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Heliostat Clustering for Aiming Point Strategies Optimization

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Abstract. The performance of solar tower systems is closely linked to the aiming point strategy of the heliostats. The optimization process of obtaining the best aiming point strategy for a field is complex and has a high computational cost. The use of the clustering technique relieves the requirements by decreasing the space of possible solutions to the problem. Results show that the application of the technique for aiming point strategy optimization reduces the time of optimization significantly.

Keywords: Concentrated Solar Energy, Tower Technology, Heliostat, Aiming Point Strategy

1. Introduction

Concentrated solar energy has been positioned to become one of the references to generat clean alternative fuels. The solar tower plants are the technology with the highest potential for this thermochemical process. The feasibility of this kind of plant is closely linked to the capacity to achieve high levels of flux concentrations for long periods in order to guarantee the proper execution of chemical reactions through an adequate aiming point strategy [1].

Aiming point strategy definition in solar power tower plants is important to guarantee the integrity of the receiver avoiding its degradation along the time produced by overheating points. An optimal aiming point strategy can allow reducing the size of the receiver achieving high levels of efficiency. This is not a trivial problem according to literature [2], [3], [4], [5], where different optimization algorithms are applied to solve this problem. These algorithms, whose procedure often involves a large computational cost because of the large number of available solutions, consist of maximizing or minimizing an objective function by choosing input values, “heliostat-aiming point”, from an allowed set.

In this study, it is proposed to set the input values by a pair of “heliostat group-aiming point”, all the heliostats belonging to a specific group aim to the same point in the receiver. In this way, the number of available solutions is reduced as it depends on the number of clusters defined instead of on the total the number of heliostats in the solar field enabling reaching a final solution with less computational cost.

The paper summarizes the work performed to compare different clustering algorithms. The structure of the subsequent sections is as follows, Section 2 summarizes the algorithms, functions, and parameters used for heliostats´ clustering; Section 3 describes the methodology used for the comparison process. Section 4 summarizes the results, and lastly, Section 5 presents the conclusion obtained from the performed analysis.

2. Clustering method

The main purpose of the clustering proposed in this study is to arrange the heliostats of the field into closed and homogenous heliostat groups to speed up the process of finding a solution to the aiming point strategy definition problem in central solar power plants. Furthermore, managing groups of heliostats is more intuitive, practical and efficient for plant operators and the operation of the plant itself. The heliostats inside a group must maintain similarities, and at the same time, must be well differentiated from heliostats belonging to other clusters.

In the scientific literature several algorithms developed to solve the task of clustering can be found. In this study, the most popular algorithms are analysed: Hierarchical agglomerative clustering, k-means clustering, and Self-Organizing Maps.

In the following subsections, a brief description of the aforementioned algorithms, the distance functions used to measure the similarity, and the 8 heliostat attributes used in the comparison are presented.

2.1 Clustering algorithms

Hierarchical clustering is based on building a hierarchy of clusters that could be represented on a tree structure. This structure could be built either on a “bottom-up” approach, where each element starts as one cluster and clusters merge, ending in the final step building the top cluster, or on a “top-down” approach where all the elements start in a unique cluster and the clusters are split, generating all the structure. In this analysis, an agglomerative approach, Hierarchical Agglomerative Clustering (HAC) [6], is used to merge the clusters using the following criteria: pairwise single-linkage clustering, pairwise maximum-linkage clustering, negative distance, pairwise average-linkage clustering, and pairwise centroid-linkage clustering. After building the tree structure, and cutting it to the appropriate height, the desired number of clusters is obtained.

The second clustering algorithm is k-means [7] which aims to divide all the elements into k groups in which elements belong to the group with the nearest distance to its center. There are different alternatives of what measure is considered the center of the group. In this case, the mean and median of the data vector are used.

Finally, the Self-Organizing Map (SOM) [8] technique, also called a Kohonen map, is a type of artificial neural network that organizes the clusters using a topology, commonly in a rectangular map. The clusters are organized in a way that two neighbours are more similar than distant clusters.

2.2 Distance functions

In order to divide the heliostats into homogeneous groups, it is important to define how similar the heliostats are. Different distance functions are used to define the similarity between each pair of observations:

- Euclidean distance: length of a segment between two points, length of the shortest path between two points.
- Manhattan distance or city-block distance: sum of distances along each dimension.
- Pearson correlation coefficient: degree of linear relationship between two observations
- Absolute correlation coefficient: the absolute value of Pearson correlation.
- Uncentered Pearson correlation
- Absolute uncentered Pearson correlation
- Spearman's rank correlation: non-linear rank correlation measure

- Kendall's tau correlation: another non-linear correlation measure, more robust than Spearman's correlation

Although all the distance functions could be used for the *k*-means algorithm, from a theoretical point of view, it is best to use the Euclidean distance for the mean method to calculate the centroid and the city-block distance for the median.

2.3 Heliostat attributes

With the purpose of creating heliostat clusters, several heliostat parameters could be considered to define the similarity among heliostats. The list of attributes considered for this comparison work and the explanation of position attributes are show in in Figure 1:

- Heliostat position (taking into account x-coordinate and z-coordinate)
- Position x-coordinate
- Position z-coordinate
- Heliostat angle α in the field (0º is the center of the receiver)
- The power that heliostat could provide to the receiver
- Heliostat reflected maximum flux peak

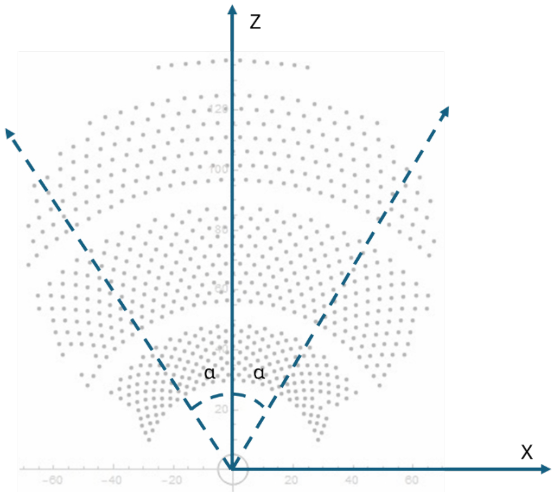


Figure 1. *Position attributes considered for heliostat grouping.*

For the calculation of the power reflected by each heliostat and the maximum flux peak of that radiation, the center of the receiver is considered the aiming point of the heliostats.

3. Comparison methodology

The comparison of different clustering methodologies to reduce the complexity of defining an optimum aiming strategy is a high-dimensional problem. Herein, a unique scenario is defined to perform all the simulations. The scenario is composed of a field of 739 heliostats placed north of a tower with a 4 m^2 flat rectangle receiver. The simulations are executed at Solar noon of the equinox in Seville (Spain). Figure 2 shows the layout of the heliostat field and the flux map distribution at the aperture of the receiver when all the heliostats aim at the center point of the receiver. In this case, the total power at the receiver is 1.59 MW with a peak flux of 3.6 MW/m^2 and a spillage of 1.58 %.

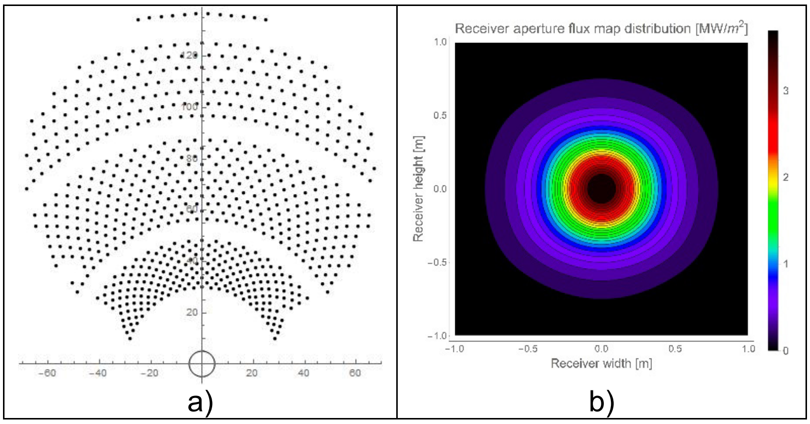


***Figure 2**. The scenario used in the comparison; a) Heliostat field layout, b) Flux map distribution at the receiver with all the heliostats aiming at the receiver center point.*

For the comparison study, the TABU search algorithm [2] is selected as the optimization method. It is a metaheuristic method that employs local search to move from a potential solution to an improved solution from its neighbourhood until the stopping criterion has been satisfied. For this study, the stopping criteria is a maximum number of iterations without improvement. Herein, 100 iterations are considered. In order to reach the optimum solution, the following objective has been defined as a combination of the total flux at the receiver and the flux distribution homogeneity:

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

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. Herein, a value of $\alpha = 0.6$ is taken, giving higher weight to the total power to reduce spillage losses when looking for homogeneity.

Figure 3 shows the optimization results of the defined scenario without the use of clustering. 25 aiming points uniformly distributed over the receiver input aperture surface are defined. Figure 2 and Figure 3 use the same color scale to perceive better the reduction of flux values and the improvement of homogeneity. The result of this optimization is used as a base case to measure the cost improvement of applying clustering to the heliostats. The optimization has required 16183 iterations and lasted 2 hours, 45 minutes, and 20 seconds. In addition, the achieved total power is 1.55 MW, with a flux peak of 0.78 MW/m^2 and a spillage of 4.17%.

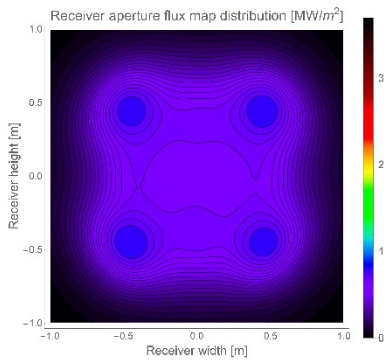


***Figure 3**. Flux map distribution for the optimization of heliostat aiming point distribution for 25 aiming points, without using clustering.*

In the comparison analysis, all valid clustering algorithms and distance function combinations are executed for creating heliostat clusters. For them, aiming point optimization is processed, achieving total flux, flux map distribution, spillage, number of iterations, and the required time for optimization.

4. Results

The flux maps distribution and the heliostat field losses efficiencies were simulated with a CENER in-house code CHELIO [9] which is based on convolution theory and was validated with Tonatiuh [10], a well-known ray-tracer.

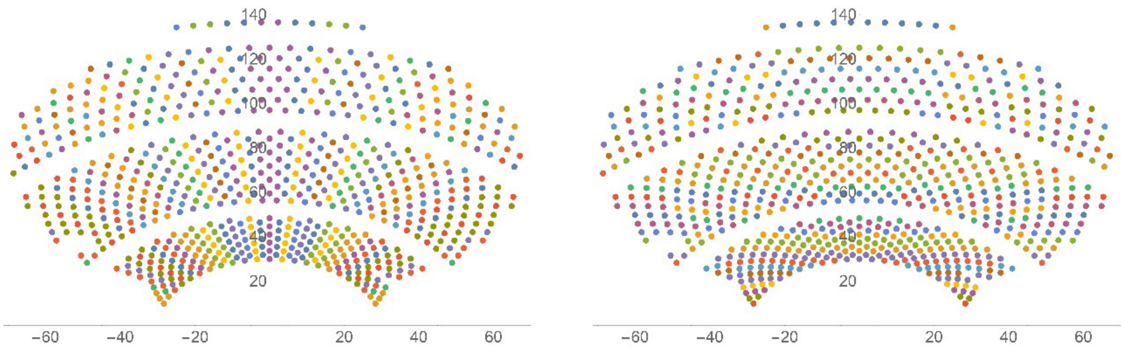
The first analysis shows that when most of the heliostats fall into one or a few clusters, the homogeneity property cannot be reached as the best optimization is the one in which almost all heliostats aim at the center. This is because a higher weight is given to the total power.

Based on this observation, the standard deviation of the number of heliostats in each cluster is calculated to discriminate those cases with few clusters concentrating most of the heliostats. Table 1 shows the percentage of the cases analyzed with a small value of the standard deviation of the number of heliostats per cluster, and the percentage of valid cases reaching a homogeneous solution for each heliostat attribute studied. There are no significant differences in run-times on average between using a specific attribute. However, all of them are considerably faster compared to not using clustering. In the worst case, only 26.7 % of the time is needed. The f_{obj} of the best case obtained is presented as a percentage with respect to the base case (without clustering).

Table 1. *Valid cases for executed optimization processes by heliostat attribute.*

Heliostat attribute	**Valid cases [%]**	**Mean f_{obj} of valid cases [-]**	**Slowest runtime [HH:MM:SS]**	**f_{obj} best case [%]**
Position	59.38	774451	00:39:21	99.43
X-coordinate	51.56	792155	00:44:11	97.74
Z-coordinate	43.75	792922	00:33:44.	99.03
Angle	40.63	795313	00:34:01	97.74
Power	25.00	769253	00:32:49	96.86
Maximum flux	25.00	781298	00:38:55	96.87

Table 1 shows that only in a few cases the last two attributes could be considered for clustering. In addition, Figure 4 shows the cluster distribution for the best optimization reached for 4 of the considered heliostat attributes. In Figure 4 b), the clusters for the case of flux peak attribute are presented. In this figure, the clusters are less clear with respect to the use of other attributes. Furthermore, the objective function value reached is also lower.



c) d)

***Figure 4**. Heliostat distribution by clusters for the best optimization for heliostat attribute; a) Taking heliostat position attribute; b) the maximum flux that heliostat can reflect into the receiver; c) heliostat angle in the field; d) heliostat z-coordinate of the position.*

The data also shows that the heliostat position is the attribute with the highest number of valid cases and, also, the attribute that has given the best optimization value. This result is very near to the objective function value obtained for the base case where the heliostat's aiming point is independently selected.

Considering the type of clustering algorithm, *k*-means is the algorithm with the highest valid cases, highest mean objective function value of the resulting solution, and lowest standard deviation value. With regard to the execution time, the *k*-means is the algorithm with the worst run-time, but this case only requires 26.7% of the time needed for the base case, wich does not consider clustering. On average, HAC is the fastest one with 458.64 s. Table 2 shows the comparison between HAC, k-means and SOM clustering algorithms.

***Table 2.** Valid cases by clustering algorithm.*

Clustering algorithm	Valid cases [%]	Mean f_{obj} of valid cases [-]	Standard deviation f_{obj} of valid cases [-]	Slowest runtime [HH:MM:SS]	f_{obj} best case [%]
HAC	23.33	763638	43588.40	00:33:24	99.03
k-means	95.83	792738	20231.27	00:44:11	99.43
SOM	18.75	778964	34021.03	00:39:21	97.18

Furthermore, Table 3 presents the analysis concerning the distance function used.

***Table 3.** Valid cases by distance function.*

Distance function	Valid cases [%]	Mean f_{obj} of valid cases [-]	Standard deviation f_{obj} of valid cases [-]	Slowest runtime [HH:MM:SS]	f_{obj} best case [%]
Euclidean distance	62.50	786486	36737.72	00:32:41	99.43
Manhattan distance	62.50	776855	25747.35	00:25:26	98.89
Pearson correlation	27.08	790894	32638.71	00:32:06	96.98
Absolute correlation	27.08	786856	33764.20	00:37:38	96.85
Uncentered Pearson c	52.08	774022	41887.69	00:38:55	97.33
Absolute uncentered	45.83	775168	45680.24	00:44:11	97.16

Spearman's rank	25.00	789968	12853.62	00:33:44	96.76
Kendall's tau	25.00	784288	12874.82	00:26:39	96.90

The well-known Euclidean and Manhattan distances are the distances with more valid cases and those presenting the best f_{obj} results. These are the cases that have lower losses compared to the base case. However, the highest mean f_{obj} value is achieved with Pearson correlation. A more exhaustive analysis shows that non-linear correlations only have obtained valid solutions with *k*-means, linear correlations bring better solutions with SOM, and Euclidean distance gives the highest f_{obj} for both HAC and *k*-means. Leaving aside the non-linear correlations due to the low valid cases percentage, correlation function solutions present worse run-times for the worst case. On average, the Manhattan distance is the function with better run-time values.

The best solution obtained between all the optimization performed is executed with the *k*-means algorithm, Euclidean distance, and using heliostat position as heliostat attribute. The f_{obj} value for this solution is 831361.18, which is 99.4% of the base case objective function. The flux map is shown in Figure 5.

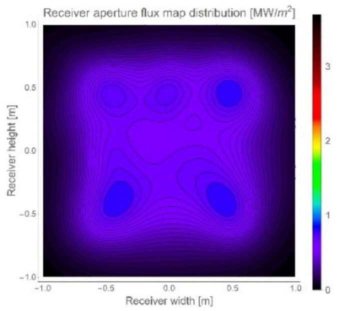


***Figure 5**. Flux map distribution for the best optimization using clustering.*

In Table 4, a comparison with the base case is performed. This solution is not as good as the base case when the aiming point of each heliostat is selected independently of the other heliostats. However, with 8% of the iterations and 13% less run-time, 99.4% of the power is achieved. Therefore, the loss of using clustering is very low compared to the remarkable cost computation improvement achieved.

***Table 4.** Valid cases for executed optimization processes by heliostat attribute.*

	Case base	**Best solution clustering**
Number of iterations	16183	1251
Optimization time [HH:MM:SS]	02:45:20	00:22:45
Total Power [MW]	1.55	1.54
Maximum flux [MW/m^2]	0.78	0.78
Spillage losses [%]	4.17	4.69

5. Conclusions

Solar fuel generation with solar power tower plants will inevitably require greater heliostat field control to achieve and maintain high fluxes on the receiver over long periods. An optimum aiming point strategy allows greater process efficiency. However, achieving an optimal solution requires a tedious simulation and optimization process of great complexity.

The use of heliostat clusters allows the reduction of the computational cost of searching for such an optimal strategy, as can be seen in the results of the present study, without considerably increasing the spillage losses. In the worst cases considered in this study, the optimization process takes 26.7% of the run-time required by the optimization without clustering. The reduction in computational cost could be higher when large heliostat fields are considered.

The study suggests that using the *k*-means algorithm is the most promising one to start the optimization process without taking into account the distance function or the heliostat attribute to use. Nevertheless, for the optimization, the Euclidean distance and the heliostat position are good starting points.

Furthermore, the study shows the use of clustering is an appropriate technique for the selection of the aiming point of the heliostats. The final goal of developing a methodology for generating an optimum aiming point strategy is to implement a dynamic, automatic, and real-time strategy on the plants. The clustering is a first approximation of the said methodology but it is necessary to decrease the spillage losses with regard to the case where the aiming points of heliostats are selected independently.

Data availability statement

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

Author contributions

Olaia Itoiz: Software development, Simulation and analysis, Writing. **Amaia Mutuberria:** Software development, Simulation and analysis, Writing**. Marcelino Sanchez:** Principal Investigator of CATION project, Review & editing of paper.

Competing interests

Authors have no conflict of interest to declare regarding the content of this article.

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