Towards the Optimal Design and Control of Solar–biomass Heating Networks for Greenhouse Applications: Methodology and Preliminary Results

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Abstract

Greenhouses are productive facilities very suitable for the consideration of distributed schemes for their energy management, including solar radiation as one of their main primary sources. This paper focuses on the optimal sizing and control of solar–biomass heating networks to be used in greenhouse environments. The methodology employed is a bi-level optimization strategy in which the lower layer, which is based on the energy hubs concept, is responsible for the optimal dispatch of the heating network, trying to reduce the operating costs while meeting demand. The upper layer includes a surrogate optimization algorithm in charge of performing the optimal sizing of the heating network to minimize the investment and long-term operating costs. Besides, this optimization problem includes some constraints such as the minimum desired solar fraction. A case study based on real facilities located in Almería (Southeast of Spain) is employed as an application example in order to show the promising outcomes achieved with the proposed methodology. The preliminary results are analyzed, regarding the economic viability, by means of the discount payback time and Levelized cost of energy.

Keywords: District heating, Energy hubs, Multi-level optimization, Sizing, Process Control.

1. Introduction

It has become clear in recent years the growing concern about building a sustainable and efficient energy sector. In this new panorama, renewable energies and carbon-neutral technologies play a major role in reducing emissions and in the transition to the energy sector of the future. Among the different options, solar–biomass cogeneration plants have emerged as an effective solution to sustainably supply heat to industries (Tilahun et al. 2021, Gil et al. 2021); especially in semi-arid areas where the availability of solar irradiance is high (Mouaky and Rachek, 2020). In such locations, these facilities and greenhouses synergize with each other, and an opportunity presents itself to use agricultural residues as biomass (Vallios, 2009). In addition to the above, these hybrid schemes are also very suitable even for isolated greenhouses thanks to the integration of storage systems (Sethi et al. 2013). Nevertheless, to exploit the benefits of these hybrid plants, it is important to i) optimally manage the energy generation and dispatch according to the resources available at each moment, through adequate control systems, and ii) reduce the investment costs through an appropriate optimal design.

Until now, there are few studies in the literature dealing with the optimal design or control of these kinds of hybrid facilities (Suresh et al., 2019; Tilahun et al. 2021). Moreover, the methodologies presented in them are mainly focused on the design, without paying attention to the optimal dispatch, yet the independent optimization of the plant size and energy management in hybrid plants can lead to performance degradation (Shu et al. 2020). The main reason is that hybrid systems normally present different operating modes that must be managed according to the available resources and energy demand to improve the operating costs. The introduction of these operating details in the design phase could be essential to reach correct plant designs as stated by Evins (2015). This can be achieved by developing optimal design procedures based on detailed process simulations.

However, the optimal design based on these detailed simulations entails a high computational burden which stands out as one of the main barriers for the development of these kinds of techniques. In this regard, the use of the Energy Hubs (EH) concept can be a good option to formulate the dispatch problem and simulate the optimal operation of the system. EH is not a novel concept but it was proposed some years ago to refer to any system in which input energy or material flows can be converted into certain output resources and stored (Geidl et al. 2006). Based on the internal structure, it is possible to establish a mathematical model to represent these processes together with the physical constraints of the system. What is more, each system's component can be characterized by a static or time-varying conversion factor, hence the computational burden of the problem is considerably

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reduced. As a result, EH is a wide applicability concept for systems including energy or material resources in which certain variables can be controlled, and others not, as the hybrid facility at hand in this study.

Even though the use of the EH approach can diminish the computational burden of the simulations, for design purposes, the system´s simulations are used to adjust the sizing parameters (i.e., solar field area, biomass power system). This could give rise to a problem when using optimization frameworks to perform the design, as these techniques require many simulations before converging and meeting given performance requirements. Consequently, the use of conventional optimization methods is often impractical and even prohibitive because of time requirements. This issue can be alleviated by using the so-called surrogate optimization approach, which diminishes the number of time-consuming cost function evaluations by using models that reliably represent it in a much simpler and analytically tractable way (Queipo et al., 2005).

By following the aforementioned ideas, this paper presents a bi-level optimization technique for the optimal sizing and control of solar–biomass heating networks in the environment of greenhouses. This technique takes into account the interdependencies and relations among the design and the operating phases to obtain suitable solutions. To do that, the upper layer employs a surrogate optimization algorithm in charge of selecting the optimal design of the heating network. This algorithm is connected to a lower optimization layer that uses the energy hubs approach to determine how energy should be dispatched. Thus, the objective functions of the two layers consider both the operating and investment costs of a case study based on an "Almería-type" greenhouse, which has been chosen to exemplify this methodology. It must be remarked that the formulation of the EH dispatch problem is the main progress and contribution in relation to our previous work in Gil et al. (2021), in which the dispatch problem was solved through a rule-based controller.

The rest of the paper is organized as follows: Section 2 presents the case study, the formulation of the management and design problems, and describes the proposed bi-level optimization technique. Besides, it also depicts the main performance metrics used to evaluate the adequacy of the solution provided by the algorithm. Section 3 shows the results obtained with the application of the proposed technique to the case study, and, finally, Section 4 summarizes the main findings.

2. Material and methods

2.1. Case study

In this study, a hybrid thermal network including a biomass boiler and a solar thermal field is employed to meet the demand of a greenhouse. This demand is associated to the thermal energy required to maintain the desired temperature range for the crops. Fig. 1 presents the schematic diagram of the case study.

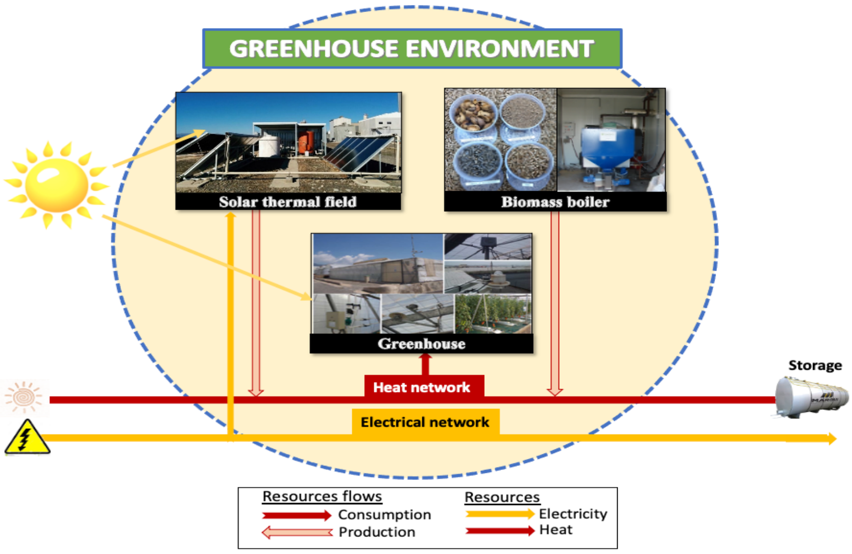

Fig. 1: Schematic diagram of the case study.

As can be observed in Fig. 1, the case study is composed of an "Almeria-type" greenhouse, a solar thermal field of flat-plate collectors, and a biomass boiler. The solar field and biomass boiler act as producer agents regarding the heating network, whereas the greenhouse is a heat consumer. The possibility of storing thermal energy is also contemplated. Besides, the electricity network is included to satisfy the needs of the solar field pumping systems. It should be remarked that all these facilities are based on real plants located in the Almeria province (Southeast of Spain) and they were fully described and modelled by Rodriguez et al. (2015), Sánchez-Molina et al. (2014), and Gil et al. (2020). In this way, the case study constitutes a real representative environment that allows us to encompass actual experiences and production concerns, which is of vital importance to validate the adequacy of the proposed method and the applicability of the obtained results.

2.2. Bi-level optimization framework

The main objective of this work is to develop a bi-level optimization technique that exploit the synergies between the design and operational phases. For this purpose, the developed algorithm has been divided into two layers related to each other as shown in Fig. 2 (see Plant design and energy hub blocks in the figure).

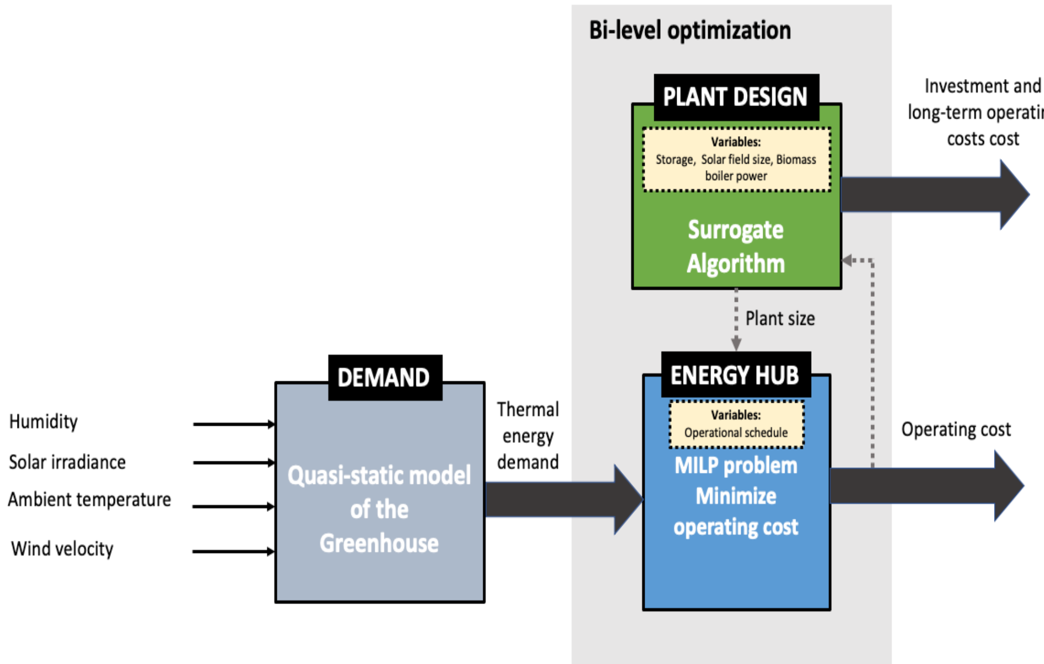

Fig. 2: Schematic diagram of the proposed bi-level framework.

In the proposed framework, first, the thermal energy demand of the greenhouse is calculated by using a validated model of an "Almeria-type" greenhouse. The reader is referred to Rodriguez's et al. work (2015) in which the model was fully described. Note that it has not been included in this work for the sake of brevity. Besides, a meteorological dataset of the selected location is required to simulate this model and the heating network's. Then, the communication between layers within the bi-level optimization framework can be depicted as follows:

i. The sizing parameters (i.e., storage capacity, solar field size, and biomass boiler power) provided by the design optimization algorithm (plant design block in Fig. 2) are sent to the lower layer (energy hub block in Fig. 2).
ii. In the lower layer, the sizing parameters are used to configure the EH model of the system and the optimal dispatch (trying to minimize the operating costs) is performed through a Mixed Integer Linear Programming (MILP) optimization problem. Once the dispatch is finished, the results in terms of operating costs are sent to the sizing layer in order to calculate the new value of the objective function.

The procedure described above is repeated continuously until the optimization algorithm of the design layer converges to the global solution. The following subsections describe each of the blocks of the bi-level optimization technique as well as the optimization problem included in each one.

2.3. Energy hub model and control problem formulation

The model for scheduling the energy dispatch is based on the general approach presented previously by Ramos-Teodoro et al. (2018), which has been adapted for the greenhouse environment (Fig. 1). By using this approach, each of the system's components can be modelled through one or several (in case more than one type of energy is required) input ports, referred to any kind of energy stream; a conversion factor, for modelling the conversion of energy or resources; and an output port, which represents the demand of any kind of energy. Thus, as illustrated in Fig. 3 and depicted in Tab. 1, the energy hub of the case study counts with electricity (I_1) coming from the public utility grid, solar radiation, (I_2), and biomass (I_3) as inputs; and with electricity (O_1) and heat (O_2) as outputs. Note that O_1 is only an actual consumption if the field of solar collectors is activated ($\delta_{D,1}$) to produce heat.

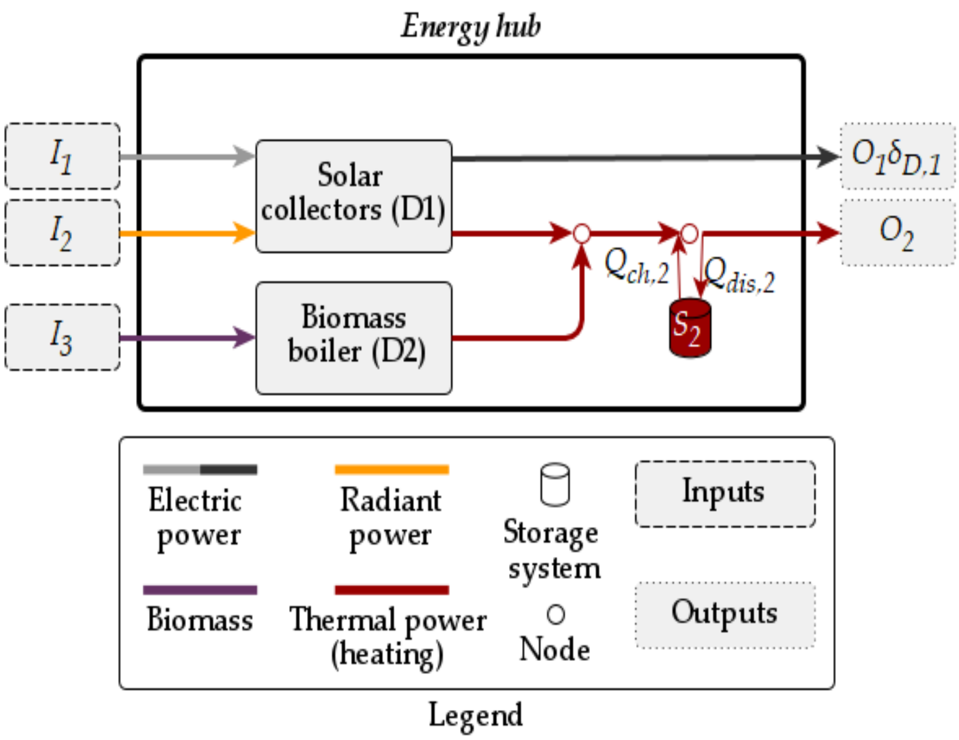

Fig. 3: EH characterization of the case study.

Tab. 1: EH inputs and outputs description.

Index	Inputs (I_i in Fig. 3)	Outputs (O_i in Fig. 3)
1	Electricity from the power grid [kW]	Electricity for the solar collectors [kW]
2	Incident radiant power on the solar facility [kW]	Thermal power for the greenhouse [kW]
3	Wood pellets for the biomass boiler [kg/h]	-

The conversion and storage processes are expressed as in equations (1) and (2), respectively. These are matrixial expressions where $\boldsymbol{O}$, $\boldsymbol{Q_c}$, $\boldsymbol{Q_d}$, and $\boldsymbol{S}$ are vectors whose size depend on the number of outputs (see Fig. 3 and Tab. 1), $\boldsymbol{P}$ is a vector that depends on the system's structure (readers are referred to Ramos-Teodoro's et al. study for clarification), $\boldsymbol{\delta_O}(k)$ is the identity matrix with the element (1,1) substituted by $\boldsymbol{\delta_{D,1}}$, and the remaining matrixes express losses in conversion ($\boldsymbol{C}$), charging ($\boldsymbol{C_c}$), discharging ($\boldsymbol{C_d}$) and storing ($\boldsymbol{C_s}$) operations.

$$\boldsymbol{\delta_O}(k)\boldsymbol{O}(k) = \boldsymbol{C}(k)\boldsymbol{P}(k) - \boldsymbol{Q_c}(k) + \boldsymbol{Q_d}(k) \quad \text{(eq. 1)}$$

$$\boldsymbol{S}(k+1) = \boldsymbol{C_s}(k)\boldsymbol{S}(k) + \boldsymbol{C_c}(k)\boldsymbol{Q_c}(k) - \boldsymbol{C_d}(k)\boldsymbol{Q_d}(k) \quad \text{(eq. 2)}$$

It is important to remark that the conversion factor of the solar field can be easily calculated by using the thermal collector efficiency equation (Allouhi et al. 2017), whereas the one of the biomass boiler can be computed according to boiler's overall efficiency and the Lower Heating Value (LHV) of the biomass. Both efficiency parameters are given by:

$$\eta_{sf}(k) = \eta_o - a_1 \cdot \left(\frac{T_m(k)-T_A(k)}{G(k)}\right) - a_1 \cdot \left(\frac{(T_m(k)-T_A(k))^2}{G(k)}\right) \quad \text{(eq. 3)}$$

$$\eta_{bb} = \eta_b \cdot LHV \quad \text{(eq. 4)}$$

Where η_{sf} is the conversion factor of the solar collector field, which relates the radiant power received by this system and the corresponding thermal power delivered. η_o is the solar collector optical efficiency, a_1 is a thermal losses parameter (W·m^{-2}·K^{-1}), a_2 is also a thermal losses parameter (W·m^{-2}·K^{-2}), T_m and T_A are the mean and ambient temperature (ºC), respectively, and G is the incident irradiance (W·m-^{2}). On the other hand, η_{bb} is he biomass boiler efficiency, which relates the biomass flow and the heat flux generated, and η_b is he boiler efficiency.

Moreover, and following with the EH formulation, equation (5) relates input vector $\boldsymbol{I}$ with vector $\boldsymbol{P}$:

$$\boldsymbol{I}(k) = \boldsymbol{C_i}\boldsymbol{P}(k) \quad \text{(eq. 5)}$$

In addition to the equations that limit the flows through either conversion or storage devices, the storage and selling capacity, and the availability of input resources, which for the sake of conciseness are not included in this work; equation (4) is required to avoid charging and discharging, at the same time, the heat storage device.

$$\delta_{c,2}(k) + \delta_{d,2}(k) \leq 1 \quad \text{(eq. 6)}$$

Finally, the optimization problem is defined by means of equation (7) that includes de economic cost of acquiring resources ($\boldsymbol{c}(\boldsymbol{k})$).

$$min \sum_{k=1}^{24} \boldsymbol{c}(k)\boldsymbol{I}(k) \quad \text{(eq. 7)}$$
$$s.t. \ \ \textit{the above restrictions}$$

2.3. Design optimization problem

The objective of the design optimization problem consists of computing the sizing parameters that provide the lower costs, including both operating and investment costs, while meeting demand. For this purpose, the optimization problem can be posed as follows:

$$min\, J = C_{inv}(\boldsymbol{x}) + \sum_{k=1}^{N} \frac{C_{op}(\boldsymbol{x}) + C_m(\boldsymbol{x})}{(1+r)^k} \quad \text{(eq. 8)}$$

$s.t.$

$$SF(\boldsymbol{x}) \geq SF_{min} \quad \text{(eq. 9)}$$

$$\boldsymbol{x_{low}} \leq \boldsymbol{x} \leq \boldsymbol{x_{up}} \quad \text{(eq. 10)}$$

In this formulation, C_{inv} is referred to the investment costs, C_{op} to the operating costs, and C_m to the maintenance costs. The two last costs are expanded in a time horizon, referred by symbol *N* in the formulation, considering a discount rate denoted by *r*. The vector of decision variables ($\boldsymbol{x}$) is composed of the solar field size, the biomass system's maximum power, and the capacity of the thermal storage system. In addition, the optimization problem is subject to some constraints related to the Solar Fraction (SF), where SF_{min} represents the minimum desired value, and the limits of the decision variables, where $\boldsymbol{x_{low}}$ and $\boldsymbol{x_{up}}$ are referred to the lower and upper limits, respectively. It should be remarked that, to solve this problem, the *surrogateopt* solver of MATLAB software (MATLAB, 2020) was used since the evaluation of the objective function is time-consuming.

2.4 Performance metrics

To assess the viability of the solution provided by the bi-level optimization technique, two different economic metrics has been selected. The first one is the well-known index Levelized Cost of Heat (LCOH). This metric provides information about the cost of energy production, and can be calculated as the ratio between the total life cycle cost and the total lifetime energy produced by the power facility as follows:

$$LCOH = \frac{C_{inv}+\sum_{j=1}^{N}\frac{C_{op}+C_m}{(1+r)^j}}{\sum_{j=1}^{N}\frac{Q}{(1+r)^j}} \qquad \text{(eq. 11)}$$

Where Q is the heat (kWh) delivered by the system (i.e., solar field or biomass power generation system) under study, and the rest of the parameters has been defined previously.

Besides, the inherent risk of the project has been also evaluated by using the discount payback time. This metric determines when profit generations starts or, in other words, when the cash flow turns positive. The discount payback time can be calculated by using the Cash Flow (CF) per year, which is given by:

$$CF(i) = -C_{inv}(i) + \sum_{j=1}^{i}\frac{-C_{op}-C_m+C_{savings}}{(1+r)^j} \quad \forall i\{1,\dots,N\} \qquad \text{(eq. 12)}$$

Where i is the year under study, and $C_{savings}$ is related to the savings obtained with the hybrid system in comparison with the cost of a conventional power system. It should be commented that in the first year, CF is negative; but the year in which the cumulative CF becomes positive, the discount payback period is reached.

3. Results

3.1. Simulation set-up.

The bi-level optimization methodology was applied to a cluster of greenhouses with a total cultivation area of 20 ha of tomato, which serves to illustrate the developed methodology in the design of a solar–biomass heating system. In this cluster, the setpoint temperature to compute the heating demand of the greenhouse was stablished at 14 and 21 ºC for the night and day periods, respectively; typical setpoint temperatures used in agricultural holdings in Almería as described in Gil et al. (2021). As a preliminary approach, a time horizon of a week was considered in the lower layer and meteorological data of a typical week in Almería (in the winter period, which is the one with the highest demand for heating) was used to generate the thermal demand of the greenhouse. Concretely, Meteornorm v7 Typical Meteorological Year (TMY) for a representative coastal location at the province of Almería was used during the days 11-18 of January.

In the upper layer (design optimization problem), the results obtained in the lower one (i.e., operating costs) were extrapolated to a time horizon of 20 years (which is N=20) considering a discount rate r of 0.03. These parameters were chosen according to Tian et al. (2018). In addition, a minimum solar fraction of 20 % was imposed to ensure a minimum solar energy contribution.

To calculate the investment costs, a price of 200 €·m^{-2} and 62 €·kWh^{-1} were considered for the solar thermal field and storage systems (Evins, 2015), respectively. The investment cost of the biomass system was computed with the relation presented by Vallios et al. (2009). Then, the term C_{op} is the objective function value of the lower layer optimization problem, whereas C_m was calculated as a percentage of the investment costs using the equations presented by Pakere and Blumberga (2020).

In the lower layer, the EH model was configured with $\eta_o = 0.775$, $a_1 = 3.72$ W·m^{-2}K^{-1}, $a_2 = 0.016$ W·m^{-2}K^{-2}, and T_m = 60 ºC. Besides, $\eta_b$was fixed at 0.8, and the LHV of the biomass at 4.86 kWh·kg^{-1}, which corresponds to the heating value of pellets at 8% moist. Most of these parameters come from real experiences or certification from the actual facilities as reported in Gil et al. (2021).

3.2. Optimal sizing

As commented, the *surrogateopt* solver of MATLAB software (MATLAB, 2020) was used to work out the design optimization problem due to the high computational burden required. Besides, within de optimization procedure, a week of hourly data was used to simulate the system and to perform the optimal dispatch in the lower layer of the bi-level optimization framework. The latter was solved using *intlingprog* solver also from MATLAB. The main benefit of considering data on such a small-time scale is that it allowed us to perform a much more precise design of the hybrid heating network taking into account the time-varying demand of the greenhouse. Thus, the optimal sizing values provided by the algorithm are presented in Tab. 2.

Tab. 2: Value of the optimal sizing parameters.

Plant sizing		Investment cost [€]	Operating cost per week [€]
Solar field size [m^2]	7,600	1,520,000	805
Biomass boiler maximum power [kW]	5,305	563,120	21,530
Thermal storage capacity [kWh]	10,000	620,000	-

The optimal size of the field of solar collectors was found to be 7,600 m^2, the maximum power of the biomass system was 5,305 kW, and the thermal storage capacity was 10,000 kWh. This system configuration led to total investment cost of 2,703,120 €, of which around 58 % corresponded to the costs of the solar collector field, 20 % to the ones of the biomass system, and 22 % to the ones of the thermal storage system.

3.3. Optimal management

This section presents the performance of the hybrid system in daily operation, which was optimally managed through the lower layer of the bi-level optimization framework. The optimal scheduling performed by the EH management technique is presented in Fig. 4. In this figure, the first graph presents the irradiance (yellow bars) and the charge level of the storage tank (green dashed line), whereas the second one reflects the greenhouse demand (red area) and the production of the solar and biomass systems (which are represented by light and dark green bars, respectively).

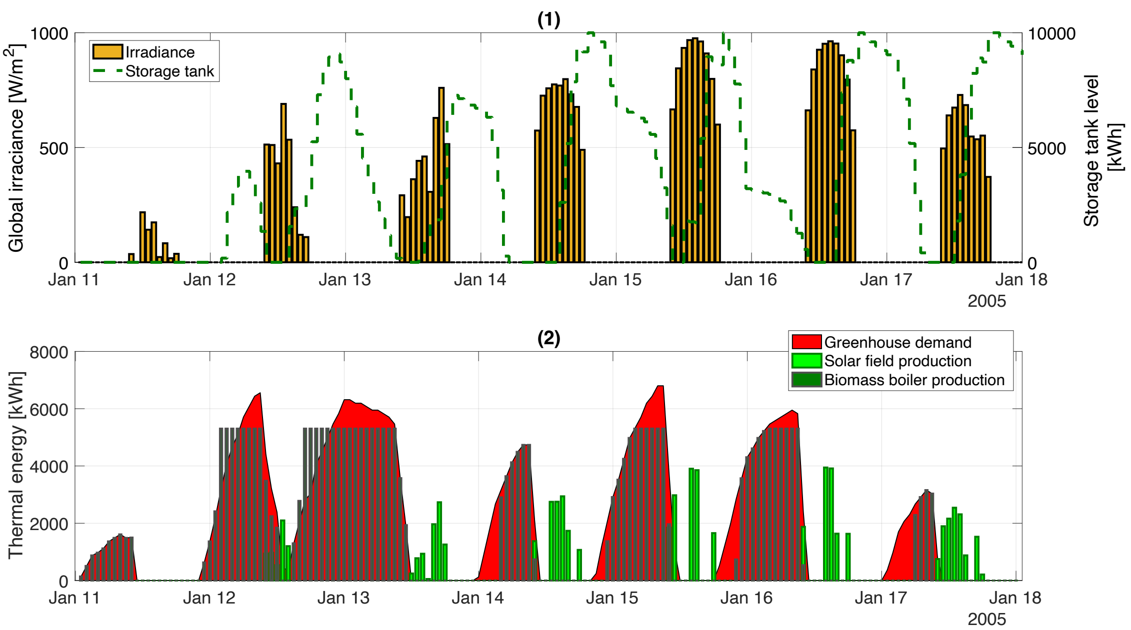

Fig. 4: Daily simulation

One should take into account that the main particularity that happens in this case study is that the demand of the greenhouse and the solar field production are decoupled in time as observed in Fig. 4. By and large, the demand of the greenhouse is mostly produced at night when the ambient temperature is low, so that an additional supply of thermal energy is needed to maintain the desired temperature for crops. This disparity supports the application of the developed bi-level optimization technique using an hourly basis simulation.

Regarding the dispatch performed by the EH optimization method, on the first day, all the demand of the greenhouse was supplied by the biomass system since there was no thermal energy stored in the storage tank. In addition, as the level of irradiance was very low (below 250 $W \cdot m^{-2}$ as the sky was overcast) the solar field was not used along the day. Thus, during the second night, all the demand was covered by the biomass system again.

In contrast, on the second day, the panorama was different since the solar field could be turned on. In this way, the energy delivered by this system was stored in the storage system being then used during the night to partially cover the greenhouse demand. This allowed us to reduce the biomass system's contribution leading to a much more efficient and sustainable operation in terms of emissions to the environment. In the rest of the days, the behavior was similar, that is, the higher the production of the solar field, the more energy could be stored in the tank and, therefore, the lower the production of the biomass system. This was especially noticeable in the last day, where, in addition, the greenhouse demand was lower than in the previous days.

3.4. Economic analysis of the solution provided by the algorithm

The solution provided by the bi-level optimization framework must not only be technically analyzed, but also its economic viability must be assessed. For this aim, the LCOH and the discount payback period were studied.

Firstly, the LCOH was calculated for each energy source using the optimal results provided by the algorithm, resulting in 0.052 and 0.041 €·kWh^{-1} for the solar and biomass systems, respectively. This confirms that the design carried out provided reasonable values in terms of cost of energy if one compares the obtained results with reference values in literature. For instance, in the work by Tilahun et al. (2021) the LCOH of a biomass system was studied, showing that prices of up to 0.10 €·kWh^{-1} could be reached depending on the price of biomass. For the case of the solar field, prices of around 0.35 €·kWh^{-1} were reported in the work by Bhusal et al. (2020).

The obtained LCOH values can be also compared with the ones of other energy sources, mainly fossil fuels, employed in greenhouse environments such as natural gas or diesel. The reference LCOH of the gas natural is 0.05 €·kWh^{-1}, but this figure can be higher if there are no nearby natural gas distribution networks. Besides, the price of the diesel can reach up to 0.45 €·kWh^{-1} in off-grid locations of Spain as discussed in the work by Soltero et al. (2018). These reference values confirm the viability of the obtained solution and suggest that the proposed hybrid system is especially attractive to be implemented in off-grid locations without access to the gas natural distribution network.

Finally, the discount payback time was studied. As this metric is highly dependent on the fuel price used for comparison purposes, since it influences the term $C_{savings}$ in equation (12), different fuel prices were considered ranging from 0.05 to 0.15 €·kWh^{-1}. This range was chosen to encompass from the reference value of natural gas to the value that this source can attain in off-grid locations. The results obtained are reflected in Fig. 5.

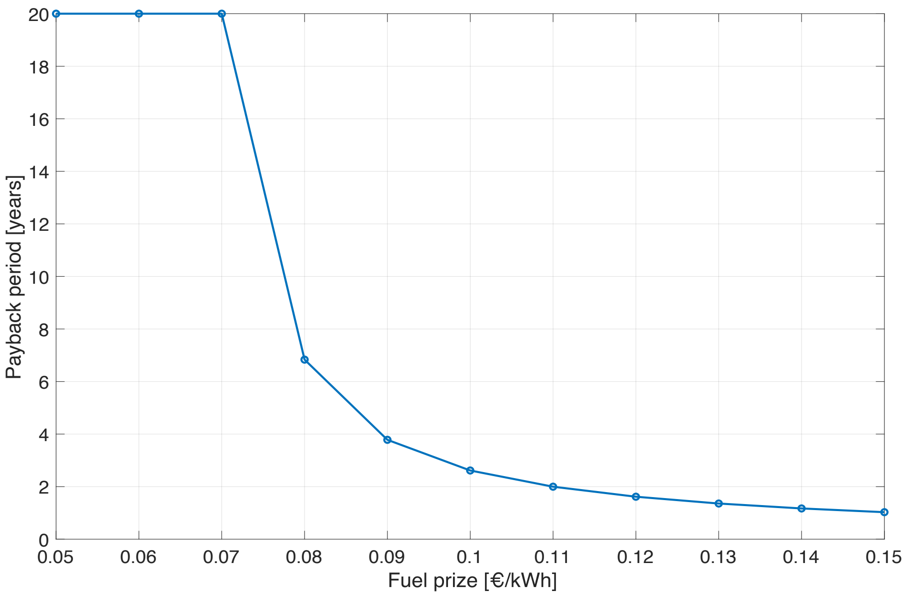

Fig. 5: Discount payback time as a function of different fuel prices.

As observed, the system was not profitable when comparing with fuel prices lower than 0.07 €·kWh^{-1}. From this value on, the discount payback time was reasonable. For example, for a value of 0.08 €·kWh^{-1}, the discount payback time was found to be around 7 years, and it reached values of around 2 years from 0.11 €·kWh^{-1} onwards. This analysis again confirms that these kinds of systems are profitable in isolated regions with fuel prices over 0.08 €·kWh^{-1}.

4. Conclusions

This paper addressed the optimal sizing and operation of solar–biomass heating networks for the environment of a greenhouse. For this aim, a bi-level optimization technique based on the EH concept is proposed and exemplified by using a representative case study in the province of Almería (Spain). From the obtained results, the following conclusions can be drawn:

- The proposed bi-level optimization algorithm resulted in an attractive tool to perform the design of solar–biomass hybrid systems for processes with time-varying demand, as the case study conducted.
- The use of the EH concept has resulted in a powerful technique to address the optimal operation of the system. Indeed, it can be used to reflect the optimal operation in the real system as long as appropriate low-level controllers are implemented.
- Regarding the economic results, LCOHs of around 0.05 and 0.04 €·kWh^{-1} for the solar and biomass systems, respectively, were obtained. This confirmed the profitability of the obtained solution in comparison with reference values in literature.
- Also, the discount payback period analysis performed indicated the suitability of these facilities especially for isolated regions with fuel prices over 0.08 €·kWh^{-1}.

Future work will be focused on optimization considering a whole year in the lower layer and exploring the inclusion of other thermal demands that may be present in these environments to obtain greater profitability.

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Appendix: Acronyms and Symbols

Table 1: Acronyms

Acronym	Description
CF	Cash Flow
EH	Energy Hubs
LCOH	Levelized Cost of Heat
LHV	Lower Heating Value
MILP	Mixed Integer Linear Programming
SF	Solar Fraction
TMY	Typical Meteorological Year

Table 2: Symbols

Quantity	Symbol	Unit
Thermal losses parameter	a_1	$W \cdot m^{-2} \cdot K^{-1}$
Thermal losses parameter	a_2	$W \cdot m^{-2} \cdot K^{-2}$
Investment costs	C_{inv}	€
Maintenance costs	C_m	€
Operating costs	C_o	€
Savings obtained with the hybrid system	$C_{savings}$	€
Incident irradiance	G	$W \cdot m^2$
Time horizon	N	years
Heat	Q	kWh
Discount rate	r	-
Minimum desired solar fraction	SF_{min}	-
Ambient temperature	T_A	ºC
Mean temperature	T_m	ºC
Lower limit of decision variables	$\boldsymbol{x}_{low}$	-
Upper limit of decision variables	$\boldsymbol{x}_{up}$	-
Vector of decision variables	$\boldsymbol{x}$	-
Boiler efficiency	η_b	-
Biomass boiler efficiency	η_{bb}	-
Conversion factor of the solar collector field	η_{sf}	-
Solar collector optical efficiency	η_o	-

Table 3: Symbols for EH equations

Meaning	Symbol	Unit
Vector containing the price of each input of the energy hub	$\boldsymbol{c}$	Multiple units
Coupling matrix	$\boldsymbol{C}$	Multiple units
Diagonal matrix of charge efficiencies	$\boldsymbol{C_c}$	-
Diagonal matrix of discharge efficiencies	$\boldsymbol{C_d}$	-
Input coupling matrix	$\boldsymbol{C_i}$	-
Diagonal matrix of resource degradation	$\boldsymbol{C_s}$	-
Vector of input flows	$\boldsymbol{I}$	Multiple units
Element of $\boldsymbol{I}$	I	Multiple units
Vector of output flows	$\boldsymbol{O}$	Multiple units
Element of $\boldsymbol{O}$	O	Multiple units
Vector of flows between inputs and outputs or "path vector"	$\boldsymbol{P}$	Multiple units
Vector of charge flows	$\boldsymbol{Q_c}$	Multiple units
Element of $\boldsymbol{Q_c}$	Q_c	Multiple units
Vector of discharge flows	$\boldsymbol{Q_d}$	Multiple units
Element of $\boldsymbol{Q_d}$	Q_d	Multiple units
Vector of stored resources	$\boldsymbol{S}$	Multiple units
Element of $\boldsymbol{S}$	S	Multiple units
Binary variable for charging heat	$\delta_{c,2}$	-
Binary variable for discharging heat	$\delta_{d,2}$	-
Binary variable for the field's electricity consumption	$\boldsymbol{\delta_{D,1}}$	-
Binary diagonal matrix of output activation	$\boldsymbol{\delta_O}$	-