Engineering Applications of Artificial Intelligence 72 (2018) 253–266

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A two-layered solution for automatic heliostat aiming

N.C. Cruz *, J.D. Álvarez, J.L. Redondo, M. Berenguel, P.M. Ortigosa

Department of Informatics, Agrifood Campus of International Excellence (ceiA3), University of Almería, Spain

ARTICLE INFO

Keywords:
Heliostat field flux distribution
Global optimization
Heliostat aiming

ABSTRACT

The efficiency and safety of a solar central receiver system depend on the flux distribution reflected by the heliostat field on its receiver. Thus, the field must be carefully controlled to avoid dangerous radiation peaks and temperature gradients while also maximizing the efficiency of the system. Control tasks include deciding which heliostats to activate and where to aim them. The field is usually under direct human supervision, which is a potential limitation, and automatic aiming procedures are of great interest. This work proposes a general aiming methodology for flat-plate receivers. It intends to cover heliostat selection and aim point assignation to replicate any given reference flux distribution on the receiver. The methodology, which addresses this situation as a large-scale optimization problem, defines two consecutive stages. The first one handles heliostat selection by applying a specific genetic algorithm. The second one, based on a local gradient descent, assigns a final aim point to every active heliostat. The proposed methodology, in contrast to other existing methods in the literature, is not limited to achieve any specific target distribution. It exploits the analytical characterization of the considered field to minimize the accumulated squared error between any reference flux distribution and the achieved one. The results show very good replication quality and, considering its execution time, this method is suitable for preliminary and high-resolution field configuration.

1. Introduction

Solar central receiver systems (SCRS) are interesting facilities for large-scale electricity generation due to their high thermodynamic efficiency (Besarati and Goswami, 2014; Collado and Guallar, 2012) and relative output stability through thermal storage systems (Avila-Marin et al., 2013). For the scope of this work, SCRS consist of a set of orientable high-reflectance mirrors, called heliostats, and a radiation receiver. The heliostats track the apparent movement of the Sun to concentrate the incident solar radiation on the receiver. Thus, there is a high-radiation density on its surface. This energy is transferred progressively to a working fluid which flows inside it to be heated. The fluid can be ultimately used to produce electricity in a classic thermodynamic cycle. Fig. 1 depicts the main parts of SCRS. Further information about them can be found in Alexopoulos and Hoffschmidt (2013), Behar et al. (2013) and Camacho et al. (2012).

It is necessary to control the flux distribution that heliostat fields form on their receivers to maximize the efficiency (Astolfi et al., 2017) and operational safety (Besarati et al., 2014) of facilities. Otherwise, thermal stress caused by temperature peaks can dramatically reduce the lifetime of receivers, which directly affects the competitiveness of SCRS (Salomé et al., 2013). Numerous aiming strategies have been developed to address this situation. The interested reader can find a review of this topic in Grobler and Gauché (2014). The instantaneous flux distribution projected by a field depends on: (i) the subset of active heliostats and (ii) their aim points. In fact, fields can be over-sized to face unfavorable conditions such as cloudy days. In this context, a complex two-layered optimization problem must be faced: it is necessary to choose the heliostats to activate and their aim points. These tasks are usually supported by human decisions, which is an implicit limitation. The most interesting optimization approaches found in the literature for flat receivers are commented below. In general, they assume a fixed set of active heliostats and possible aim points from a combinatorial perspective.

In Salomé et al. (2013), the goal is to obtain a homogeneous flux distribution while maintaining an acceptable spillage factor. A TABU search is successfully applied. At every cycle, a heliostat is randomly selected to set its aim point to a different one. This method permits non-improving changes and forbids repeated ones for several steps to escape from local optima. Additionally, when their solver finds a solution, it is randomly restarted to explore a different region of the search space. Problem knowledge is also applied: heliostats are forced to aim at certain zones depending on their position. In Besarati et al. (2014), the goal is to

* Corresponding author.
E-mail address: ncalvocruz@ual.es (N.C. Cruz).

https://doi.org/10.1016/j.engappai.2018.04.014
Received 12 October 2016; Received in revised form 1 April 2018; Accepted 13 April 2018
Available online 8 May 2018
0952-1976/

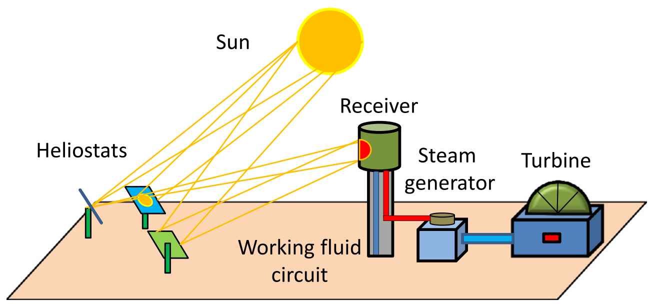

Fig. 1. Scheme of a solar central receiver power facility.

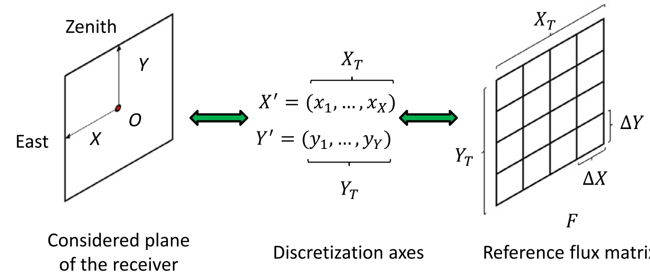

Fig. 2. Coordinate system and discretization of the receiver plane.

achieve a homogeneous flux distribution too. However, their proposal is a genetic algorithm whose individuals benefit from problem knowledge. In Grobler (2015), the two previous methods are analyzed to propose a hybrid approach. The TABU search is used to generate the initial population of the genetic algorithm, which leads to better results. A more descriptive version of the objective function used in Salomé et al. (2013) is applied. It combines the flux density differences between the maximum and the other aim points instead of just the maximum and minimum ones. In Gallego et al. (2014), the goals are achieving a homogeneous flux distribution and maximizing the total power on the receiver, which can be prioritized. The objective function is defined by two linked and weighted parts for this purpose. In that case, there is not a fixed set of aim points. An interior-point method is applied to solve the non-linear optimization problem. In Belhomme et al. (2014), the objective is to maximize the power output of the receiver while keeping it in a safe state through ant colony optimization. The ray-tracer STRAL (Ahlbrink et al., 2012) is used to compute the flux distributions with high precision. This is an interesting difference from the four previous works, which rely on analytical models that are faster but potentially less precise. Specifically, Besarati et al. (2014) and Salomé et al. (2013) opt for HFLCAL (Schwarzbözl et al., 2009), which represents the flux maps of heliostats as circular Gaussian distributions. In Gallego et al. (2014) and Grobler (2015) bi-variant Gaussian distributions are preferred due to their better adaptability to reality.

This work proposes a generalization of the previous strategies. It aims to be able to replicate any given flux distribution on the receiver by selecting the active heliostats and their aim points. It defines two consecutive stages. The first one applies a genetic algorithm to select the most appropriate heliostats to activate. Specific logic is used to aim every selected heliostat automatically depending on its potential power contribution and the target distribution. This strategy links the first stage to the second one by providing every active heliostat an initial aim point. The second stage does not alter the heliostat selection anymore but tries to sharpen the final result by applying a gradient descent to adjust their aim points. Thus, it is necessary to represent the flux map of every heliostat analytically. There are three differences between the proposed methodology and the reviewed ones: First, it is not limited to achieve any specific flux distribution. Second, heliostat selection is not fixed but optimized. Third and last, the optimization problem is ultimately addressed in a continuous search space by analytically studying the gradient vector of the objective function. Consequently, the proposed methodology allows configuring the whole field by generating a reference flux map featuring any desired property (for instance, but not limited to, homogeneity). Although it does not consider feedback, it is interesting to compute field configurations offline for regular non-cloudy days.

The rest of the paper is structured as follows: Section 2 defines the optimization problem. Section 3 describes the methodology proposed. Section 4 shows three application test cases in a virtual field. Section 5 presents the conclusions and future work. Finally, Appendix includes a nomenclature table for convenience.

2. Problem definition

The problem at hand, as introduced, is focused on replicating a given flux distribution on a flat receiver. It encompasses from selecting the set of active heliostats to defining their aim points, which are the first and second problem layer, respectively. Thus, it is necessary to face a large-scale optimization problem whose formulation is a generalization of that described in Cruz et al. (2017b).

The flux distribution to be replicated on the receiver at a certain instant will be denoted by F. It is represented as a matrix of size $Y_T \times X_T$, where Y_T and X_T are the number of rows and columns, respectively. This matrix maps to the receiver and every element, K, is linked to a certain region on its surface. All the elements of F need to be known, both in position and magnitude (flux density on every zone, e.g., kW/m^2), as it forms the base input information of the problem. As no attention is paid to the way in which F is initially generated, this approach is source-independent. Thus, it can be seen as a raster image or 'picture' of the flux density desired at every point of the receiver plane. In this context, a Cartesian system formed by directions X and Y, with their discretization steps, ΔX and ΔY respectively, needs to be defined on the receiver. It must also be known to interpret F. Its axes will be the vectors $X' = (x_1, \ldots, x_{X_T})$ and $Y' = (y_1, \ldots, y_{Y_T})$, of length X_T and Y_T, respectively. Every consecutive pair of elements satisfies that $x_{i+1} - x_i = \Delta X$ for X' and $y_{i+1} - y_i = \Delta Y$ for Y'. These ideas are depicted in Fig. 2, where the origin of coordinates is the center of the receiver and directions X and Y points to East and Zenith, respectively. These aspects can be adapted to specific requirements, though.

In relation to the heliostat field, it is defined as an ordered set, $H_T = \{h_1, \ldots, h_N\}$, where N is the number of heliostats in the field. At a certain instant, they can be either active or inactive. When a heliostat, $h \in H_T$, is active, it forms a flux distribution, f_h, on the receiver. f_h is expected to follow a known two-dimensional function expressing the radiation density at every point. It should also be described around a central point, $A = \{a_x, a_y\}$, where a_x and a_y are its X and Y coordinates on the receiver plane, respectively. Consequently, the field state can be defined by the configuration vector, $C = (A_1, \ldots, A_N)$, where the element at position i is the aim point of heliostat h_i. A configuration vector, C, defines a certain flux distribution reflected on the receiver, F_C^*, which is formed by superimposing the flux distribution, f_h, of every active heliostat, h. It is important to mention that non-active heliostats are aimed at the imaginary null point $A_\emptyset = (\emptyset_x, \emptyset_y)$, and their flux distributions are not considered. This special point is only defined for the first layer of the problem and can be referred to a standby point in the real field. Considering two dimensions per heliostat, a $2N$−dimensional problem must be theoretically faced. However, by dividing it into two layers, its dimensionality can be ultimately reduced to $2N^*$, where N^* is the number of active heliostats.

It is now possible to define an optimization problem, O, that states the minimization of the difference between a desired flux distribution, F, and the achieved one, F_C^*. It can be expressed as $min\ diff(F, F_C^*)$, where $diff$ is an abstract objective function which compares F with F_C^* and returns a real value defined in $[0, \infty)$. The lower it is, the