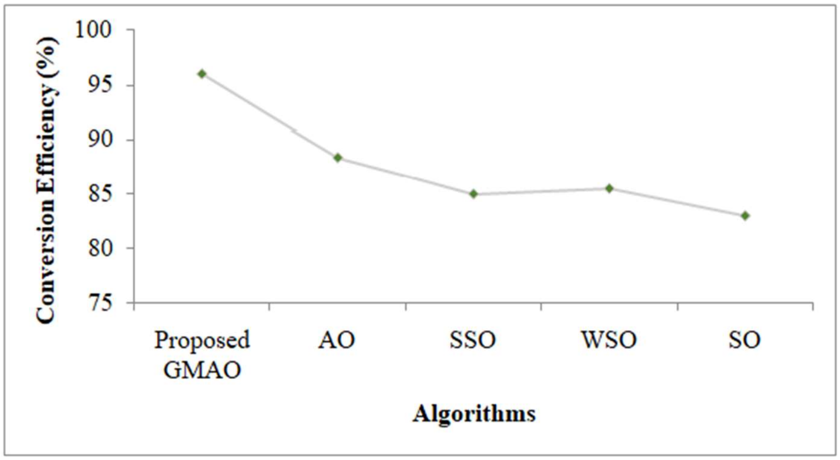

Figure 3: Conversion efficiency analysis

The conversion efficiency analysis for the proposed GMAO-centered optimal TEG device with conventional mechanisms like AO, WSO, SSO, and SO is displayed in figure 3. The conversion efficiency attained by the proposed one is 96%, however, the prevailing approaches like AO, SSO, WSO, and SO have 88.32%, 85%, 85.5%, and 83% conversion efficiency, correspondingly. Here, a large difference is present betwixt the proposed and conventional models. Hence, it exhibited that the proposed one attains better performance than the previous algorithm outcomes.

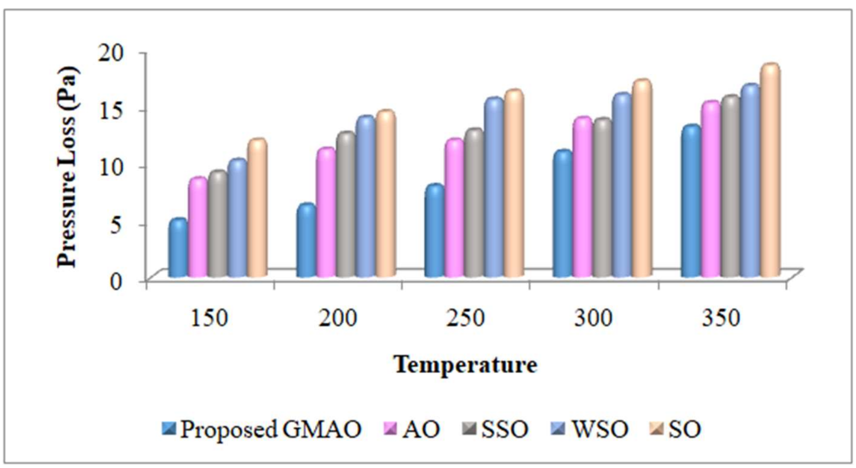

Figure 4: Pictorial plot for pressure loss analysis

Figure 4 depicts the pressure loss analysis for the proposed and conventional systems. For 250 ^{0}C, the pressure loss attained by the proposed technique is very lower, that is 8Pa. For the same temperature, higher pressure loss is achieved by the prevailing approaches, which are 12Pa for AO, 12.89Pa for SSO, 15.6Pa for WSO, along with 16.3Pa for WSO, respectively. The proposed CMAO-centric TEG device has 11Pa for the 300 ^{0}C temperature, whereas the conventional techniques have a higher pressure loss similar to the 250 ^{0}C temperature level.

The remaining temperature level-centric evaluation also exhibits that the proposed CMAO-based system achieves lower pressure loss when analogized with the other models. Better outcomes are given by the proposed one as it utilizes the Gaussian mutation function for avowing the local optimum problem.

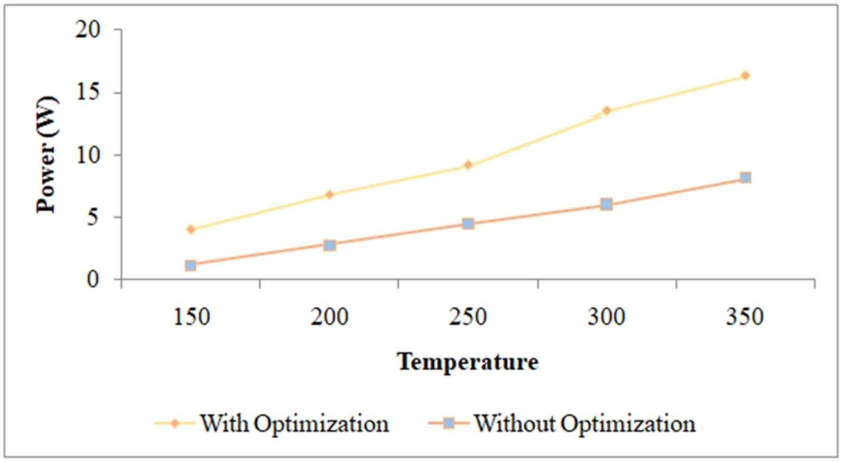

Figure 5: Power output analysis for optimal device and without optimal device

Utilizing an optimal algorithm-centered TEG device, the power output is evaluated without considering the optimal device, that is, a normal device in figure 5. It is also evaluated concerning the temperature variation. With considering, the power attained by the optimization is 4W for 150 ^{0}C, 6.8W for 200 ^{0}C, 9.2W for 250 ^{0}C, 13.5W for 300 ^{0}C, 16.3W for 350 ^{0}C, correspondingly. However, without the fin's optimal selection for the TEG device attains 1.2W for 150 ^{0}C, 2.8W for 200 ^{0}C, 4.5W for 250 ^{0}C, 6W for 300 ^{0}C, 8.1W for 350 ^{0}C, respectively as the optimal selection of fin is considered the objective function.

Table 1: Fitness Vs Iteration Analysis

Iteration	Proposed GMAO	AO	SSO	WSO	SO
50	72	64	61.96	59.87	60
100	78.23	71	65	62	61
150	84	76	68.12	64	65.3
200	89	81	75.6	69.8	68
250	97.65	87	81	76	78.23

The proposed one's fitness Vs iteration assessment with the prevailing approaches is elucidated in table 1. Here, 5 iterations are considered. When the iteration count is 150, the proposed technique attains the fitness value of 84, which is higher when analogized with the prevailing frameworks that attain 76, 68.12, 64, and 68 for AO, SSO, WSO, and SO systems, correspondingly. Here, the AO technique is superior to the other prevailing approaches, however, it has lower fitness than the proposed one. When contrasted with the other approaches and the proposed technique, poor performance is provided by the SO and WSO algorithms. Similarly, the proposed methodology attains higher fitness grounded on the remaining iterations. The graphical representation for table 1 is shown in Figure 6,

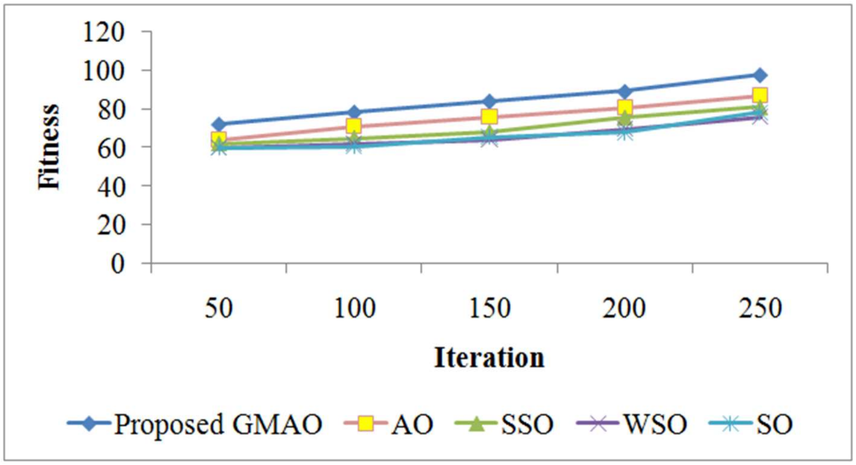

Figure 6: Fitness Vs iteration analysis

4.2 Performance Analysis of Maximize the power generation

Here, the maximization of power generation by the proposed PS-MPPT is evaluated with the conventional power generation algorithm MPPT.

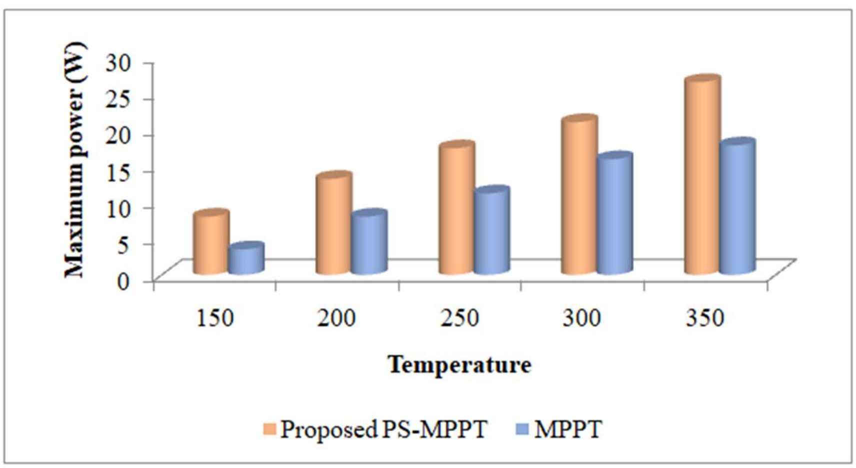

Figure 7: Maximize power generation analysis for PS-MPPT and MPPT

The maximization of power generation analysis by the PS-MPPT is analyzed with the MPPT algorithm, which is exhibited in figure 7. Here, the proposed technique attains 8W for 150 ^{0}C, 13.2Wfor 200 ^{0}C, 17.4W for 250 ^{0}C, 21W for 300 ^{0}C, and 26W for 350 ^{0}C, respectively. But, the conventional MPPT achieves less power generation than the proposed PS-MPPT.

5. CONCLUSION

For enhancing the heat exchange in a TEG device, this paper proposes the multi-objective function-centered optimal fin utilizing GMAO. The amalgamation of three factors is wielded as the objective function in the proposed technique. The proposed PS-MPPT algorithm is utilized for maximizing the attained energy. The model's performance is evaluated in the experimental assessment. Regarding conversion efficiency, fitness versus iteration, power, along with pressure drop, the proposed mechanism's performance is evaluated with the prevailing approaches like SSO, SO, AO, together with WSO. Better conversion efficiency was attained by the proposed technique, which is 96%; also, concerning other measures, the proposed one attains superior outcomes. Moreover, the proposed PS-MPPT is analyzed with the MPPT. When analogized with the MPPT, PS-MPPT attains better-maximized power. This research only considers the three factors as the fitness function and input parameters are not adequate. Thus, by considering other relevant fitness functions with more input parameters and advanced approaches for enhancing performance, this approach can be enhanced in the future.

REFERENCES

Aljaghtham, M., & Celik, E. (2020). Design optimization of oil pan thermoelectric generator to recover waste heat from internal combustion engines. *Energy*, *200*, 1-9. https://doi.org/10.1016/j.energy.2020.117547

Burnete, N. V., Mariasiu, F., Moldovanu, D., & Depcik, C. (2021). Simulink model of a thermoelectric generator for vehicle waste heat recovery. *Applied Sciences*, *11*(3), 1–36. https://doi.org/10.3390/app11031340

Deng, W., Wang, X., Pan, X., Zhang, S., Ding, J., & Li, G. (2021). Geometry design and performance optimization of a terrestrial radioisotope thermoelectric generator based on finite element analysis. *Annals of Nuclear Energy*, *151*, 1-10. https://doi.org/10.1016/j.anucene.2020.107883

Elghool, A., Basrawi, F., Ibrahim, T. K., Ibrahim, H., Ishak, M., Hazwan bin Yusof, M., & Bagaber, S. A. (2020). Multi-objective optimization to enhance the performance of thermo-electric generator combined with heat pipe-heat sink under forced convection. *Energy*, *208*, 1-36. https://doi.org/10.1016/j.energy.2020.118270

Garud, K. S., Seo, J. H., Patil, M. S., Bang, Y. M., Pyo, Y. D., Cho, C. P., & Lee, M. Y. (2021). Thermal electrical structural performances of hot heat exchanger with different internal fins of thermoelectric generator for low power generation application. In *Journal of Thermal Analysis and Calorimetry*, *143*(1), 1-33. https://doi.org/10.1007/s10973-020-09553-7

Ge, M., Li, Z., Wang, Y., Zhao, Y., Zhu, Y., Wang, S., & Liu, L. (2021). Experimental study on thermoelectric power generation based on cryogenic liquid cold energy. *Energy*, *220*, 1-9. https://doi.org/10.1016/j.energy.2020.119746

He, M., Wang, E., Zhang, Y., Zhang, W., Zhang, F., & Zhao, C. (2020). Performance analysis of a multilayer thermoelectric generator for exhaust heat recovery of a heavy-duty diesel engine. *Applied Energy*, *274*, 1-18. https://doi.org/10.1016/j.apenergy.2020.115298

He, W., Guo, R., Takasu, H., Kato, Y., & Wang, S. (2019). Performance optimization of common plate-type thermoelectric generator in vehicle exhaust power generation systems. *Energy*, *175*, 1153–1163. https://doi.org/10.1016/j.energy.2019.03.174

Huang, K., Yan, Y., Li, B., Li, Y., Li, K., & Li, J. (2018). A Novel Design of Thermoelectric Generator for Automotive Waste Heat Recovery. *Automotive Innovation*, *1*(1), 54–61. https://doi.org/10.1007/s42154-018-0006-z

Kim, D., Kim, C., Park, J., & Kim, T. Y. (2019). Highly enhanced thermoelectric energy harvesting from a high-temperature heat source by boosting thermal interface conduction. *Energy Conversion and Management*, *183*, 360–368. https://doi.org/10.1016/j.enconman.2018.12.108

Kumar, P. M., Babu, V. J., Subramanian, A., Bandla, A., Thakor, N., Ramakrishna, S., & Wei, H. (2019). The design of a thermoelectric generator and its medical applications. *Designs*, *3*(2), 1–26. https://doi.org/10.3390/designs3020022

Li, G. N., Yi, M. B., Tulu, M. B., Zheng, Y. Q., Guo, W. W., & Tang, Y. J. (2021). Miniature self-powering and self-aspirating combustion-powered thermoelectric generator burning gas fuels for combined heat and power supply. *Journal of Power Sources*, *506*(318), 1-11. https://doi.org/10.1016/j.jpowsour.2021.230263

Li, W., Poudel, B., Nozariasbmarz, A., Sriramdas, R., Zhu, H., Kang, H. B., & Priya, S. (2020). Bismuth Telluride/Half-Heusler Segmented Thermoelectric Unicouple Modules Provide 12% Conversion Efficiency. *Advanced Energy Materials*, *10*(38), 1–9. https://doi.org/10.1002/aenm.202001924

Li, X., Xie, C., Quan, S., Shi, Y., & Tang, Z. (2019). Optimization of thermoelectric modules' number and distribution pattern in an automotive exhaust thermoelectric generator. *IEEE Access*, *7*, 72143–72157. https://doi.org/10.1109/ACCESS.2019.2919689

Luo, D., Wang, R., Yu, W., & Zhou, W. (2020). A novel optimization method for thermoelectric module used in waste heat recovery. *Energy Conversion and Management*, *209*, 1-11. https://doi.org/10.1016/j.enconman.2020.112645

Lv, H., Liang, L., Zhang, Y., Deng, L., Chen, Z., Liu, Z., Wang, H., & Chen, G. (2021). A flexible spring-shaped architecture with optimized thermal design for wearable thermoelectric energy harvesting. *Nano Energy*, *88*, 1-10.

https://doi.org/10.1016/j.nanoen.2021.106260

Lv, S., Liu, M., He, W., Li, X., Gong, W., & Shen, S. (2020). Study of thermal insulation materials influence on the performance of thermoelectric generators by creating a significant effective temperature difference. *Energy Conversion and Management*, *207*, 1-9. https://doi.org/10.1016/j.enconman.2020.112516

Manikandan, S., Selvam, C., Pavan Sai Praful, P., Lamba, R., Kaushik, S. C., Zhao, D., & Yang, R. (2020). A novel technique to enhance thermal performance of a thermoelectric cooler using phase-change materials. *Journal of Thermal Analysis and Calorimetry*, *140*(3), 1003–1014. https://doi.org/10.1007/s10973-019-08353-y

Sheikh, R., Gholampour, S., Fallahsohi, H., Goodarzi, M., Mohammad Taheri, M., & Bagheri, M. (2021). Improving the efficiency of an exhaust thermoelectric generator based on changes in the baffle distribution of the heat exchanger. *Journal of Thermal Analysis and Calorimetry*, *143*(1), 523–533. https://doi.org/10.1007/s10973-019-09253-x

Tang, S. Z., Wang, F. L., He, Y. L., Yu, Y., & Tong, Z. X. (2019). Parametric optimization of H-type finned tube with longitudinal vortex generators by response surface model and genetic algorithm. *Applied Energy*, *239*, 908–918. https://doi.org/10.1016/j.apenergy.2019.01.122

Wang, Y., Peng, Y., Guo, K., Zheng, X., Darkwa, J., & Zhong, H. (2021). Experimental investigation on performance improvement of thermoelectric generator based on phase change materials and heat transfer enhancement. *Energy*, *229*, 1-12. https://doi.org/10.1016/j.energy.2021.120676

Wu, J., Chen, Y., Dou, Y., Ma, C., Du, Q., & Liu, Q. (2021). Optimal design and performance analysis of thermoelectric power generation device based on multi-objective genetic algorithm. *Advanced Theory and Simulations*, *4*(6), 1–11. https://doi.org/10.1002/adts.202000271

Xiao, H., Qiu, K., Gou, X., Liu, X., & Li, Z. (2022). Development and heat transfer analysis of thermoelectric self-powered fuel-fired residential boiler. *Energy Science and Engineering*, 3344–3357. https://doi.org/10.1002/ese3.1222

Yang, W., Xie, H., Sun, L., Ju, C., Li, B., Li, C., Zhang, H., & Liu, H. (2021). An experimental investigation on the performance of TEGs with a compact heat exchanger design towards low-grade thermal energy recovery. *Applied Thermal Engineering*, *194*, 1-11. https://doi.org/10.1016/j.applthermaleng.2021.117119

Zoui, M. A., Bentouba, S., Velauthapillai, D., Zioui, N., & Bourouis, M. (2022). Design and characterization of a novel finned tubular thermoelectric generator for waste heat recovery. *Energy*, *253*, 1-10. https://doi.org/10.1016/j.energy.2022.124083