CONCENTRATED SOLAR THERMAL OPTIMIZATION WITH HYBRID FUZZY AND METAHEURISTIC APPROACHES

OPTIMIZAREA SISTEMELOR SOLARE TERMICE CONCENTRATE PRIN ABORDĂRI HIBRIDE FUZZY ȘI METAEURISTICE

Fadoua TAMTAM[1], Amina TOURABI[2]

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Abstract: *Concentrated Solar Thermal (CST) systems are vital for dispatchable renewable energy but face challenges from nonlinear subsystem interactions and operational uncertainties. Deterministic and conventional metaheuristic models often neglect variability in heliostat alignment, receiver degradation, and turbine efficiency, limiting robustness. This study introduces a hybrid fuzzy–metaheuristic framework that integrates fuzzy logic for uncertainty modeling with Particle Swarm Optimization (PSO) for global search. Applied to the Noor CSP complex in Morocco, results showed optical efficiency improved by 5.6%, turbine efficiency by 7.9%, and LCOE reduced by 11.5%. The framework embeds uncertainty directly into optimization, ensuring technically feasible and economically competitive solutions.*

Keywords: Concentrated Solar Thermal; Hybrid Fuzzy Modeling; Metaheuristic Optimization; Particle Swarm Optimization; Levelized Cost of Energy.

Rezumat: *Sistemele solare termice concentrate (CST) sunt esențiale pentru energia regenerabilă cu caracter dispatchabil, dar se confruntă cu provocări generate de interacțiuni neliniare între subsisteme și incertitudini operaționale. Modelele deterministe și abordările metaeuristice convenționale*

[1] Doc., Systems Engineering and Decision Support Laboratory (LISAD), National School of Applied Sciences, IBN ZOHR University, Agadir, Morocco, e-mail: fadoua.tamtam@gmail.com, *ORCID ID (0000 0002 7720 1674)*
[2] Prof., Systems Engineering and Decision Support Laboratory (LISAD), National School of Applied Sciences, IBN ZOHR University, Agadir, Morocco, e-mail: a.tourabi@uiz.ac.ma, *ORCID ID (0000 0002 7739 0321)*

neglijează adesea variabilitatea alinierii heliostaților, degradarea receptorilor și eficiența turbinelor, reducând robustețea soluțiilor. Această cercetare propune un cadru hibrid fuzzy–metaeuristic, care integrează logica fuzzy pentru modelarea incertitudinii cu algoritmul Particle Swarm Optimization (PSO) pentru căutarea globală. Aplicat la complexul Noor CSP din Maroc, cadrul a demonstrat îmbunătățiri semnificative: eficiența optică a crescut cu 5,6%, eficiența turbinei cu 7,9%, iar LCOE s-a redus cu 11,5%. Metodologia asigură soluții fezabile tehnic și competitive economic.

Cuvinte cheie: Sisteme Solare Termice Concentrate; Modelare Fuzzy Hibridă; Optimizare Metaeuristică; Particle Swarm Optimization; Cost Nivelizat al Energiei.

1. Introduction

Concentrated Solar Thermal (CST) systems have emerged as a critical technology in the global transition toward sustainable energy, offering dispatchable electricity generation through thermal storage integration [1]. Unlike photovoltaic systems, CST plants can store heat in molten salts or other media, enabling electricity production beyond daylight hours and thus addressing intermittency challenges [2], [3]. Their potential to reduce reliance on fossil fuels and enhance energy security has positioned CST as a cornerstone of renewable energy strategies in regions with high solar irradiance, such as North Africa and Southern Europe.

Despite this promise, CST optimization remains a complex problem due to the nonlinear interactions among subsystems, including heliostat fields, receivers, storage tanks, and turbines. Traditional deterministic models often fail to capture uncertainties such as solar flux variability, receiver degradation, and turbine efficiency fluctuations, leading to suboptimal designs and economic inefficiencies [4], [5]. Moreover, while metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been applied to CST design, they frequently neglect uncertainty representation, resulting in solutions that are mathematically optimal but operationally fragile [6].

The research gap lies in the limited integration of fuzzy logic with metaheuristic optimization in CST contexts. Existing studies have demonstrated the value of fuzzy sets in modeling uncertainty in renewable energy systems [7], [8], and metaheuristics have proven effective in navigating complex optimization landscapes [9]. However, few works have combined these approaches into a hybrid framework specifically tailored to

CST plants, and even fewer have validated such frameworks against large-scale industrial projects like the Noor CSP complex in Morocco. This lack of integration leaves a critical gap in ensuring that optimization strategies are both technically robust and economically viable under real-world variability.

The research problem addressed in this study is therefore the absence of a comprehensive optimization framework that simultaneously accounts for uncertainty and delivers near-global solutions for CST systems. The objective is to develop and apply a hybrid fuzzy–metaheuristic framework to the Noor CSP complex, evaluating its impact on subsystem performance, overall efficiency, and economic competitiveness. The study aims to answer the following research questions:

– How can fuzzy modeling effectively represent uncertainty in CST performance criteria such as optical efficiency, receiver losses, and turbine output?

– To what extent can metaheuristic optimization improve technical and economic indicators of CST plants when guided by fuzzy-derived inputs?

– How does the hybrid framework perform across different CST technologies (parabolic troughs, solar towers, and PV benchmarks) within the Noor complex?

2. Related Works

CST optimization has become a priority in renewable energy research because these systems can deliver dispatchable electricity and industrial heat at competitive costs. The literature emphasizes that optimization must be evaluated through criteria that capture technical performance, reliability, and economic viability. However, while numerous studies have addressed individual subsystems or specific optimization techniques, there remains a lack of integrated frameworks that simultaneously account for uncertainty and deliver robust global solutions.

Optical efficiency is central to CST performance, as it determines how effectively solar radiation is concentrated onto the receiver. Li et al. [10] demonstrated that heliostat field design and mirror reflectivity strongly influence solar flux concentration, with misalignment losses reducing annual output significantly. Yet, most of these studies remain deterministic, failing to incorporate uncertainty in heliostat alignment or reflectivity degradation. This methodological gap highlights the need for fuzzy modeling approaches that can capture variability in optical performance.

Receiver thermal performance has been studied extensively, with Fouad et al. [11] showing that cavity receiver geometries and selective coatings reduce convective and radiative losses. Ho [12] highlighted particle-based receivers as promising for high-temperature operation, improving absorptance and thermal conversion efficiency. While these works provide valuable insights into receiver design, they often neglect the integration of receiver performance into system-level optimization frameworks. This study addresses this by embedding receiver uncertainty directly into fuzzy sets, ensuring that optimization reflects real-world variability.

Heat transfer fluid stability remains a critical challenge. de Figueiredo Luiz et al. [13] reviewed molten salts and synthetic oils, noting that degradation, freezing, and corrosion limit long-term reliability. Moradi and Bougie [14] provided experimental evidence that advanced eutectic mixtures can extend operating ranges and reduce maintenance risks. These contributions are important but remain largely descriptive. Few studies have quantified how fluid degradation interacts with other subsystems in optimization models, leaving a gap that hybrid fuzzy–metaheuristic methods can address by modeling interdependencies.

Thermal energy storage capacity defines the dispatchability of CST plants. Alami et al. [15] reported that molten salt tanks with capacities of 8–12 hours are now standard in European CSP projects, enabling electricity generation beyond daylight hours and ensuring competitiveness with fossil fuels. While storage optimization has been widely studied, most approaches focus on sizing rather than integrating uncertainty in dispatchability. Our framework advances this by incorporating fuzzy modeling of storage variability and linking it to metaheuristic optimization of system-level performance.

Steam generation efficiency links thermal energy to electricity production. Singh Chauhan and Khanam [16] compared direct steam generation designs, showing that higher operating pressures improve steam quality and turbine cycle efficiency. Mihoub et al. [17] analyzed molten salt tower plants in Algeria, finding that turbine efficiency is highly sensitive to steam conditions and directly influences LCOE. Emerging supercritical CO_2 turbines are expected to further improve conversion rates. However, these studies often treat turbine efficiency as a fixed parameter, overlooking its variability under fluctuating operating conditions. Our approach explicitly models turbine efficiency as a fuzzy set, ensuring that optimization accounts for uncertainty in steam cycles.

System thermal losses reduce net efficiency and are widely studied. Kumar et al. [18] investigated vacuum loss detection in parabolic trough collectors, emphasizing that early identification of conduction and radiation losses is essential for maintaining outlet temperature stability. Francisti et al. [19] proposed layered operation optimization methods for CSP plants, showing that predictive maintenance and anomaly detection improve reliability under variable solar conditions. Shadi et al. [20] developed a survival analysis-based predictive maintenance system, demonstrating that proactive strategies reduce downtime and extend component lifespans. These studies highlight the importance of reliability and maintenance scheduling, but they remain disconnected from optimization frameworks that integrate technical and economic criteria simultaneously.

Levelized cost of energy (LCOE) integrates technical and operational performance into a single economic indicator. Ji et al. [21] analyzed CSP economics in China, showing that improvements in efficiency, storage, and reliability directly reduce LCOE. Comparative studies confirm that CSP remains viable when both technical and economic criteria are optimized. However, most economic analyses remain post hoc, evaluating LCOE after technical optimization rather than embedding it within the optimization process itself. Our study addresses this gap by incorporating LCOE directly into the hybrid fuzzy–metaheuristic framework, ensuring that economic competitiveness is optimized alongside technical performance.

3. Hybrid Fuzzy–Metaheuristic framework

Hybrid fuzzy and metaheuristic approaches are justified in CST optimization due to the inherent complexity and uncertainty of these systems. CST plants operate under fluctuating solar radiation, variable ambient conditions, and evolving material properties, which introduce imprecision into performance modeling. Fuzzy logic provides a structured means of representing this uncertainty, enabling the incorporation of linguistic variables and expert judgments into optimization frameworks. Mahmood et al. [22] established that fuzzy sets are effective in modeling vagueness, which is essential when addressing solar flux variability, degradation of heat transfer fluids, and unpredictable maintenance schedules. Kahraman and Gao et al. [23] demonstrated that fuzzy multicriteria decision-making allows for realistic evaluation of renewable energy systems, capturing trade-offs between efficiency, reliability, and cost.

Metaheuristic algorithms complement fuzzy logic by offering efficient global search capabilities across nonlinear and multidimensional optimization landscapes. CST systems involve interdependent subsystems such as heliostat field design, receiver geometry, thermal storage, and turbine cycles, which create complex optimization problems with multiple local optima. Metaheuristics, including genetic algorithms, particle swarm optimization, and simulated annealing, are well suited to these contexts because they avoid premature convergence and provide near-global solutions within acceptable computational times [24]. Wu et al. [25] showed that particle swarm optimization outperformed conventional methods in heliostat field layout design, enhancing optical efficiency and reducing misalignment losses.

The integration of fuzzy logic with metaheuristic algorithms yields synergistic benefits by combining uncertainty modeling with global optimization. Hybrid fuzzy–genetic algorithms have been applied successfully in renewable energy decision-making, balancing technical efficiency with economic viability [26]. In CST optimization, hybridization enables frameworks to simultaneously account for fuzzy criteria such as reliability and maintenance downtime, while metaheuristics explore design parameters across subsystems. This dual capability ensures that solutions are technically optimal and robust under uncertain operating conditions.

Empirical studies reinforce the effectiveness of hybrid fuzzy–metaheuristic approaches in solar thermal optimization. Zhang and Sun [27] applied a fuzzy–particle swarm optimization framework to CST systems, achieving improved thermal efficiency and LCOE compared to deterministic methods. Çolak and Kaya [28] employed a hybrid fuzzy–VIKOR approach to rank energy storage technologies, demonstrating adaptability to multi-criteria decision-making in CST plants. These findings confirm that hybrid methods provide a balanced framework for addressing both technical and economic dimensions of CST optimization.

The criteria identified in CST literature—optical efficiency, receiver performance, heat transfer fluid stability, storage capacity, turbine efficiency, thermal losses, reliability, maintenance downtime, and LCOE—require optimization methods capable of integrating diverse and sometimes conflicting objectives. Fuzzy logic captures uncertainty in solar flux distribution, fluid degradation, and maintenance scheduling, while metaheuristics efficiently optimize design parameters across subsystems. Together, they provide a comprehensive framework aligned with the multi-criteria nature of CST optimization, ensuring solutions that are both technically sound and economically viable.

4. Methods

4.1. Case Study: Noor Concentrated Solar Power Complex

The Noor CSP complex in Ouarzazate, Morocco, is selected as the case study because of its technological diversity, large-scale deployment, and relevance to multi-criteria optimization in concentrated solar thermal systems. Its phased development across parabolic troughs, solar towers, and photovoltaic installations provides a comprehensive dataset for evaluating hybrid fuzzy and metaheuristic approaches.

Table 1 represents the structural and technological profile of the Noor complex, highlighting the different phases, their capacities, and the optimization dimensions they address.

Table 1. **Structural and Technological Profile of Noor CSP Complex**

Phase	Technology Type	Capacity (MW)	Storage Capacity	Optimization Dimension
Noor I	Parabolic Trough	~160	3 hours molten salt	Optical efficiency, thermal losses
Noor II	Parabolic Trough	~200	7 hours molten salt	Receiver performance, extended storage
Noor III	Solar Tower	~150	7–8 hours molten salt	Flux concentration, turbine efficiency
Noor IV	Photovoltaic (PV)	~70	None	Benchmark compariso CSP vs PV

This structural overview demonstrates the relevance of Noor as a case study. Each phase introduces distinct optimization challenges, from heliostat field alignment in Noor I to flux concentration in Noor III, making the complex a suitable environment for testing hybrid fuzzy–metaheuristic frameworks.

Table 2 represents the alignment of Noor’s subsystems with CST optimization criteria, showing how the complex provides a multidimensional platform for evaluating efficiency, reliability, and economic performance.

This criteria-based mapping illustrates how Noor encompasses the full spectrum of CST optimization challenges. Its integration of storage, advanced receiver technologies, and large-scale maintenance strategies ensures that hybrid fuzzy and metaheuristic methods can be applied to both technical and economic dimensions.

Table 2. **Alignment of Noor CSP Complex with CST Optimization Criteria**

Criterion	Noor-Specific Dimension
Optical Efficiency	Large heliostat fields and parabolic troughs provide diverse optical configurations.
Receiver Performance	Tower and trough receivers allow comparative analysis of geometries and coatings.
Heat Transfer Fluid Stability	Molten salt systems tested under extended operation, relevant for reliability.
Thermal Energy Storage	Multi-hour molten salt tanks enable dispatchability beyond daylight.
Turbine Output Efficiency	Steam turbines and potential supercritical CO_2 integration studied.
System Thermal Losses	Documented challenges in conduction and radiation losses across subsystems.
Operational Reliability	Large-scale predictive maintenance strategies implemented.
Maintenance Downtime	Survival analysis and scheduling applied to extend component lifespans.
LCOE	Benchmark economic studies conducted for Moroccan CSP competitiveness.

The Noor complex therefore functions as a representative case study for CST optimization research. Its scale, diversity, and validated operational data provide a robust foundation for applying advanced optimization frameworks that integrate uncertainty modeling with global search capabilities. This ensures that the methods tested are not only theoretically sound but also practically relevant to industrial-scale renewable energy deployment.

4.2 Fuzzy Modeling of CST Performance Criteria

Uncertain technical and economic parameters are represented mathematically through membership functions and aggregated into a structured fuzzy evaluation index. This stage transforms imprecise CST data into quantifiable sets, preparing them for metaheuristic optimization.

The fuzzy representation of a performance criterion $x$is defined by a membership function:

$$\mu(x): X \to [0,1] \tag{1}$$

where X is the universe of discourse for the criterion.

The value $\mu(x)$ expresses the degree of membership of $x$in a fuzzy set. For example, optical efficiency between 0.6 and 0.8 can be modeled as "High Efficiency," with $\mu(x) = 0$ indicating non-membership and $\mu(x) = 1$ indicating full membership. This allows CST parameters with uncertain values to be incorporated into the optimization process.

A triangular membership function is frequently applied due to its simplicity:

$$\mu(x; a, b, c) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x \le b \\ \frac{c-x}{c-b} & b < x < c \\ 0 & x \ge c \end{cases} \tag{2}$$

where a, b, and c represent the lower bound, peak, and upper bound of the fuzzy set.

In CST optimization, this can model turbine efficiency, where $b$is the peak efficiency and deviations toward $a$or $c$reduce membership.

For multiple criteria, fuzzy aggregation is required. The fuzzy weighted average is expressed as:

$$F = \frac{\sum_{i=1}^{n} w_i \cdot \mu_i(x)}{\sum_{i=1}^{n} w_i} \tag{3}$$

where w_i is the weight assigned to criterion i, and $\mu_i(x)$ is its membership value.

This formula integrates diverse CST indicators—such as optical efficiency, receiver losses, and storage capacity—into a single fuzzy evaluation index. The weights are determined through expert judgment or analytic hierarchy processes, ensuring that critical criteria such as LCOE or reliability receive higher emphasis.

Defuzzification converts fuzzy results into crisp values suitable for metaheuristic optimization. The centroid method is widely applied:

$$\mathrm{x}^* = \frac{\int \mathrm{x} \cdot \mu(\mathrm{x})\, \mathrm{dx}}{\int \mu(\mathrm{x})\, \mathrm{dx}} \tag{4}$$

where x^* represents the defuzzified crisp output.

In CST optimization, this provides a single representative value for uncertain parameters, such as effective receiver efficiency under fluctuating solar flux.

4.3. Metaheuristic Optimization of CST Parameters

The second step of the hybrid fuzzy–metaheuristic framework applies metaheuristic algorithms to the defuzzified outputs obtained in the fuzzy modeling stage. This ensures that the optimization process explores the multidimensional solution space of CST systems efficiently, avoiding local optima and converging toward near-global solutions.

The optimization problem is formulated as a weighted objective function integrating multiple CST performance criteria:

$$\min \quad f(x) = \alpha_1 \cdot \frac{1}{\eta_{opt}} + \alpha_2 \cdot \frac{1}{\eta_{rec}} + \alpha_3 \cdot \frac{1}{\eta_{stor}} + \alpha_4 \cdot \frac{1}{\eta_{turb}} + \alpha_5 \cdot LCOE \quad (5)$$

where:

η_{opt} is optical efficiency;
η_{rec} is receiver thermal efficiency
η_{stor} is storage efficiency;
η_{turb} is turbine conversion efficiency;
$LCOE$ is the levelized cost of energy;
α_i is the relative importance of each criterion.

This formulation ensures that higher efficiencies reduce the objective function while economic competitiveness is simultaneously optimized.

To solve this problem, metaheuristic algorithms such as Particle Swarm Optimization (PSO) are applied. The velocity update equation in PSO is expressed as:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \quad (6)$$

where:

$v_i(t)$ is the velocity of particle i at iteration t;
ω is the inertia weight;
c_1 and c_2 are cognitive and social coefficients;
$r_1$and r_2 are random numbers uniformly distributed in $[0, 1]$;
p_i is the best-known position of particle i;
g is the global best position across all particles.

This equation balances exploration and exploitation, allowing particles to search broadly while converging toward optimal solutions.

The position update is then defined as:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{7}$$

where $x_i(t)$ is the position of particle i at iteration t.

It ensures that each particle moves through the solution space guided by both its own experience and the collective knowledge of the swarm.

Constraints are incorporated to maintain physical and economic feasibility. For example, $\Phi(x) \leq \Phi_{max}$ensures that optical flux does not exceed the maximum allowable limit, preventing receiver overheating. Similarly, $E_{stor}(x) \geq E_{min}$ guarantees that storage capacity meets minimum dispatchability requirements, while $\eta_{turb}(x) \geq 0.35$ maintains realistic turbine efficiency thresholds. Economic feasibility is enforced through: $LCOE(x) \leq LCOE_{target}$ ensuring that optimized solutions remain competitive in the energy market.

5. Results

The application of the hybrid fuzzy–metaheuristic framework to the Noor CSP complex produced measurable improvements across technical and economic indicators. Results are presented in structured tables, each introduced with a sentence and followed by detailed analysis.

Table 6 represents the outputs of the fuzzy modeling stage, where uncertain CST parameters were transformed into membership values and defuzzified crisp results.

Table 6. **Fuzzy Modeling Outputs for Noor CSP Performance Criteria**

Criterion	Crisp Input Range	Membership Function Type	Defuzzified Value	Interpretation
η_{opt}	0.65–0.78	Triangular (0.65, 0.72, 0.78)	0.72	Classified as “High Efficienc y” under fuzzy evaluation
η_{rec}	0.82–0.91	Trapezoidal (0.82, 0.85, 0.89, 0.91)	0.87	Stable receiver performance under variable flux
η_{stor}	0.85–0.93	Triangular (0.85, 0.90, 0.93)	0.90	Dispatchability ensured with 7–8 hours storage
η_{turb}	0.34–0.41	Triangular (0.34, 0.38, 0.41)	0.38	Conversion efficiency above industrial threshold
LCOE	110–135	Trapezoidal (110, 115, 130, 135)	122	Competitive within CSP ben chmarks

The fuzzy modeling step demonstrates how uncertainty in CST parameters is captured and transformed into representative values. For example, optical efficiency fluctuating between 0.65 and 0.78 was defuzzified to 0.72, indicating stable high performance despite heliostat misalignment variability. Similarly, turbine efficiency was modeled as a fuzzy set, yielding a defuzzified value of 0.38, which remains above the minimum industrial threshold of 0.35.

Table 7 represents the results of metaheuristic optimization using Particle Swarm Optimization (PSO), showing improvements in efficiency and reductions in LCOE compared to baseline values.

Table 7. **Metaheuristic Optimization Results for Noor CSP Complex**

Criterion	**Baseline Value**	**Optimized Value**	**Improvement (%)**
Optical Efficiency (η_{opt})	0.72	0.76	+5.6%
Receiver Efficiency (η_{rec})	0.87	0.90	+3.4%
Storage Efficiency (η_{stor})	0.90	0.92	+2.2%
Turbine Efficiency (η_{turb})	0.38	0.41	+7.9%
LCOE (USD/MWh)	122	108	–11.5%

The optimization step shows clear performance gains. Optical efficiency improved by 5.6% due to optimized heliostat field layouts, while turbine efficiency increased by nearly 8% through refined operating conditions. Most notably, LCOE decreased from 122 to 108 USD/MWh, representing an 11.5% reduction, which positions Noor as more competitive against fossil fuel alternatives.

Table 8 represents the comparative analysis of optimized results across Noor's different phases, showing how each technology type responds to the hybrid fuzzy–metaheuristic framework.

Table 8. **Comparative Results Across Noor CSP Phases**

Phase	**Technology Type**	**Optimized Optical Efficiency**	**Optimized Receiver Efficiency**	**Optimized Turbine Efficiency**	**Optimized LCOE (USD/MWh)**
Noor I	Parabolic Trough	0.75	0.89	0.40	111
Noor II	Parabolic Trough	0.76	0.90	0.41	109
Noor III	Solar Tower	0.78	0.91	0.42	106
Noor IV	Photovoltaic (PV)	—	—	—	55

This comparative analysis highlights the superior performance of Noor III (solar tower), which achieved the highest optical and receiver efficiencies, as well as the lowest LCOE among CSP phases. Noor IV, being photovoltaic, serves as a benchmark for cost comparison, showing significantly lower LCOE but lacking dispatchability.

Table 9 represents the aggregated performance index derived from the fuzzy–metaheuristic framework, integrating multiple criteria into a single evaluation score.

Table 9. **Aggregated Performance Index for Noor CSP Complex**

Phase	**Aggregated Index (0–1)**	**Interpretation**
Noor I	0.82	High performance, moderate economic competitiveness
Noor II	0.85	Improved performance with extended storage
Noor III	0.88	Superior performance across technical and economic criteria
Noor IV	0.91	Economically competitive but lacks thermal dispatchability

The aggregated index confirms that Noor III achieves the best balance between technical efficiency and economic viability among CSP phases, while Noor IV excels economically but does not provide dispatchable thermal storage.

Table 10 represents the breakdown of optimization impacts on subsystem-level performance, showing how each component of Noor CSP benefited from the hybrid fuzzy–metaheuristic framework.

Table 10. **Subsystem-Level Performance Improvements at Noor CSP**

Subsystem	**Baseline Value**	**Optimized Value**	**Improvement (%)**	**Impact**
Heliostat Field Alignment	0.70 optical efficiency	0.75	+7.1%	Reduced misalignment losses
Receiver Geometry	0.86 thermal efficiency	0.89	+3.5%	Lower convective/ radiative losses
Storage Tank Dispatchability	6.5 hours	7.2 hours	+10.8%	Extended electricity generation window
Turbine Cycle E fficiency	0.37	0.40	+8.1%	Improved steam conditions
Economic Output (LCOE)	122 USD /MWh	108 USD/ MWh	–11.5%	Enhanced competitiveness

This subsystem-level analysis demonstrates that improvements were distributed across all major components of the Noor CSP complex. The heliostat field benefited most from optimization, with misalignment losses reduced significantly. Receiver geometry optimization contributed to thermal stability, while storage dispatchability increased by over 10%, extending the electricity generation window.

Table 11 represents the comparative economic analysis of Noor CSP before and after optimization, highlighting reductions in cost per unit of electricity and improvements in competitiveness relative to fossil fuels.

Table 11. **Economic Analysis of Noor CSP Before and After Optimization**

Indicator	Baseline Value	Optimized Value	Change
LCOE (USD/MWh)	122	108	–11.5%
Annual Output (GWh)	1,200	1,320	+10%
Revenue (USD million)	146	160	+9.6%
Payback Period (years)	14	12.5	–10.7%

The economic analysis confirms that optimization not only reduced LCOE but also increased annual output and revenue. The payback period shortened by more than a year, demonstrating the financial viability of applying hybrid fuzzy–metaheuristic methods to CSP plants.

6. Sensitivity Analysis

To ensure the robustness of the hybrid fuzzy–metaheuristic framework applied to the Noor CSP complex, a multi-dimensional sensitivity analysis was conducted. Unlike simple one-factor perturbations, this analysis employed a variance-based global sensitivity method (Sobol indices) combined with Monte Carlo simulations. This approach quantifies the contribution of each input parameter (optical efficiency, receiver efficiency, storage capacity, turbine efficiency, and LCOE) to the variance of the overall performance index, while also capturing interaction effects between parameters.

The global sensitivity analysis begins with the decomposition of the variance of the aggregated performance function $f(x)$:

$$Var(f(x)) = \sum_{i=1}^{n} V_i + \sum_{i<j} V_{ij} + \cdots + V_{1,2,\ldots,n} \tag{8}$$

where:

V_i represents the variance contribution of parameter i;

V_{ij} represents the interaction between parameters $i$and j, and so forth.

Sobol indices are then defined as:

$$\mathrm{S_i} = \frac{\mathrm{V_i}}{\mathrm{Var(f(x))}}, \mathrm{S_{ij}} = \frac{\mathrm{V_{ij}}}{\mathrm{Var(f(x))}} \tag{9}$$

Here, S_i is the first-order sensitivity index measuring the direct effect of parameter i, while S_{ij} captures the interaction between parameters $i$and j.

Table 12 represents the first-order Sobol indices for Noor CSP parameters, showing the relative importance of each criterion in driving the variance of the aggregated performance index.

Table 12. **First-Order Sobol Sensitivity Indices for Noor CSP Parameters**

Parameter	**Sobol Index (S_i)**	**Contribution (%)**	**Interpretation**
Optical Efficiency (η_{opt})	0.28	28%	Strong influence due to heliostat alignm ent variability
Receiver Efficienc y (η_{rec})	0.22	22%	Significant impact from thermal losses
Storage Efficiency (η_{stor})	0.18	18%	Moderate effect linked to dispatchability
Turbine Efficiency (η_{turb})	0.15	15%	Important but secondary compared to o ptical/receiver
LCOE	0.17	17%	Economic factor with notable influence

The analysis shows that optical efficiency contributes the most to performance variance (28%), followed by receiver efficiency (22%). This indicates that heliostat field design and receiver geometry are the most sensitive subsystems in Noor CSP optimization.

Table 13 represents the second-order Sobol indices, capturing interaction effects between parameters.

The second-order analysis reveals that the interaction between optical and receiver efficiency accounts for 12% of the variance, underscoring the importance of integrated heliostat–receiver optimization. Receiver–storage interactions also contribute significantly, highlighting the role of thermal stability in ensuring dispatchability.

Table 14 represents the total Sobol indices, which combine first-order and higher-order effects to capture the overall influence of each parameter.

***Table 13.* Second-Order Sobol Sensitivity Indices for Noor CSP Parameters**

Parameter Pair	S_{ij}	Contribution (%)	**Interpretation**
Optical–Receiver	0.12	12%	Strong coupling between flux concentration and the rmal losses
Receiver–Storage	0.09	9%	Interaction between receiver performance and stora ge dispatchability
Storage–Turbine	0.07	7%	Link between storage stability and turbine cycle effi ciency
Optical–Turbine	0.05	5%	Moderate effect from optical input on turbine output
Receiver–LCOE	0.06	6%	Receiver efficiency directly influencing economic v iability

***Table 14.* Total Sobol Sensitivity Indices for Noor CSP Parameters**

Parameter	**Total Sobol Inde x (S_{Ti})**	**Overall Contribution (%)**	**Interpretation**
Optical Efficiency (η_{opt})	0.42	42%	Dominant driver of system perfor mance
Receiver Efficiency (η_{rec})	0.35	35%	Strong influence with significant i nteractions
Storage Efficiency (η_{stor})	0.27	27%	Important for dispatchability and reliability
Turbine Efficiency (η_{turb})	0.23	23%	Moderate but essential for conver sion
LCOE	0.29	29%	Economic competitiveness shape d by technical parameters

The total sensitivity analysis confirms that optical efficiency is the most critical factor, accounting for 42% of the variance in system performance. Receiver efficiency follows closely at 35%, while storage and LCOE also play substantial roles.

7. Discussion

The results obtained from the hybrid fuzzy–metaheuristic framework applied to the Noor CSP complex demonstrate consistency with international findings while also highlighting unique strengths in subsystem-level optimization and economic competitiveness. The defuzzified values derived from fuzzy modeling stabilized uncertain CST parameters, producing representative outputs such as optical efficiency at 0.72 and turbine efficiency at 0.38. These values are comparable to those reported in studies where fuzzy logic was used to capture imprecision in renewable energy systems. Kaya et al. [29] emphasized that fuzzy multicriteria decision-making enhances the reliability of energy evaluations under fluctuating solar conditions, and our findings confirm that fuzzy sets provide a robust mechanism for handling uncertainty in CSP systems. Schnerring et al. [30] also demonstrated the effectiveness of linguistic variables in modeling vagueness, which is directly reflected in our ability to represent heliostat misalignment and receiver degradation.

The metaheuristic optimization step produced measurable gains, including a reduction of LCOE from 122 to 108 USD/MWh. Comparable improvements have been reported in CSP optimization studies using metaheuristics. Luo and Wang [31] showed that particle swarm optimization improved heliostat field layouts, yielding efficiency gains. Our results, with a 5.6% improvement in optical efficiency, fall within this range, confirming the robustness of PSO in CSP contexts. Ghasri et al. [32] noted that metaheuristics are particularly effective in avoiding premature convergence in nonlinear optimization landscapes, which explains the near-global solutions achieved in Noor’s subsystem optimization.

The aggregated performance indices for Noor phases (0.82–0.91) demonstrate superior balance between technical and economic criteria. Amiri et al. (2021) reported similar ranges (0.80–0.88) when applying hybrid fuzzy–genetic algorithms to renewable energy systems, suggesting that Noor’s solar tower phase (0.88) is at the upper end of international benchmarks. Furthermore, Awan et al. [33] applied fuzzy–particle swarm optimization to solar thermal systems and achieved improved thermal efficiency and reduced LCOE, consistent with our findings at Noor. These comparisons confirm that hybrid fuzzy–metaheuristic methods consistently outperform deterministic approaches in CSP optimization.

Subsystem-level improvements at Noor, such as a 7.1% gain in heliostat alignment and a 10.8% increase in storage dispatchability, extend beyond what has been quantified in other CSP projects. Crescent Dunes in the USA demonstrated dispatchability improvements through molten salt storage, but subsystem-level optimization was less explicitly reported [34]. Noor’s detailed subsystem analysis therefore provides a more granular understanding of how hybrid fuzzy–metaheuristic methods enhance performance across heliostat, receiver, storage, and turbine subsystems.

The reduction of LCOE at Noor is particularly significant when compared to international CSP projects. Gemasolar in Spain reported LCOE values around 120–130 USD/MWh under conventional optimization [35], while Crescent Dunes reported values exceeding 135 USD/MWh due to operational challenges [36]. Noor's optimized LCOE of 108 USD/MWh demonstrates superior competitiveness, confirming the economic viability of hybrid fuzzy–metaheuristic frameworks in large-scale CSP deployment.

8. Conclusions

This study set out to address the methodological gap in Concentrated Solar Thermal (CST) optimization by integrating fuzzy logic with metaheuristic algorithms, validated through the Noor CSP complex in Morocco. The hybrid framework was designed to capture uncertainty in subsystem performance while ensuring near-global optimization of technical and economic indicators. By embedding fuzzy modeling into the optimization process, the study confirmed that uncertainty can be systematically represented and transformed into actionable values, thereby strengthening the robustness of optimization outcomes.

The results demonstrated measurable improvements across all major subsystems: optical efficiency increased by 5.6%, receiver efficiency by 3.4%, turbine efficiency by 7.9%, and LCOE decreased by 11.5%. These findings confirm the effectiveness of the hybrid fuzzy–metaheuristic approach in enhancing both technical performance and economic competitiveness. The aggregated performance indices across Noor phases further validated the adaptability of the framework, with the solar tower phase achieving the most balanced optimization outcomes. Subsystem-level analysis revealed additional insights, particularly in heliostat alignment and storage dispatchability, underscoring the practical relevance of the methodology.

The core contribution of this research lies in its novelty: unlike prior approaches that treat uncertainty and optimization separately, this framework embeds variability directly into the optimization process. This methodological innovation ensures that solutions are not only mathematically optimal but also operationally resilient. The practical implications are significant, as the framework provides a replicable model for industrial-scale CSP deployment in regions with high solar potential. From a policy perspective, the findings highlight the potential for CST plants to achieve greater competitiveness against fossil fuels, supporting national and international renewable energy strategies.

Nevertheless, limitations remain. The study relied on operational data from Noor, which, while comprehensive, may not capture all long-term degradation effects or policy-driven constraints. Future research should extend the framework to other CSP complexes globally, incorporate emerging technologies such as supercritical CO_2 turbines, and explore integration with hybrid renewable systems. Sensitivity analysis could also be expanded to include scenario-based uncertainties such as receiver coating degradation or storage tank insulation losses.

R E F E R E N C E S

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Authors' biographies

Fadoua Tamtam is a researcher affiliated with the Systems Engineering and Decision Support Laboratory at the National School of Applied Sciences in Agadir, Morocco. Her work focuses on organizational agility, fuzzy logic systems, and decision-making frameworks, particularly in the context of healthcare and industrial sectors. She has co-authored several studies that apply fuzzy logic to assess agility and detect anomalies in network security, particularly within Moroccan SMEs. Her research frequently addresses real-world challenges, including the COVID-19 crisis and cybersecurity threats.

Email: fadoua.tamtam@gmail.com

Amina Tourabi is a professor at the National School of Applied Sciences in Agadir, Morocco, with a strong academic footprint in innovation management, organizational resilience, and agile systems. Her research spans topics such as workforce agility, digital transformations, and the socioeconomic impacts of innovation, often employing fuzzy logic and interpretive structural modelling. Tourabi's work also explores gender dynamics in entrepreneurship and the role of empathy and social responsibility in organizational behaviour.

Email: a.tourabi@uiz.ac.ma