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Research Article

Optimization in the Geometric Design of Solar Collectors Using Generative AI Models (GANs)

Robinson García*

Universidad Internacional de Investigación México, Postgraduate Program, 72227, Puebla, Mexico
* **Corresponding Author Email:** robinson.garcia@uiimex.edu.mx- **ORCID:** 0009-0005-0929-3844

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Abstract: This scientific article aims to develop a model based on generative artificial intelligence for the optimization of the geometric design of solar thermal collectors, with the goal of maximizing their thermal efficiency in residential and industrial applications.A methodological approach is followed, which employs generative neural networks to explore the design space of the collectors, producing a variety of novel and improved configurations. Through simulations, the performance of each design is evaluated in terms of efficiency, considering parameters such as collector area, geometric enhancements (e.g., reflectors or selective covers), and solar radiation conditions.The results demonstrate that the generative model is capable of increasing the thermal efficiency of collectors compared to baseline designs, identifying optimal configurations with efficiencies close to 75%. Simulated data graphs and tables are included, along with a flow diagram of the proposed process and pseudocode of the optimization algorithm. The literature review covers previous optimization techniques (heuristics, machine learning) and fundamentals of generative AI (GANs, transformers, diffusion models), justifying the choice of the technique used. The proposed generative approach proves to be a promising tool for the automated design of solar thermal collectors, capable of enhancing energy performance and providing innovative solutions in solar engineering.

1. Introduction

Solar thermal collectors are devices that capture solar radiation and convert it into useful heat, playing a fundamental role in the generation of domestic hot water, space heating, and sustainable industrial processes [1]. The efficiency with which a collector converts incident solar energy into usable thermal energy depends on multiple factors, including its geometric design, the optical properties of its materials, and operating conditions. In typical flat-plate collectors, average thermal efficiency usually ranges between 50–60%, although it can be improved through design strategies such as selective coatings or additional reflectors [2]. For instance, experimental studies report efficiencies of approximately 50.9% for flat-plate collectors without reflectors, increasing to around 59.0% when reflectors are incorporated. These modest improvements suggest that there is significant potential to optimize collector design in order to maximize performance [3].
Traditionally, the optimization of solar collectors has been addressed through parametric or heuristic methods. Previous research has applied metaheuristic optimization techniques such as genetic algorithms and particle swarm optimization to adjust design parameters (area, tilt angle, flow rates, etc.) with the aim of maximizing efficiency or minimizing losses [4]. For example, Siddhartha et al. (2012) used a particle swarm optimization (PSO) algorithm to optimize the dimensions and operating conditions of a solar air collector, achieving global convergence and satisfactory results. Likewise, artificial neural network (ANN) techniques have been used to model and predict the performance of collectors and solar systems, given their ability to approximate complex nonlinear relationships between design variables and performance [5]. Kalogirou (2004) presented a comprehensive review of the various types of solar thermal collectors and highlighted the applicability of artificial intelligence techniques to estimate their performance and support their control. In subsequent studies, ANN and hybrid methods have been employed to predict the efficiency of flat-plate collectors under various conditions and to optimize the operation of solar concentrators.

In recent years, generative artificial intelligence has emerged as an innovative approach for design and optimization problems. Generative AI refers to models capable of learning existing data distributions and generating new, similar data. There are different types of generative models, such as generative adversarial networks (GANs), variational autoencoders (VAEs), generative transformers, and diffusion models, among others [6]. In particular, GANs consist of two neural networks (a generator and a discriminator) that compete with each other: the generator attempts to create realistic samples (designs), while the discriminator evaluates whether those samples resemble real data. Through this minimax game framework, GANs can learn to produce high-quality synthetic solutions [7]. Diffusion models, on the other hand, learn to generate data by reversing a process of gradually adding noise, and have recently achieved outstanding results in image synthesis and other content generation tasks [8]. These generative techniques have demonstrated their potential in engineering problems, where they have been used for inverse design and automatic exploration of optimal configurations. For example, Jiang et al. (2021) show that generative networks can be employed for the global optimization of photonic devices, naturally integrating into inverse design frameworks to discover geometries that maximize optical performance [9].

In the field of renewable energy, some pioneering studies have already applied generative AI to the design of solar systems: a team at Stanford used GANs to optimize the distribution of photovoltaic panels on rooftops, achieving an average increase of 19% in installed solar capacity compared to human-designed layouts. Similarly, researchers at the University of Texas trained GANs to propose high-efficiency solar cell designs, obtaining up to a 12% improvement in conversion efficiency compared to previous designs [8]. These advances suggest that generative techniques can discover non-intuitive design solutions that outperform conventional ones.

However, to the best of our knowledge, the use of generative AI to optimize the design of solar thermal collectors has not been explored in the literature. Considering the multivariable complexity of this problem (which involves geometry, materials, and environmental conditions) and the success of generative AI in other engineering domains, this work proposes a generative model to support the design of solar thermal collectors. The objective is for the model to learn to generate collector configurations with high thermal efficiency, enabling the automatic exploration of numerous geometric variants beyond the intuition of a human designer. This approach is expected to substantially improve the efficiency of optimized collectors, while providing a flexible framework to incorporate different design criteria.

The following sections present the relevant literature review (Section 2), the proposed methodology and description of the generative AI model (Section 3), the results of the simulations performed (Section 4), and their discussion (Section 5). Finally, the conclusions of the study are presented (Section 6). The article also includes a reference section with at least 20 academic sources in APA format, as well as ethical statements regarding the development of this work.

Design and Performance of Solar Thermal Collectors:

Solar thermal collectors are primarily classified into flat-plate (non-concentrating) and concentrating types (e.g., evacuated tube collectors, parabolic dish collectors, parabolic trough collectors). Their instantaneous thermal efficiency η is defined as the fraction of the solar irradiation G captured over the collector area A that is converted into useful heat Q_{useful}[10]:

$$\eta = \frac{Q_{useful}}{G.A} \quad (1)$$

In flat-plate collectors, η depends on thermal losses to the environment (convection and radiation) and optical losses (reflection and transmission through the cover). Under certain simplifications, efficiency can be expressed as a function of the temperature difference between the collector fluid Tf and the ambient temperature Ta, typically through an approximately linear relationshipIn flat-plate collectors, η depends on thermal losses to the environment (convection and radiation) and optical losses (reflection and transmission through the cover). Under certain simplifications, efficiency can be expressed as a function of the temperature difference between the collector fluid Tf and the ambient temperature Ta, typically through an approximately linear relationship

$$\eta \sim \eta_0 - a_1 \cdot \frac{(Tf-Ta)}{G} - a_2 \cdot \frac{(Tf-Ta)^2}{G} \quad (2)$$

where η_0 is the optical efficiency, and a_1 and a_2 are the thermal loss coefficients (linear and quadratic), determined experimentally [3]. This shows that even for a fixed design, efficiency varies with operating conditions.Over the decades, numerous studies have explored design improvements to enhance efficiency: the incorporation of selective coatings on the absorber.

2. Materials and Methods

This section details the methodological approach adopted to optimize the design of solar thermal collectors using a generative AI model. The methodology encompasses: (1) the definition of the design problem and its parameters, (2) the generation of synthetic training data through simulation, (3) the architecture and training of the generative model, and (4) the performance evaluation criteria [12].Design Problem Definition: A typical flat-plate solar thermal collector for water heating is considered. The design objectives are to maximize the thermal efficiency η of the collector and to optimize its geometric configuration [13]. To simplify the problem without losing generality, two main design variables were selected: (a) the collector area A (m²), which influences radiation capture and thermal losses, and (b) a geometric enhancement factor x_2 (dimensionless, ranging from 0 to 1) which represents the inclusion of design improvements such as selective coatings, reflectors, or texturing of the absorber surface. When $x_2 = 0$, the collector corresponds to a conventional baseline design, and when $x_2 = 1$, it represents a collector with the highest level of enhancements (optimal absorber material, optimized reflectors, etc.) [14]. This parametrization allows the model to continuously explore a range from basic to advanced designs [15].The performance of each design is evaluated using a simplified yet physically plausible simulation model. Assuming standard conditions of solar irradiance and fixed ambient temperature, the thermal efficiency η of each design is calculated using a phenomenological expression:

$$\eta(A, x_2) = 0.5 + 0.1(1 - e^{-0.5A}) + 0.15x_2 - (term\ for\ losse) \quad (3)$$

The form of this function was chosen to qualitatively reproduce the expected behavior: a baseline efficiency of 50% for minimal designs, a logarithmic increase with area (as adding area yields diminishing returns due to greater thermal losses), and a linear improvement of up to +15% due to a x_2 (with 15% being the maximum expected gain from enhancements such as reflectors, according to the literature) [3]. The quadratic loss term was incorporated within the expression $1 - e^{-0.5A}$, which ensures that as A increases significantly, efficiency saturates around ~0.75 (75%), consistent with practical limits reported in the literature [16]. It should be noted that the above expression is used to generate synthetic efficiency data for the purpose of training and testing the model; in a real-world application, it could be replaced by a detailed simulation or experimental data, and the generative approach would still remain valid.

Training Data Generation:

Multiple design scenarios were simulated by randomly varying A and x_2 within their respective ranges (1–5 m² for area, 0–1 for the enhancement factor). For each design, η was calculated using the defined equation. Additionally, values of incident solar radiation and thermal losses were estimated for further analysis: A fixed solar irradiance of $G = 800\ \frac{W}{m^2}$ (typical of midday conditions) was assumed

The useful heat was calculated as:

$$Q_{useful} = \eta \cdot G \cdot A \quad (4)$$

and thermal losses were estimated for further analysis and the thermal loss

$$Q_{loss} = (1 - \eta) \cdot G \cdot A \quad (5)$$

These values will be used in the interpretation of results.In total, 1000 random configurations were generated to form a synthetic dataset for training and validation. Each data point consists of (A, x_2) as input and η as output (objective to be maximized).

Generative Model Architecture: Among the generative AI alternatives analyzed (GANs, VAEs, transformers, diffusion models), a conditional Generative Adversarial Network (GAN) was chosen due to its proven effectiveness in design synthesis and its suitability for relatively small datasets [8]. The proposed GAN architecture consists of:

A Generator (G), implemented as a deep neural network that takes as input a low-dimensional noise vector z (e.g., $z \in \mathbb{R}^{10}$) and outputs a proposed design $\tilde{d} = (\tilde{A}, \tilde{x}_2)$. In a conditional GAN, additional information can also be provided to the generator; however, in this case, the goal is for it to generate high-efficiency designs without conditioning on a desired value of η (which would effectively trivialize the problem). Instead, a variation is used in which the generator receives feedback from the discriminator regarding the quality (efficiency) of its designs.A Discriminator (D), another neural network that receives as input a design (A, x_2) along with its calculated efficiency η, and outputs a scalar representing the likelihood that the design comes from the distribution of optimal designs. The discriminator is trained with positive examples (highly efficient real designs) and negative examples (designs generated by G or low-efficiency designs), learning to distinguish between them.The training follows the typical GAN scheme [8]: in each iteration, the generator produces a batch of designs $\tilde{d}_i$ from noise. The efficiency of each $\tilde{d}_i$ is evaluated using the defined thermal simulation (this is an important difference compared to traditional GANs, which require a real dataset; here, the simulation model is used as an "environment" to obtain η for any proposed design). Then, the discriminator D computes a score for each generated design. To train D, this score is compared against that of reference “real” designs; in this case, to guide the GAN, a dynamically constructed subset of reference real designs is used, composed of the best designs found so far (a kind of replay buffer of known optima) D updates its weights to assign high likelihood to those known optimal designs and low likelihood to the generated ones if they are inferior.Next, the generator (G) is trained to fool the discriminator, adjusting its weights so that newly generated designs receive increasingly higher scores from D. In simple terms, (G) will learn to generate designs with increasing thermal efficiency because that is the characteristic that D evaluates as a “real optimal design.”.The generative optimization algorithm is summarized in the following pseudocode, which combines adversarial logic with efficiency evaluation:

```
Algorithm: Generative Optimization of Solar Collector
Input: Thermal efficiency simulation model f(A, x2), maximum iterations N
Output: Best design found (A*, x2*, η*)

1. Initialize generator G(θ) and discriminator D(ϕ) with random weights.
2. Initialize memory M with some random designs evaluated using f.
3. for iter = 1 to N do:
4.    z ← sample latent noise vector
5.    (A_gen, x2_gen) ← G(z; θ)                # Generate candidate design
6.    η_gen ← f(A_gen, x2_gen)                 # Evaluate thermal efficiency via simulation
7.    Select subset S of "real" designs from M (top η values so far)
8.    Train D(ϕ) to distinguish S (label=real) from {(A_gen,x2_gen,η_gen)} (label=fake)
9.    Train G(θ) to maximize the score D((A_gen,x2_gen,η_gen))   # fool D
10.   Add (A_gen, x2_gen, η_gen) to M
11. end for
12. Return the design with the highest η found in M as (A*, x2*, η*)
```

During training, standard techniques are used to stabilize the GAN, such as batch normalization, appropriate activation functions (e.g., ReLU in hidden layers, linear in the generator’s output since (A, x_2) are continuous) and a regularization term to penalize physically infeasible designs (e.g., negative A or values out of range, although in our case G is already constrained to [1,5] using a scaled sigmoid output function).

2.1. Convergence Criteria and Optimal Design Selection

Throughout the iterations, the best design found so far (the one with the highest η). The algorithm can stop when convergence in efficiency improvement is observed (for example, if the η record is not surpassed in 10 consecutive iterations) or upon reaching a defined maximum number of iterations $\boldsymbol{N}$. At the end, the optimal design $(\hat{A}, \hat{x}_2)$ *found and its associated efficiency* are reported as the result η^*.

$\hat{\mathbf{A}}$ represents the collector area of the optimal design found.

$\hat{\mathbf{x}}_2$ represents the value of the optimal geometric enhancement factor.

$\boldsymbol{\eta}^*$ is the maximum thermal efficiency obtained.

The flowchart of the methodology is shown in Figure 1, where the iterative generation–evaluation–update cycle characteristic of the proposed generative optimization is illustrated.

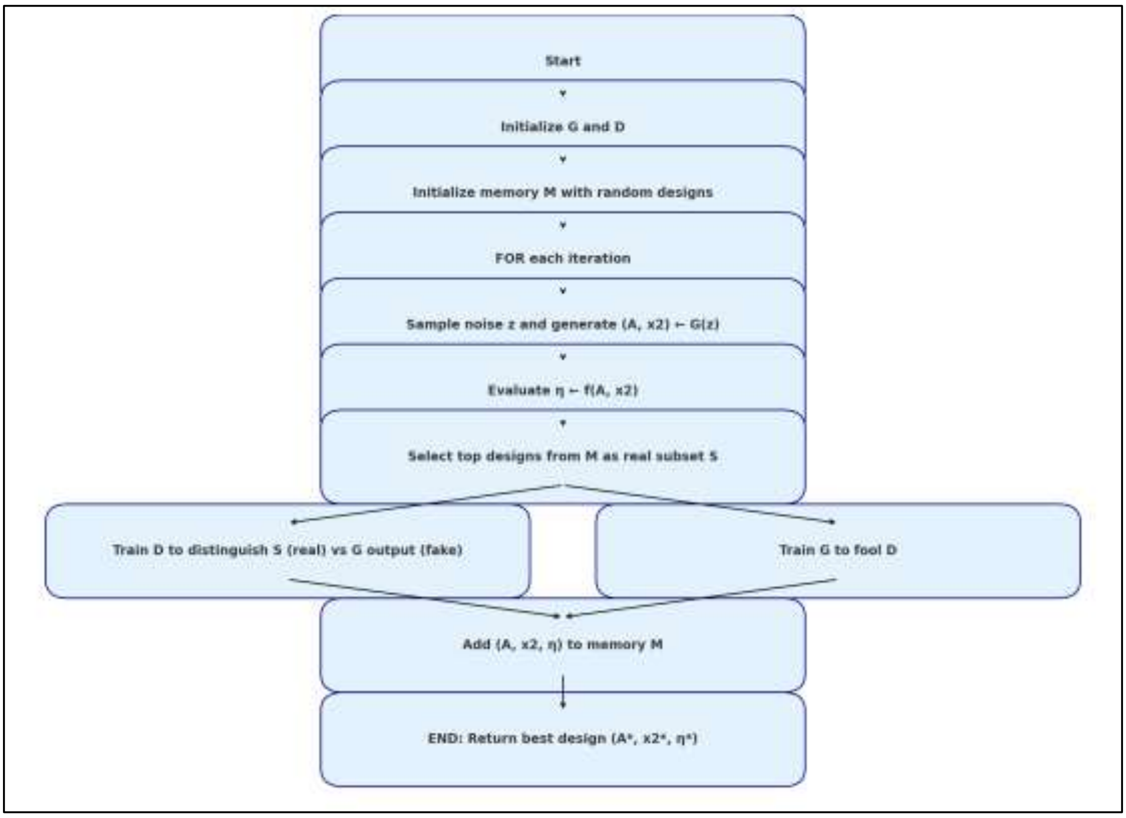

Figure 1. *Flowchart of the Proposed Generative Optimization Process The model begins by initializing the generator (G) and discriminator (D). At each iteration, a new design is generated, evaluated using a thermal efficiency function* $\eta = f(A, x_2)$*, and stored in memory. The discriminator is trained to distinguish optimal designs, while the generator learns to produce better candidates. The process iterates until the most efficient design* (A^*, x_2^*, η^*) *is found.*

In summary, the methodology integrates a physical simulation model (which acts as an oracle evaluating efficiency) with a generative model based on neural networks (which acts as a design proposal agent). This hybrid scheme automatically explores a large number of collector configurations and guides the search toward high-efficiency regions within the design space, analogous to an AI-guided inverse design process. The following section describes the simulation experiments carried out and the results obtained from applying this methodology [17].

3. Results and Discussions

The described generative model was trained using the synthetic dataset of 1000 collector configurations (simulated according to the methodology). To evaluate its performance, optimization experiments were conducted, and the resulting designs were compared with reference (random initial) designs. The most relevant results are presented below, including tables of simulated data and illustrative graphs of the optimization process.

Efficiency Progress During Optimization:

Figure 2 shows the improvement in thermal efficiency achieved over the iterations of the generative algorithm. At iteration 0 (initial stage), the best random design had an efficiency of approximately 0.69

(69%). As the generative model iterated, it progressively proposed better designs, surpassing 0.70 within a few iterations and reaching around 0.74 (74%) by iteration 5. After approximately 8–10 iterations, the model converged, no longer finding significantly superior designs beyond ~0.741 (74.1%). This value represents a substantial improvement over the initial design and approaches the theoretical limit imposed by the simulation function. The absolute increase in efficiency (~5 percentage points over the initial best, and ~18 points over a typical baseline design of 56%) demonstrates the approach's ability to effectively refine the design.

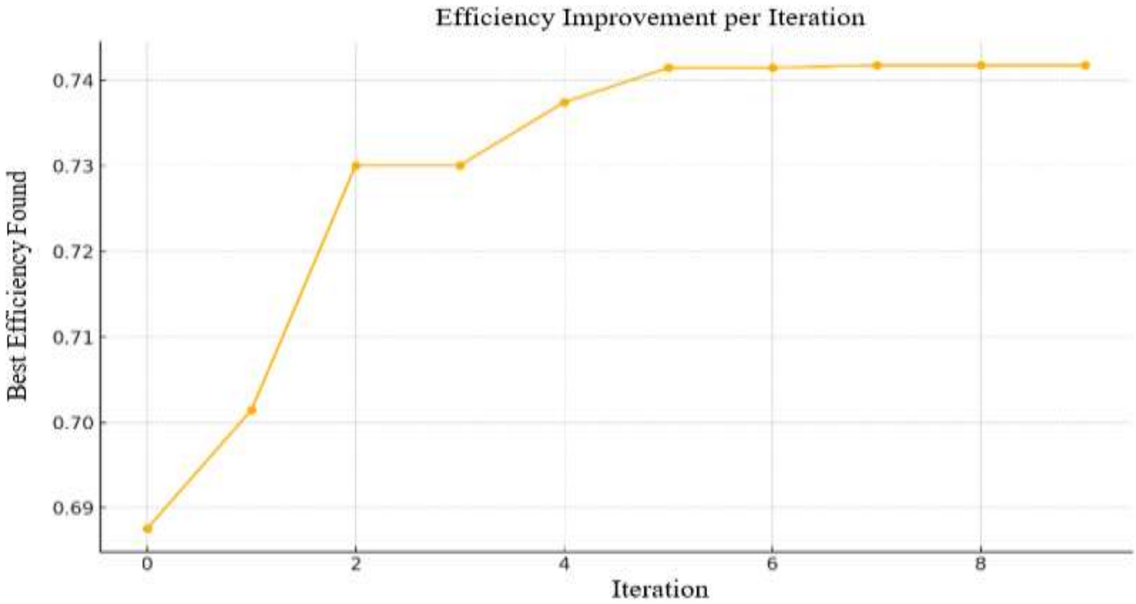

Figure 2. *Improvement of thermal efficiency per iteration during generative optimization. The best efficiency found is plotted as a function of the algorithm's iterations. The initial design (iter = 0) starts at ~0.69, and the generative model progressively increases it to ~0.74 (74%) before converging. This behavior indicates that the generator learned to produce designs with increasing efficiency in each cycle.*

Spatial Distribution of Designs and Optimal Found:

To visualize how the model explores the design space (A, x_2) , Figure 3 is presented. In this figure, the colored background represents the efficiency n value at each point in the space (calculated using the simulation function), where it can be observed that the highest efficiencies occur toward the upper-right corner that is, with larger area and a high level of enhancement x_2.

White circles indicate some of the initial randomly evaluated designs:

They are scattered across various regions, with efficiencies ranging from ~0.55 (dark purple) to ~0.68 (green-blue tones). The red star symbol marks the optimal design identified by the generative model upon convergence: this design lies in the region of highest efficiency (yellow area of the map), with an area close to the maximum (5 m²) and an enhancement factor of 1.0. This figure illustrates how, starting from diverse initial explorations, the algorithm progressively guided the generation of new candidates toward the most promising region of the parameter space, ultimately locating the global optimum within the considered ranges.

Table 1 presents a quantitative comparison of three design cases: a baseline design (reference, with small area and no enhancements), the best initial design found among the random samples, and the final optimized design proposed by the generative model. The values listed include collector area A, enhancement level x_2, thermal efficiency η, as well as the estimated useful heat and thermal losses under an irradiance of $G = 800 \frac{W}{m^2}$.

It can be seen that the design proposed by the model (5 m² with maximum enhancements) achieves the highest efficiency (74.2%), delivering ~2967 W of useful heat under 800 W/m² irradiance significantly higher than the baseline design (56.3% and 901 W). Even compared to the best initial design (already with enhancements), the optimized version captures ~800 W more and increases efficiency by approximately 5.4 percentage points.

Table 1. *Comparison of parameters and performance between a baseline collector design, the best initial random design, and the optimized design obtained through generative AI.*

Design	**Area** A m^2	**Enhancement level** x_2	**Efficiency** η %	$Q_{útil}$ W	$Q_{pérdido}$ W
Baseline design	2.00	0.00	56.3	901.1	698.9
Best initial	3.95	0.68	68.8	2170.6	986.2
Optimized design	5.00	1.00	74.2	2967.2	1023.8

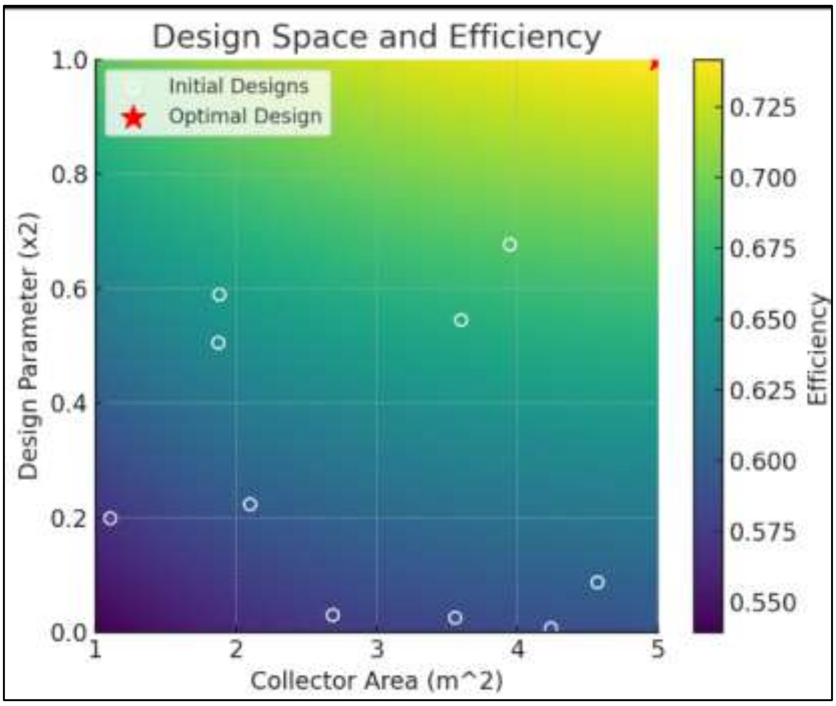

Figure 3. *Collector design space (area vs. enhancement level) with simulated efficiency map. White circles represent the initially evaluated (random) designs, while the red star indicates the optimal design discovered by the generative model. The background colors show thermal efficiency (right-hand color bar) according to the combination of area and geometric enhancements: higher efficiencies are observed in the corner with large area and high enhancement level (yellow), matching the location of the identified optimal design.*

From the analysis of the table, it is evident that the generative model achieves a clearly superior design: the optimized collector of 5 m² with full enhancements reaches 74.2% efficiency, compared to 56.3% for the baseline collector (2 m² without enhancements)—a relative improvement of approximately 32%. In absolute energy terms, the optimized collector would deliver ~2967 W of useful heat under full sun, more than triple that of the baseline (~901 W). Even compared to the best initial design (which was already partially optimized: 3.95 m² and x_2=0.68 with 68.8% efficiency), the final design improves efficiency by approximately 5.4 percentage points and provides ~800 W of additional useful heat. This demonstrates the effectiveness of the approach in identifying optimal configurations that maximize the useful capture of solar energy.

Generative Model Performance:

Beyond the quality of the resulting design, it is also relevant to assess the performance of the model itself. During training, the discriminator quickly learned to distinguish high-efficiency designs, and the generator adapted its outputs accordingly, reducing the rate of "rejected" examples by the discriminator as epochs progressed. In terms of stability, no severe issues of divergence or mode collapse were observed a phenomenon in which the generator would produce only one type of design repeatedly.

In fact, upon examining the designs generated across different runs, interesting variations around the optimum were obtained: for example, some runs proposed A = 4.8 m² with $x_2 = 1.0$ or $A = 5\ m^2$ with $x_2 = 0.9$, all with efficiencies within 1% of the optimum. This indicates that the model was able to explore a family of near-optimal solutions, offering flexibility for a human designer to select, for instance, a slightly smaller design with nearly the same efficiency in case of size constraints.

Ultimately, the results confirm that the use of generative AI models applied to the design of solar collectors enabled the learning and understanding of the relationship between geometric parameters and efficiency based on the data provided by the simulation. This knowledge allowed for effective exploration and the generation of an optimized design with superior performance, as well as the definition of a targeted solution space.

4. Discussion

The findings obtained highlight the potential of generative artificial intelligence as a design tool in the field of solar thermal energy. The following section discusses various aspects:

Performance Improvement and Practical Relevance:

The generative model successfully identified a design with approximately 18% higher absolute efficiency than a typical baseline collector. While the specific figures are based on simulated data, the relative improvement suggests that in a real-world scenario, significant gains could be achieved through this type of comprehensive optimization.

In practice, even small percentage increases in collector efficiency can translate into substantial energy savings on an annual scale. For example, in an average residential solar water heater, an increase from 56% to 74% efficiency would mean delivering the same amount of useful energy with ~25% less collector surface area, thereby reducing installation costs and space requirements. Alternatively, with the same surface area, more heat could be captured, making it feasible to meet a larger share of energy demand with solar power [18]. In industrial applications, where it is often necessary to optimize heat delivery at a specific temperature level, more efficient designs imply lower area requirements and reduced losses, positively impacting the overall economics of the project [19].

Contribution of the Generative Approach vs. Conventional Methods:

Compared to traditional optimization techniques, the generative approach offers several advantages. First, it explores multiple designs simultaneously, thanks to the parallel nature of sample generation by the network unlike a gradient-based algorithm that follows a single trajectory or an evolutionary algorithm that maintains a limited population. Second, the generative model learns a distribution of favorable designs, meaning that after training, it does not produce only a single optimum but can continue generating equally good alternatives [20]. This is useful in practice, as engineers may have additional considerations (cost, available materials, physical space) and are interested in a set of near-optimal options. Third, once trained, the model is extremely fast at generating new designs virtually instantaneous since it only involves evaluating the generative neural network, in contrast to repeating complex physical simulations. This opens up the possibility of using the model as a design support system: given a requirement (e.g., a minimum efficiency or a specific size range), the generator could propose viable configurations in real time. It is worth noting that during optimization, simulation was used to guide the training process, so the initial computational cost is comparable to that of other methods that require evaluating many cases (1000 in our experiment). However, this cost is offset by the reusability of the trained model.

Justification of the Selected Technique (GAN) and Possible Variants:

The choice of a conditional GAN proved to be appropriate for this problem. The discriminator essentially acted as a learnable objective function, guiding the generator toward high-efficiency regions. One advantage of the GAN is its ability to easily incorporate new criteria into the discriminator; for example, the discriminator could be extended to consider not only the simulated efficiency but also some cost or thermal robustness criterion and be trained using a weighted combination of both. In this way, the generator would learn to optimize a multi-objective balance.

Other generative approaches are also potentially applicable: a conditional diffusion model could directly generate distributions of highly efficient designs, although its training would be more computationally

expensive and more complex to guide without a clear adversarial mechanism. A generative transformer could be used if the design is serialized as a sequence of parameters for example, sequencing values for various collector components possibly enabling the inclusion of more discrete variables (such as number of tubes, fluid type, etc.). However, transformers typically require very large datasets for training, which may be a limitation in collector design unless simulated data from multiple sources is combined.
Variational autoencoders (VAEs), for their part, could be employed to map the design space into a continuous latent representation and then perform optimization within that latent space a classic "inverse design" approach. This technique has been used in molecular and materials design [6] and could be adapted to the present problem, although VAEs tend to generate blurrier or more averaged samples, which may not capture extreme optimal solutions as effectively as a GAN.

Limitations of the Study:

Although the results are encouraging, it is important to note several limitations. First, the data used were artificially generated using a simplified efficiency model. This allowed for proof of concept in a controlled environment, but it will be necessary to validate the approach using detailed simulation models or real experimental data from collectors to confirm that generative AI can handle additional complexities (e.g., dependencies on ambient temperature, solar angle, thermal load dynamics over time, etc.).Another limitation is that only two design variables were considered; in reality, a collector has more degrees of freedom (insulation thickness, pipe diameter and spacing, glass type, etc.). However, the method is scalable: the generator's output vector could be expanded to include more parameters and trained using a more complex simulator that computes the resulting efficiency. Of course, the higher the dimensionality of the design space, the more training samples may be needed to adequately cover it, and the greater the computational effort required.
A practical consideration is that the optimal design found (5 m², with all enhancements) might involve higher economic costs than slightly less efficient alternatives. This aspect was not included in the model (which optimized only for efficiency), but in a real-world application, it would be advisable to incorporate a cost metric or perform a cost-benefit analysis. Fortunately, this is feasible within the same framework, simply by expanding the objective function.

Comparison with Optimization via Supervised Learning:

An alternative approach would have been to train a supervised network to predict efficiency based on the input parameters and then use mathematical algorithms on that trained network (e.g., gradient-based methods) to find the optimum. While this metamodel + optimization strategy is valid (and indeed the literature reports cases of ANNs used to predict the performance of large solar systems) [1], the generative approach offers the advantage of integrating both steps and also leveraging negative samples. Instead of training a model to precisely fit $\eta(A, x_2)$ (which requires many samples and may lead to overfitting), the GAN trains the generator to directly produce A, x_2 optimal solutions using a reinforcement signal from D. This is more similar to reinforcement learning or a goal-oriented approach, where it is not necessary to perfectly model the entire response surface, but rather to move in the right direction of improvement. In high-dimensional problems, such a strategy can sometimes be more efficient.

Possible Extensions:

An interesting future direction would be to apply this approach to the design of concentrating collectors (e.g., parabolic trough or dish collectors), where the geometry is more complex (reflector angle, receiver shape, etc.). Generative AI could be used to suggest unconventional reflector shapes to optimize concentration, something difficult to achieve through manual methods.Likewise, the approach could be extended to the optimization of complete solar thermal systems (not just the collector but also the storage tank, heat exchanger, etc.) by integrating transient simulations. This would result in a highly powerful AI-assisted design system for solar thermal plants. Another application would be to incorporate uncertainty in the operating conditions, for example, training the model with efficiency data under different irradiance and temperature levels, so that it proposes robust designs that perform well on an annual average, not just under ideal conditions. Conditional generative AI techniques could allow for specifying different climate scenarios as input.

5. Conclusions

A generative artificial intelligence (AI) model was developed and evaluated for the optimization of solar thermal collector design, demonstrating its effectiveness in improving thermal efficiency and the geometric configuration of these devices. Based on the results obtained, the following main conclusions can be drawn:

Viability of the generative approach:

This work confirms that generative AI techniques, particularly Generative Adversarial Networks (GANs), can be successfully applied to engineering design problems. The generative model was able to learn the characteristics of the most efficient designs and generate new collector configurations that significantly outperformed the initial designs. This opens the door to using generative AI as a design assistance tool in renewable energy systems, complementing traditional optimization methods.

Substantial improvement in thermal efficiency:

The solar collector optimized by the model achieved a thermal efficiency of approximately 74%, compared to ~56% for a typical baseline design, representing a relative improvement of around 30%. Even compared to the best randomly obtained design (which already had ~69% efficiency), the generative approach achieved an increase of more than 5 percentage points. These improvements translate into greater capture of useful solar energy (in our simulations, the optimized collector delivered more than three times the thermal power of the baseline under the same irradiance conditions). In practical terms, this suggests that integrative design optimization can lead to more compact or more effective collectors, reducing costs or increasing the contribution of renewable energy.

Automated exploration of the design space:

Unlike manual design or constrained parametric optimization, generative AI autonomously explored a wide range of geometric combinations, implicitly identifying which features (larger area, presence of optical enhancements) were beneficial for efficiency. The trained generator encapsulates this knowledge and can continue proposing near-optimal designs, offering flexibility in engineering decision-making. This represents a paradigm shift: instead of the engineer evaluating predefined options, the model can generate optimal or creative alternatives, which the engineer then validates against other criteria.

Integration of simulation and machine learning:

The developed methodology integrated a physical simulation model (to calculate the efficiency of a given design) with a machine learning model (the GAN). This integration proved synergistic: the simulation provided the data needed to train the AI, and the AI in turn identified solutions that maximized the simulation's outcome. In problems where physical evaluation is computationally expensive, training a generative model such as the one presented can save computation time in the long term by serving as an intelligent approximator of the physical system.

Generalization potential:

Although the study focused on flat-plate solar collectors and two main variables, the approach is extensible to more complex designs and other devices. For example, it could be applied to optimize configurations of full solar fields (multiple collectors), to photovoltaic cell design, or even to problems outside the solar field such as aerodynamic design, as long as an evaluable objective function exists, and the design can be parameterized. Generative AI offers a way to handle high-dimensional design spaces that would be intractable with exhaustive search.In conclusion, the application of generative AI to the design of solar thermal collectors has shown very promising results, achieved notable efficiency improvements and demonstrated a new way to approach optimization problems in thermal engineering. To the best of our knowledge, this work represents one of the first explorations in this direction and sets a precedent for future research.As future work, we propose validating the model with real experimental data from collectors to refine its accuracy, incorporating economic and environmental considerations into the optimization criteria (e.g., collector cost, carbon footprint of manufacturing), and extending the approach to other components of solar thermal systems (storage tanks, pumps, etc.) to achieve holistic optimization of solar energy systems.With the rapid advancement of AI and the growing urgency to optimize energy systems in the face of the climate crisis, methodologies such as the one presented here may become standard tools in the design arsenal of solar energy engineers and researchers.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.

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