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Comparison of Aiming Point Strategy Algorithms and Their Assessment for Volumetric Solar Receivers

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Abstract. The present work summarizes the work done within the scope of CATION, CHLOE, and HECTOR projects related to the aiming point strategies optimization algorithms applied to volumetric solar receivers. Several optimization methods have been applied in the literature for optimizing the aiming strategy of solar power tower plants. However, the use of these algorithms for the requirements of volumetric solar receivers and solar fuel applications has not been accomplished. Herein, the problem is formulated as a constrained optimization problem whose objective function is a combination of the total power on the receiver surface and the flux homogeneity. A comparison of the results is presented in this work. It will be seen that TABU search and SA algorithms are the most efficient in terms of computation time and, in addition, the first one shows very good results in power and spillage. The rest of the mentioned algorithms are much slower and, in general, the results are slightly worse.

Keywords: Solar Tower Pants, Aiming Point Strategy, Optimization, Heuristic, Metaheuristic, Local Search

1. Introduction

Nowadays, solar tower plants have been proposed as systems to put solar fuels in the energy production industry. One of the main challenges that solar fuels currently face is the operation conditions of the solar receivers when they are used as high-temperature thermochemical reactors that involve very high average solar flux densities typically above 1.500 kW/m^2. In order to concentrate solar power in an optimum way, precise and accurate control of the solar field is required at any time.

The control of the solar flux distribution on the receiver in a solar tower plant is closely related to the heliostats' aiming points' definition. Aiming strategies provide information about where and when each heliostat aims during the operation time and the main objective of defining an optimal aiming strategy is to maximize the efficiency of the solar tower plant, and besides, to guarantee better reliability and durability of the receiver over time avoiding accelerated aging and deterioration. Another important aspect to consider in the strategy is spillage, which is the proportion of power that exceeds the limits of the receiver surface and is therefore wasted. Thus, the lowest possible spillage is desired.

Determining a dynamic pointing strategy to maintain high-level fluxes over a long period is a complex problem. As a first step, the validation of the methodology for selecting the optimal focus point for each heliostat among those predetermined is addressed. In the future, with this part solved, the definition of the best coordinates for aiming points will be carried out. In this work, several algorithms have been studied from the literature and those with the greatest potential have been developed in order to compare and determine the benefits and drawbacks of each of them focusing on volumetric solar receivers. Moreover, with the methodology used, the study could be extended to compare other scenarios or include new algorithms.

The structure of the subsequent sections is as follows. Section 2 describes the algorithms considered in the comparison. Section 3 describes the methodology carried out; section 4 describes the power plant used for the simulation and presents the results obtained in the optimization process. Finally, section 5 summarizes the results and the conclusion obtained in the results section.

2. Optimization algorithms

Related to the literature, plenty of methods and algorithms have been already developed to solve combinatory optimization problems where finding the best solution analytically requires a lot of computational cost. These algorithms pretend to reduce the space of possible solutions to perform the search more efficiently. These algorithms can be classified as heuristic, meta-heuristic, or integer linear programming.

Some publications have already addressed the aiming point optimization problem [1], but there is still a long way to go in order to establish a proven reference methodology. Along this work, some of the most promising algorithms have been developed and compared between them taking into account certain key performance characteristics: spillage, peak flux andpower. All of this parameters have been simulated by CHELIO [6], a CENER in-house code. In the following subsections, a brief description of the algorithms implemented is presented.

2.1 Tabu Search

TABU search (TS) [2] is a metaheuristic method that employs local search for mathematical optimization. Essentially, TS uses local search to move from a potential solution to an improved solution from its neighborhood until the stopping criterion has been satisfied (usually a maximum number of iterations or a score threshold previously fixed). In this case, a maximum number of iterations has been used as the stopping criterion. Besides, when defining the neighborhood of each potential solution, TS uses memory structures so that there are no unexplored areas of solutions.

In this particular case, at each iteration, each heliostat aims at an arbitrary point. If the objective function improves, the heliostat stays with the new aiming point, if on the contrary, it does not improve, it aims at the previous aiming point. In the search process, a history of tested aiming points is stored to avoid repeated combinations.

2.2 Genetic Algorithms

Genetic Algorithms (GA) [3] are a type of evolutionary algorithm (EA), which are metaheuristic algorithms based on the Darwinian principle of survival of the fittest. GA creates high-quality solutions to optimization and search problems using three operators: selection, mutation, and crossover. First, an initial population is created and fitness, the value of the objective function, is calculated for each individual. In the present case, each individual is composed of heliostat-aiming point pairs. After that, parents with the best fitness are selected from the population and a crossover operation is performed. For this operation, the aiming point of one heliostat in two individuals is exchanged thus creating a completely new individual. Finally, the mutation operation is performed changing the aiming point of one heliostat of one individual randomly to maintain the diversity in the population and avoid premature convergence without searching for a global best solution.

In addition, a new version of the genetic algorithm has been implemented. This algorithm introduces a new operation based on the Ant Colony Optimization (ACO) algorithm, the Modified Genetic Algorithm (MGA). This modification aimed to find improvements in the results and to reduce convergence times. However, this objective has not been achieved as the results show.

2.3 Artificial Bee Colony

Artificial Bee Colony (ABC) algorithm [4] is inspired by Bee Colony foraging behavior and explores solution space at random, at multiple points, converging to a better solution with every successive generation. This algorithm consists of four essential components. Food Sources represent feasible solutions for the optimization problem. Employed bees search around the food sources to fine-tune and evolve to produce more nectar. Onlooker bees watch the employed bees and explore the most promising food sources. This ensures that the more promising a food source is the more it gets explored. Finally, scout bees choose random new food sources to ensure that it does not fall into local minima.

In this case, the initial random population of bees corresponds with the employed bees. Each employed bee corresponds to a solution of the aiming strategy and each heliostat - aiming point pair corresponds to a food source.

2.4 Simulated Annealing

Simulated annealing (SA) [5] is a metaheuristic algorithm based on the Metropolis Hastings method. At each step, the SA heuristic considers some neighboring state of the current state and probabilistically decides between moving the system to the new neighbor state or staying in the precious one. Typically, this step is repeated until the system reaches a state that is good enough for the corresponding application, or until a maximum given computation iterations.

3. Methodology

The designing of an optimal aiming strategy leads to finding the best position of the aiming point for each heliostat in the heliostat field. The optimization of the strategy is a continuous nonlinear constrained optimization problem of very large dimensions. For this reason, a fixed scenario is defined (heliostats, tower, aiming points, time instant, dni)

Every optimization algorithm process, including the aiming point strategy optimization, needs to define the objective function to either maximize or minimize, the receiver power constraints and the aiming point distribution. Herein, the strategy aims to maximize the total power at the receiver input aperture while maintaining a homogeneous flux distribution. Thus, in this comparison, the function to maximize has been considered as a combination of both concepts. More specifically, the considered objective function is shown in equation (1).

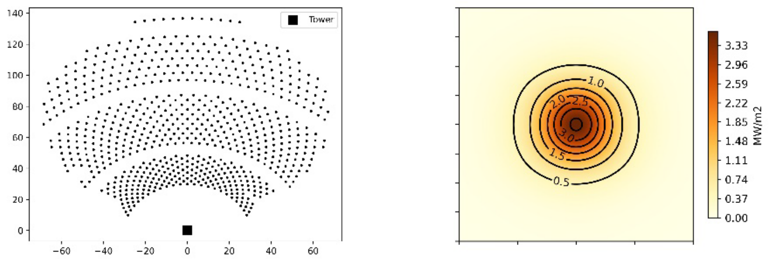
$$f_{obj} = \alpha \cdot p_t - (1-\alpha) \cdot \sigma_f \tag{1}$$

where $\alpha \in [0,1]$ indicates the weight given to each term, p_t denotes the total power, and σ_f the flux density standard deviation on the receiver. Indeed, if $\alpha=1$ is considered, the expression in (1) maximizes the total power, whereas if $\alpha=0$, it maximizes $-\sigma_f$, which is equivalent to maximizing the homogeneity. A parametric study has been carried out to analyze the relationship between power and flux dispersion as a function of alpha. As we increase the value of the parameter, the maximum power increases but the flux is stored at the center of the receiver, which makes the flux distribution very inhomogeneous. This is why α = 0.6 has been taken in this work.

To calculate the flux map at the receiver during the aiming point strategy optimization process, the main software used is CHELIO [6], a CENER in-house code that is adequate software for this application since it is based on mathematical simplified models with computational cost and simulation time much lower than the ray-tracing software.

4. Simulation case and results

In this comparison work, a power tower plant with 739 heliostats has been considered. The positions of the heliostat are shown in Figure 1 a). A rectangular flat surface has been used to represent the volumetric solar receiver input aperture, and a cylindrical tower has been modeled. Figure 1 b) shows the flux map and contour lines when all the heliostats are focusing at the center of the receiver. In this case, the spillage is only 1.38%, but it is clear that the flux distribution is not homogeneous and that its concentration in a single point of 3.59MW/m^2 that can cause irreparable damage to the materials of the receiver, which is one of the consequences to be avoided by optimizing the aiming strategy. The total power in this case is 1.58MW.



a) b)

Figure 1. a) Simulated heliostat field distribution; b) Flux map when all heliostats aim to the center of the receiver.

Several distributions for the aiming points have been tested. More specifically, uniform distributions of 9, 15, and 21 aiming points have been considered in this work (see Figure 2). Note that an odd number of aiming points must be defined on each axis of the receiver surface so that the center of the receiver is one of the aiming points. For each aiming point distribution, the optimization with the algorithms mentioned above and with different numbers of iterations have been run.

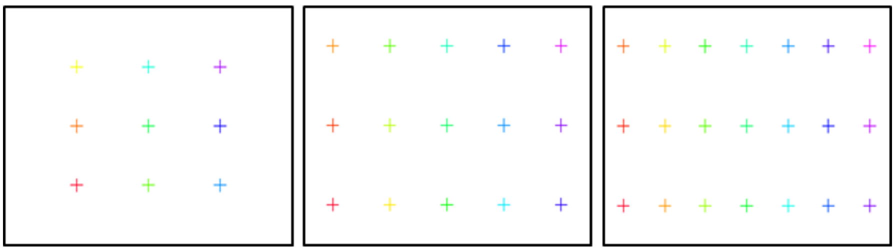


Figure 2. The different aiming point distributions used in the simulation.

The following figures and tables show the results of the aiming point optimizations. For the first simulations, 9 aiming points uniformly arranged in the aperture have been defined. Table 1 shows the results of the simulations.

Table 1. *The obtained flux deviation, total power, peak flux, and spillage for the different algorithms for 9 predefined aiming points.*

Number of aiming points	Method	Iterations	Deviation [kW/m²]	Total Power [MW]	Maximum flux peak [kW/m²]	Spillage [%]
9	TABU	300	197.40	1.48	682.76	7.03
9	TABU	3000	213.12	1.52	748.20	4.93
9	GA	100	217.10	1.48	763.86	7.15
9	GA	1000	215.54	1.47	837.12	7.53
9	MGA	100	201.39	1.47	747.66	7.65
9	MGA	1000	230.56	1.47	954.90	7.42
9	SA	300	199.91	1.48	664.85	7.40
9	SA	3000	206.11	1.48	734.87	7.02
9	ABC	100	200.29	1.48	696.55	7.31
9	ABC	1000	206.64	1.48	722.56	7.20

Figure 3 are resulting flux distribution maps for each simulation. In these maps, the aiming points are clearly visible.

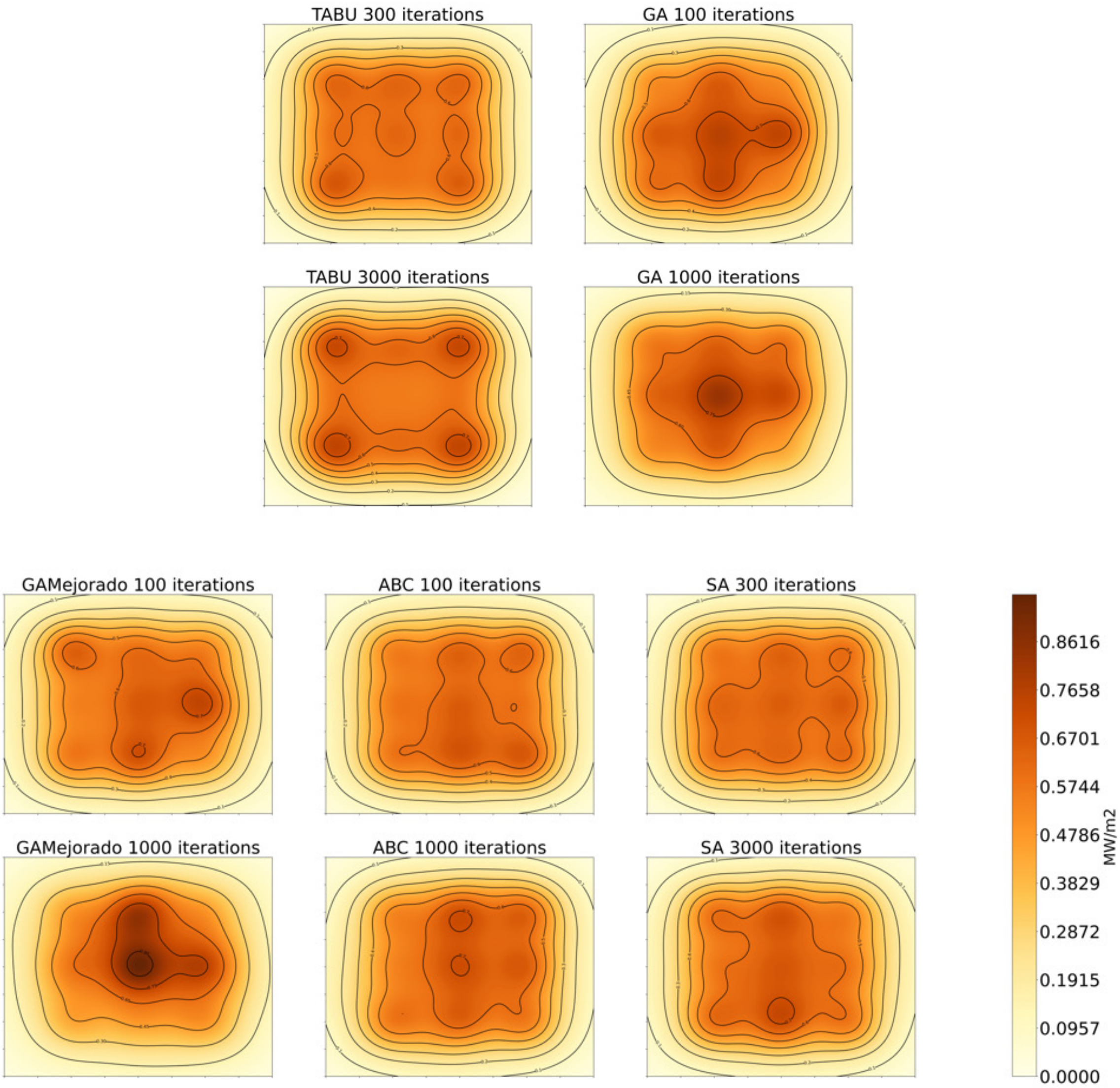


Figure 3*. The flux maps distributions with 9 aiming point optimizations.*

The previous results suggest that 9 aiming points are not enough for achieving a homogenous flux map. For this reason, Table 2 shows the results of the optimizations for 15 aiming points.

Table 2. *The obtained flux deviation, total power, peak flux, and spillage for the different algorithms for 15 predefined aiming points.*

Number of aiming points	Method	Iterations	Deviation [kW/m2[	Total Power [MW]	Maximum flux peak [kW/m^2]	Spillage [%]
15	TABU	300	90.63	1.32	485.25	15.63
15	TABU	3000	133.43	1.44	608.80	9.14
15	GA	100	73.56	1.28	462.94	17.91
15	GA	1000	71.25	1.27	505.50	18.32
15	MGA	100	65.62	1.28	451.33	18.15
15	MGA	1000	71.86	1.26	584.63	19.14
15	SA	300	83.62	1.31	525.73	16.27
15	SA	3000	88.25	1.31	520.39	16.05
15	ABC	100	78.74	1.30	478.32	16.86
15	ABC	1000	83.85	1.31	488.75	16.44

In this case, the deviation has been reduced. However, the spillage has increased reducing the incident power on the receiver. Figure 4 presents the flux map distribution for 15 aiming points.

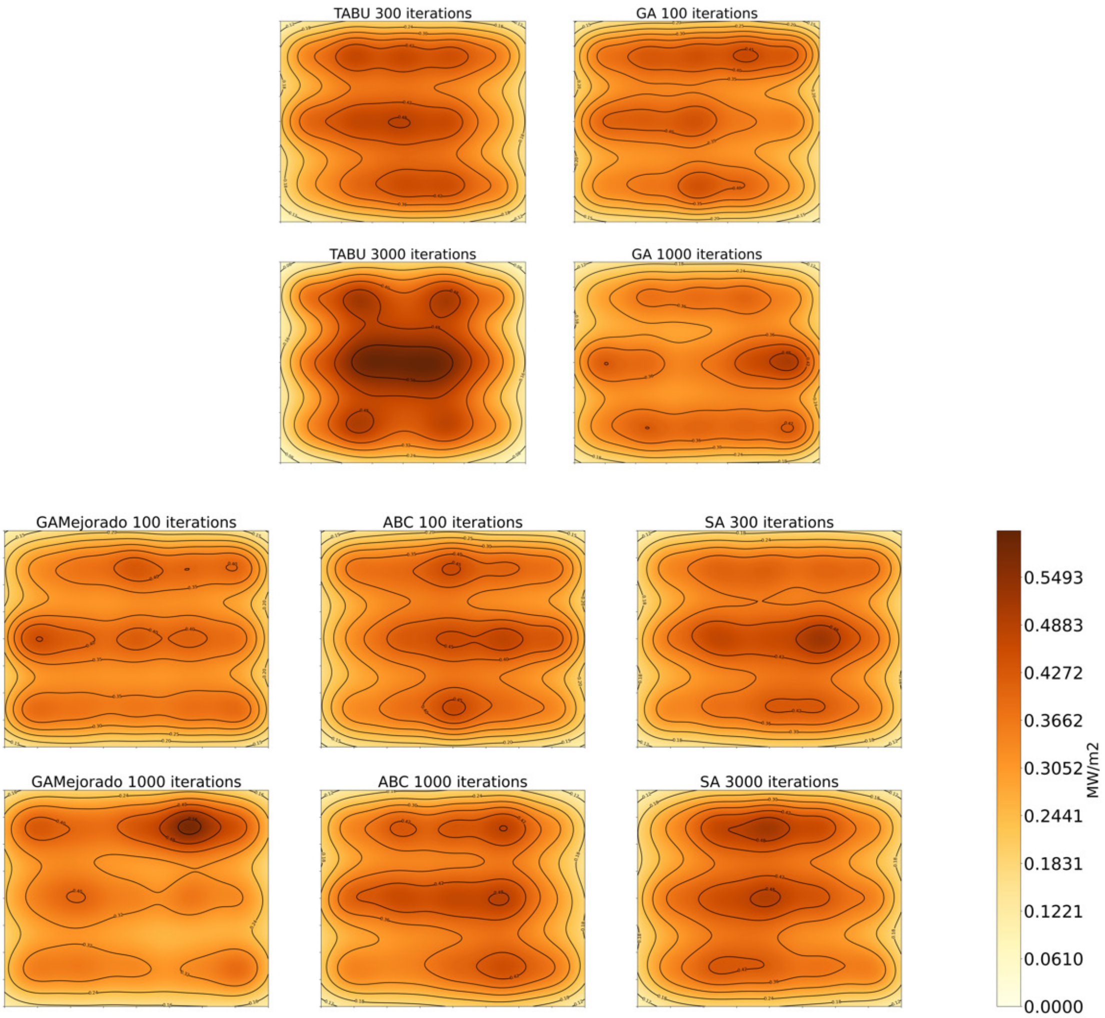


Figure 4*. The flux maps distributions with 15 aiming point optimizations.*

Finally, optimizations with 21 uniformly distributed aiming points have been carried out. Table 3 and Figure 5 show the corresponding results.

Table 3. *The obtained flux deviation, total power, peak flux, and spillage for the different algorithms for 21 predefined aiming points.*

Number of aiming points	Method	Iterations	Deviation [kW/m2[	Total Power [MW]	Maximum flux peak [kW/m2]	Spillage [%]
21	TABU	300	91.60	1.32	518.33	15.75
21	TABU	3000	143.16	1.45	621.27	8.69
21	GA	100	76.91	1.28	498.56	17.83
21	GA	1000	78.36	1.27	535.82	18.67
21	MGA	100	81.92	1.27	495.73	18.34
21	MGA	1000	77.71	1.25	536.64	19.72
21	SA	300	77.99	1.30	452.57	17.07
21	SA	3000	87.75	1.31	491.90	16.48
21	ABC	100	79.21	1.29	487.22	17.22
21	ABC	1000	85.81	1.30	485.53	17.01

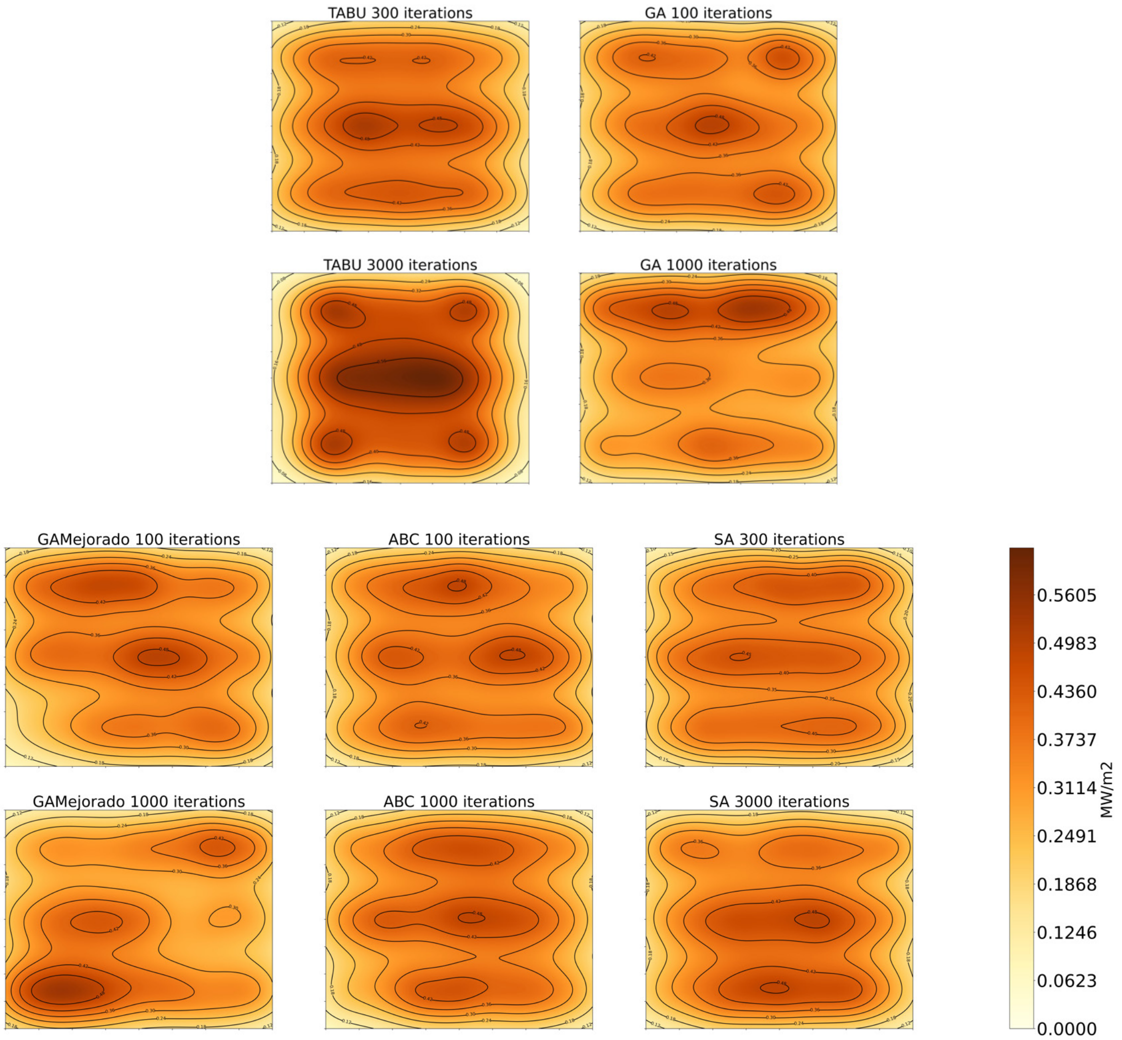
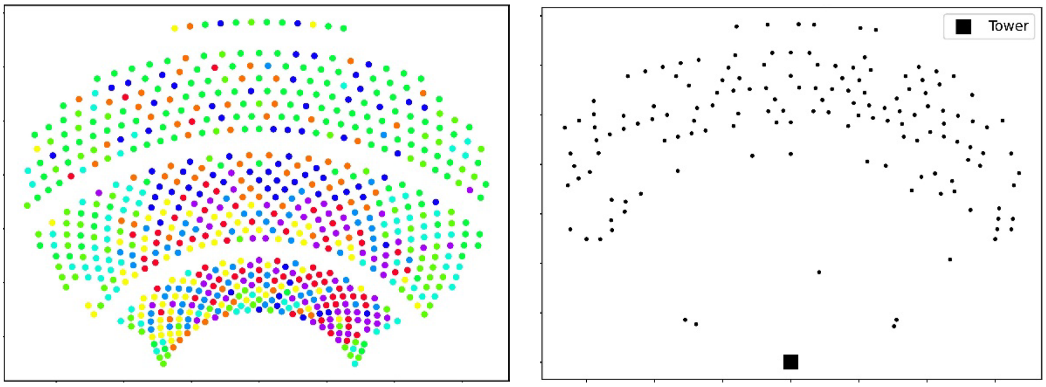


Figure 5*. The flux maps distributions with 21 aiming point optimizations.*

In general, with fewer aiming points, being further away from the edge of the receiver surface results in less spillage and, therefore, higher total power. However, in this case, the homogeneity drops, because there is more receiver surface that has not been covered. In the same way, when there are more aiming points, the flux deviation decreases, as there are more points spread over the surface of the receiver. This also causes the spillage to increase.

Regarding the comparison between algorithms, genetic algorithms are the ones that obtain solutions with higher spillage, i,e., less total power. In terms of time, the GA and ABC algorithms have taken the longest to run, while TS and SA algorithms are the most computationally efficient. We also note that the TS with a high number of iterations (+2000) provides very good results in terms of power and spillage. In the case of 9 aiming points, the flux is mainly concentrated at the corners, even though most of the heliostats point to the center. This is because those aiming at the center of the receiver are the heliostats farthest from the tower (see Figure 6).



a) b)

***Figure 6**.The solution obtained with 9 aiming points, TS with 3000 iterations; a) Optimal aiming strategy; b) Heliostats aiming the center of the receiver.*

5. Conclusions and future work

Five different optimization methods were applied in the aiming strategy optimization of a solar power tower with a volumetric receiver. All these algorithms were implemented with different parameter settings and the results have been compared. Although the results do not present big differences, TS performs well when a high number of iterations are used. GA takes more evaluations to reach a good performance. In general, the highest values of spillage and therefore, less power, are achieved with these algorithms. Finally, both ABC and SA provide good results, although the second one is more computationally efficient.

The optimum solution is the one that maximizes total power and minimizes standard deviation. The value of spillage and maximum flux peak must be taken into account in order to guarantee the receiver integrity.

***Table 4.** The obtained flux deviation, total power, peak flux, and spillage for the different algorithms for 9, 15 and 21 predefined aiming points.*

Method	**Iterations**	**Deviation [kW/m^2]**			**Total Power [MW]**			**Maximum flux peak [kW/m^2]**			**Spillage [%]**		
Number of Aiming Points		**9**	**15**	**21**	**9**	**15**	**21**	**9**	**15**	**21**	**9**	**15**	**21**
TABU	300	197.4	90.63	91.6	1.48	1.32	1.32	682.8	485.3	518.3	7.03	15.63	15.8

TABU	**3000**	**213.1**	**133.4**	**143**	**1.52**	**1.44**	**1.45**	**748.2**	**608.8**	**621.3**	**4.93**	**9.14**	**8.69**
GA	100	217.1	73.56	76.9	1.48	1.28	1.28	763.9	462.9	498.6	7.15	17.91	17.8
GA	1000	215.5	71.25	78.4	1.47	1.27	1.27	837.1	505.5	535.8	7.53	18.32	18.7
MGA	100	201.4	65.62	81.9	1.47	1.28	1.27	747.7	451.3	495.7	7.65	18.15	18.3
MGA	1000	230.6	71.86	77.7	1.47	1.26	1.25	954.9	584.6	536.6	7.42	19.14	19.7
SA	300	199.9	83.62	78	1.48	1.31	1.3	664.9	525.7	452.6	7.4	16.27	17.1
SA	3000	206.1	88.25	87.8	1.48	1.31	1.31	734.9	520.4	491.9	7.02	16.05	16.5
ABC	100	200.3	78.74	79.2	1.48	1.3	1.29	696.6	478.3	487.2	7.31	16.86	17.2
ABC	1000	206.6	83.85	85.8	1.48	1.31	1.3	722.6	488.8	485.5	7.2	16.44	17

Table 4 shows a comparison between all the algorithms executed with the three aiming points distribution proposed along this work. For the distribution of 15 and 21 aiming points the spillage increases considerably in all cases except for TS algorithm with 3000 iterations. The configuration with 9 aiming points keep the spillage in an acceptable value for every algorithm. The best value of total power is for the 9 aiming points distribution and TS algorithm with 3000 iterations but with a high value of standard deviation. 15 and 21 aiming points distribution decrease the total power but the value of standard deviation is lower with more flux homogeneity in the receiver.

The methodology presented in this work is successful in the comparison optimization algorithms. As a next step, these results will be extended with other algorithms like Ant Colony Optimization or Linear Programming.

In the near future, the approach of the generation of an automatic and dynamic strategy for the definition of aiming point distribution will be carried out. Finally, note that all this work has been done for a static state, that is, for a specific solar position, but different dynamic strategies will be studied once the static problem is completely covered.

Data availability statement

The data supporting these results has been generated within the CATION project and they are available on request from the author, Olaia Itoiz. The data are not publicly available since their use could compromise CENER's interest in their exploitation.

Author contributions

Elena Mellado: Software development, Simulation and analysis, Writing. **Olaia Itoiz**: Software development, Simulation and analysis, Writing. **Amaia Mutuberria:** Software development, Simulation and analysis, Writing. **Justo Puerto:** Review & editing of the paper.

Competing interests

Authors have no conflicts of interest to declare that they are relevant to the content of this article.

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