MOSES – The New Techno-Economic Optimization Modeling Tool for Hybrid Solar Power Plants

Salvatore Guccione[1] and Rafael Guedez[1]

[1] KTH Royal Institute of Technology, Stockholm (Sweden)

Abstract

Techno-economic performance simulations play a crucial role in assessing the feasibility, cost-effectiveness, and overall impact emerging renewable energy system designs. Concentrating Solar Power (CSP) is a promising technology for decarbonizing the electricity grid by integrating cost-effective thermal energy storage (TES). However, their development is hindered by their high levelized cost of electricity compared to other energy sources. Hybrid systems that connect with solar photovoltaic (PV) and battery systems are a viable solution to reduce the cost of these plants while maintaining flexibility and guaranteeing firm production despite the intermittence of solar availability. This paper presents MoSES (Modeling of Solar Energy Systems), an open-source techno-economic modeling tool designed to evaluate the feasibility and cost-effectiveness of hybrid PV-CSP plants. While existing simulation tools perform well with established systems, they face challenges when adapting to new components, configurations, and operating strategies. MoSES addresses this challenge by providing a simulation framework and a versatile library of components and control strategies that can be modified to meet end-users' needs. The tool enables simulation activities to assess the advantages, optimize the design, and benchmark different hybrid PV-CSP plant layouts. This paper outlines the methodology employed to determine system design, costs, and key performance indicators, as well as to estimate operational performance. Furthermore, a case study is presented to illustrate MoSES's effectiveness as a tool for conducting annual simulations despite being in its early stages of development. MoSES provides a valuable contribution to the solar community by enabling the evaluation of the impact of emerging solar-based system designs.

Keywords: Solar Energy, CSP, PV, Hybridization, Simulation Tool, Open-Source, Techno-economic Optimization

1. Introduction

Techno-economic performance simulations play a vital role in evaluating the feasibility, cost-effectiveness, and overall impact of emerging renewable energy system designs. Among renewable energy sources, solar energy stands out as the most abundant worldwide. Solar Photovoltaic (PV) and Concentrating Solar Power (CSP) are two distinct technologies used to harness solar energy for electricity generation. The integration of cost-effective Thermal Energy Storage (TES) has made CSP a promising technology for decarbonizing the electricity grid (IRENA, 2020). However, the heigh levelized cost of electricity associated with CSP plants has limited their development in comparison to alternative renewable energy systems. To enhance the cost competitiveness of CSP systems, various options and pathways have been identified. Hybrid systems that combine CSP with PV and battery systems offer a viable solution to reduce costs while maintaining flexibility and ensuring consistent electricity production despite solar availability fluctuations. Developing efficient and dependable electric heaters becomes crucial to maximize current advantages and enhancing the flexibility of hybrid PV-CSP plants. These heaters serve the purpose of converting PV-generated electricity into heat, subsequently storing it within the TES system of the CSP facility. This endeavor enables an active hybridization that facilitates the exchange of energy flows between the two plants (Guccione & Guedez, 2023). Hybridizing CSP and solar PV can lower costs by up to 25% compared to a CSP-only plant of the same size, depending on the hybridization strategy (Zurita et al., 2018). Additionally, increasing the operating temperature of the system by exploring new Heat Transfer Fluids (HTFs) and power cycles can further improve the economic feasibility of CSP plants. Integrating a compact and efficient supercritical CO_2 (sCO2) power block into CSP plants can increase deployment and overall thermal efficiency, resulting in lower electricity production costs. To determine the most cost-competitive pathway for different locations, scales, meteorological conditions, and electrical markets, robust and customizable techno-economic performance simulations are essential. This study introduces MoSES (Modeling of Solar Energy Systems), an open-source techno-economic modeling tool designed to assess the feasibility and cost-effectiveness of hybrid PV-CSP plants. Among the available tools, the System Advisor Model (SAM) emerges as one of the most extensively used options (National Renewable Energy

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Laboratory (NREL), 2022). SAM serves as an open-source instrument primarily designed for assessing the operational and financial feasibility of solar PV and CSP plants. However, it is important to note that SAM's current functionalities do not encompass the simulation of hybrid systems or the incorporation of user-defined components. Another open-source tool catering to the modeling of CSP plants is SolarTherm (Scott et al., 2017). This tool offers a platform for simulating unconventional designs and conducting annual performance simulations of systems, including all main components. SolarTherm's applicability extends beyond CSP systems; it is designed to support various applications such as solar fuels, solar metallurgy, and Concentrated Solar Thermal (CST) industrial process heat. While SAM and other existing simulation tools perform well for established systems, they face challenges when adapting to new components, configurations, and operating strategies. MoSES overcomes this challenge by providing a simulation framework and a versatile library of components and control strategies that can be tailored to meet the specific needs of end-users. The tool facilitates simulation activities to evaluate advantages, optimize designs, and compare different hybrid PV-CSP plant layouts. This paper outlines the methodology employed to determine system design, costs, key performance indicators, and estimated operation. Additionally, a case study is presented to demonstrate the effectiveness of MoSES as a tool for conducting annual simulations, despite being in its early stages of development. MoSES makes a valuable contribution to the solar community by enabling the evaluation of the impact of emerging solar-based system designs.

2. Solar Energy System Description

An illustration of a hybrid PV-CSP plant that can be modeled using MoSES is depicted in Figure 1. This hybrid plant is characterized by a state-of-the-art PV plant and a central tower CSP system that utilizes molten salt as the HTF. It incorporates a two-tank TES and employs a sCO_2 Brayton power block for power generation. The electricity generated by the PV system is converted from DC to AC using an inverter and then transmitted to the grid. Another option is to store the electricity directly into a Battery Energy Storage System (BESS). Alternatively, the excess electric power generated by the PV field can be converted into thermal power by utilizing a molten salt electric heater, which allows for its storage in the TES system. On top of the tower, a tubular molten salt receiver is placed to convert the power collected by the heliostat field into thermal power with operating temperatures ranging between 295 and 565 °C (Turchi et al., 2019). The molten salts are stored in a two-tanks TES that decouples the sCO_2 power block electricity production from the intermittent solar-based heat production. During the TES discharge phase, the molten salts flow in a molten salt-to-sCO_2 heat exchanger, guaranteeing a Turbine Inlet Temperature (TIT) of 550 °C. Likewise, the BESS is discharged when it becomes advantageous to supply electricity to the grid.

3. Modeling Tool

MoSES is a Python-based modeling tool, developed by KTH Royal Institute of Technology to estimate the techno-economic performance of hybrid PV-CSP power plants. A representation of the modeling methodology's flowchart is presented in Figure 2. The thermodynamic performance of the plant is estimated interconnecting the sub-systems quasi-steady-state models and integrating a CoolProp environment (Bell et al., 2014) to estimate the properties of the fluids involved in the plant. Moreover, the NREL-PySAM wrapper for System Advisor Model (SAM) (Gilman et al., 2019) has been integrated into MoSES for designing the solar field and PV plant. The techno-economic performance of the system model is estimated by combining the thermodynamics with an economic model based on a bottom-up estimation method. The resulting system model is customizable in terms of location (meteorological data, grid availability, electricity market, and economics of location), design assumptions, and dispatch strategy.

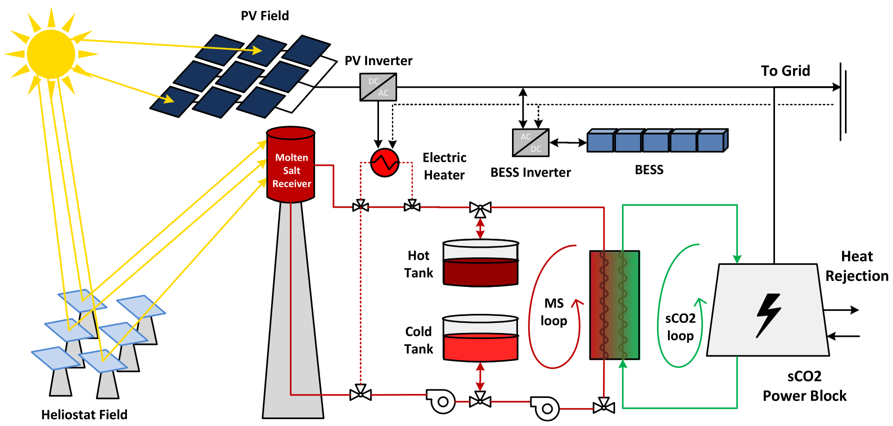

Fig. 1: Hybrid PV-CSP plant schematic layout

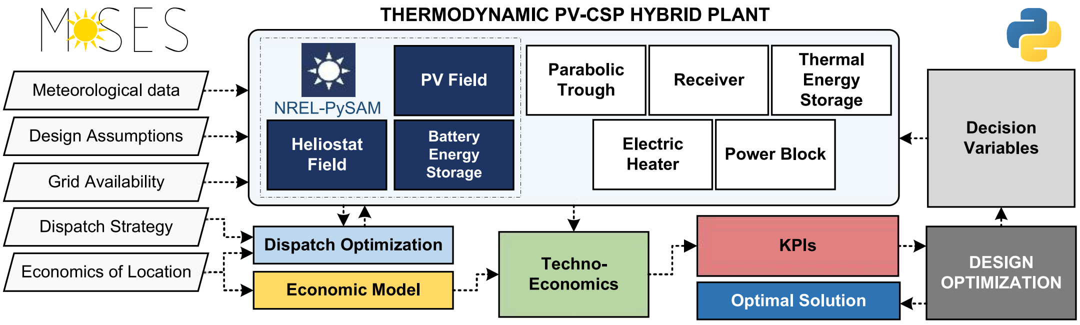

Fig. 2: MoSES modeling methodology flowchart

To identify an optimal design of these hybrid solar plants a multi-objective optimization problem has been implemented so that a set of decision variables can be suggested to minimize/maximize user-selected objective functions such as Levelized Cost of Electricity (LCOE), Hybrid Capacity Factor (H-CF), Capital Expenditure (CAPEX), Annual Energy Yield (AEY), and maximum profit.

3.1 Definition of the system design

Figure 3 presents the outlined approach for defining the design of a specific solar power plant. Initially, the power block design is established by considering various inputs such as gross power, design temperatures and pressures, as well as component efficiencies and effectiveness. Design outputs from the power block model include overall efficiency, required thermal power, mass flow rate, and component size. Simultaneously, the receiver and heliostat field designs are determined. The receiver model takes into account factors such as the heat transfer fluid, design temperatures, and aspect ratio, and based on the solar multiple and thermal power required by the power block, estimates the receiver size, thermal efficiency, and mass flow rate. Subsequently, the heliostat field is designed to ensure the necessary incident power on the receiver, considering user-defined heliostat optical properties. The design of the field impacts the tower height and receiver size, which are iteratively adjusted until convergence. As design outputs for the heliostat field, the solar field area, design optical efficiency, and tower height are provided. Additional inputs are necessary to describe the TES system, including the storage medium, number of TES hours, design temperatures, and tank aspect ratio. The storage model computes the size of the tank(s) capable of storing the maximum amount of energy and determines the thermal losses at the design point. If the CSP plant is integrated with PV or connected to the grid using an electric heater, the electric heater model needs to be customized with specific parameters such as the medium, nominal electric power input, design efficiency, and temperatures. The expected outputs consist of the nominal heat duty, design thermal losses, and mass flow rate. If a PV plant with BESS is co-located or hybridized with the CSP plant, a PV field, an inverter, and a BESS model are incorporated. The PV plant is fully characterized based on the type of PV module, AC nominal power, DC-AC ratio, ground coverage ratio, inverter efficiency, hours of BESS and installed BESS power.

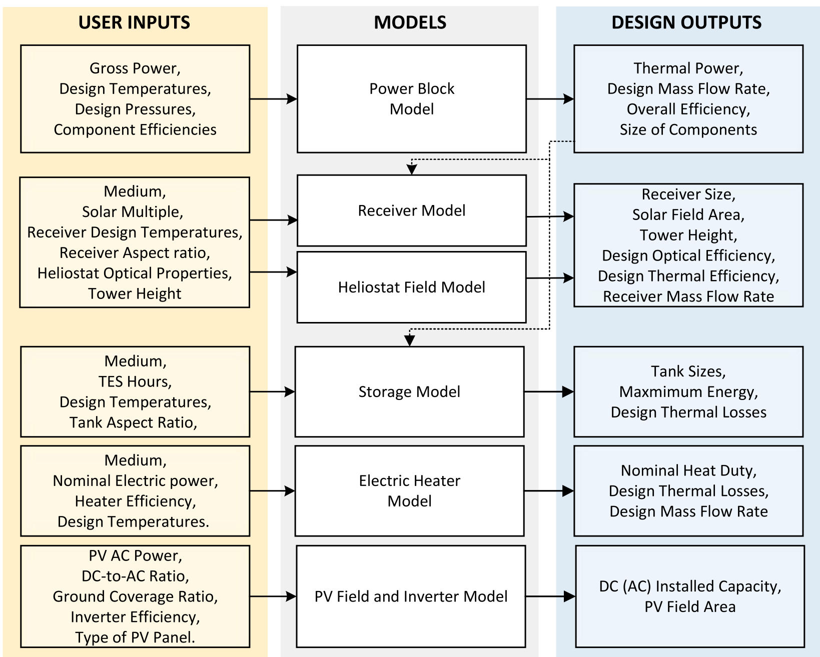

Fig. 3: Schematic representation of the definition of the system design

3.2 Definition of the system costs

In this section, the methodology employed to determine the system costs and the user inputs that can be utilized to tailor the cost model is presented. Specifically, the user can provide component reference costs, as well as financial assumptions including the real discount rate, interest rate, contingency, Engineering Procurement and Construction (EPC) costs, and decommissioning share of the capital cost. Using the design outputs and the specified financial assumptions, the cost model calculates the costs of the subsystems and provides an overall cost estimation, as depicted in Figure 4.

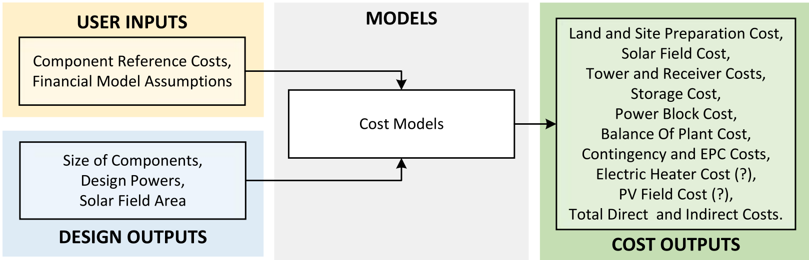

Fig. 4: Schematic representation of the definition of the system costs

3.3 Estimation of the system operating performance

This section presents the methodology employed to estimate the operational outputs of the solar power plant at each time step. For a specific location, the user can choose or supply a weather file, which contains location-specific variables such as irradiance, ambient temperature, and wind speed. These variables are vital in assessing the energy generation potential of both the PV and CSP components, as well as in evaluating the overall performance of the plant. In addition to considering weather-related factors, a dispatch strategy can be selected to determine the plant's operation. If applicable, the strategy can prioritize PV production, align with a user-defined load profile, or be designed to harmonize with a specific tariff scheme. This dispatch strategy selection plays a significant role in optimizing the utilization of the hybrid PV-CSP system based on the prevailing pricing structure or user requirements. The operational performance of the hybrid PV-CSP plant is determined by solving an optimization problem. The objective of this problem is to maximize revenues under a tariff scheme, minimize energy waste, or maximize energy injected into the grid. This problem was solved by adopting a Mixed Integer Linear Programming (MILP) approach. By utilizing the MILP approach, the operational strategy for the plant is derived as an output, providing guidance for its efficient and effective operation. An example of the daily operation of the power plant is presented in Figure 5. The figure showcases key variables, including the raw PV production (black line), the PV production supplied to the grid (yellow area), the State Of Charge (SOC) of the TES (red dashed line), and the CSP production contributed to the grid (blue area). In this case, the objective of the dispatch strategy is to maximize the electricity injected into the grid. The hybrid solar power plant presented in section 2 is characterized by an oversized PV field and a 12h TES. When the PV output exceeds the grid's maximum injectable capacity, surplus electricity is converted into thermal energy via the electric heater and stored in the TES. The CSP plant's power cycle generates electricity to bridge the gap between PV production and the maximum injectable grid power.

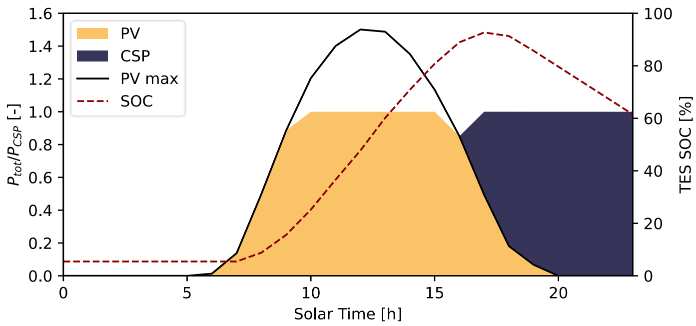

Fig. 5: Schematic representation of the estimation of the system performance

Figure 6 shows that, considering these inputs and based on the design outputs estimated in section 3.1, the subsystem models estimate the operational outputs. Specifically, the sun model extracts Direct Normal Irradiance (DNI), ambient temperature, and wind speed from the weather file and calculates solar angles such as solar elevation and azimuth angles. The user-defined control strategy characterizes the dispatch control model, which takes as inputs the subsystem designs, DNI, solar elevation, SOC of the TES, and PV production (if applicable). It defines the operation of the solar field and determines the mass flow rate of the receiver, electric heater, and power block. Based on the control outputs and DNI values, the heliostat field model estimates the incident power on the receiver, the optical efficiency, and the losses. The receiver model takes the inputs from the controller and the solar field and calculates the thermal power output, operating temperatures, and thermal losses. Similarly, the electric heater estimates the thermal power output, operating temperatures, and thermal losses based on the dispatch control output that interacts with the PV field. Based on the controller outputs and the ambient temperature, the power block model calculates the net electric output, the operating efficiency, and the parasitic losses. The storage model updates the SOC of the TES based on the inlet and outlet mass flow rate, as well as the average temperatures of the tanks and the related thermal losses.

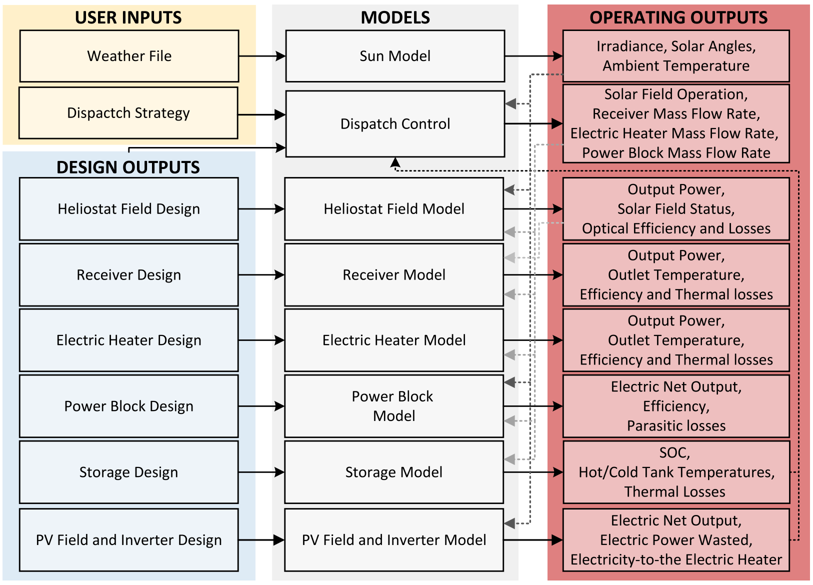

Fig. 6: Schematic representation of the estimation of the system performance

3.4 Definition of the Key Performance Indicators

This section outlines the methodology employed in MoSES to calculate the key performance indicators (KPIs) necessary for benchmarking and comparing different types of CSP plants, including hybrid PV-CSP, PV-CSP with BESS, and various hybridization configurations with the grid. Figure 7 illustrates that, based on specific design, cost, and operational outputs, the model generates the relevant KPIs as outputs for the user's analysis. For independent systems, conventional design variables and performance indicators have been extensively standardized for both CSP (Hirsch & et al., 2017) and PV systems (Stein & et al., 2017). However, these design and performance indicators are insufficient for capturing the complexity and interdependent nature of PV-CSP hybrid systems.

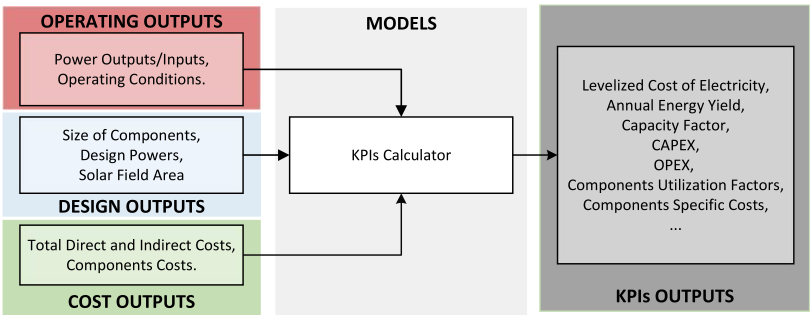

Fig. 7: Schematic representation of the definition of the key performance indicators

Hence, MoSES introduces new Key Design Indicators (KDI) and KPIs specifically tailored for hybrid plants. The newly defined design indicators in MoSES include the Hybrid Solar Multiple (HSM), which compares the total thermal power generated by the solar field (Q_{MSR}^{nom}) and the electric heater (Q_{EH}^{nom}) to the thermal power demand at the power block (P_{PB}^{nom}) as shown in equation (1). Additionally, the Storage Capacity Ratio (SCR), defined in equation (2), represents the ratio between the capacity of the BESS (E_{BESS}) and the equivalent electricity capacity of the TES system ($E_{TES} \cdot \eta_{PB}^{nom}$). To examine the relationship between installed capacities, a Nominal Power Ratio (NPR) is introduced in equation (3), which compares the installed capacity of PV (P_{PV}^{nom}) with the net capacity of CSP ($P_{CSP,net}^{nom}$). Furthermore, the Thermal Production Ratio (TPR), defined in equation (4), measures the ratio between the thermal production through the electric heater ($\dot{Q}_{EH}^{nom}$) and the thermal production of the solar receiver (Q_{MSR}^{nom}). To consider the relative sizes of the PV and BESS in relation to the occupied area of the CSP, the Aperture Ratio (AR) is introduced in equation (5). This metric provides a measure of the footprint of the PV and BESS compared to the area utilized by the CSP component. Additionally, the Irradiance Ratio (IR) is defined as the ratio between the annual Global Horizontal Irradiance (GHI) and the annual Direct Normal Irradiance (DNI) for a specific location. This ratio offers insights into the relative levels of solar irradiance available at the location, providing valuable information for evaluating the energy potential of the system.

$$HSM = (Q_{EH}^{nom} + Q_{MSR}^{nom})/P_{PB}^{nom} \tag{1}$$

$$SCR = E_{BESS}/(E_{TES} \cdot \eta_{PB}^{nom}) \tag{2}$$

$$NPR = P_{PV}^{nom}/P_{CSP,net}^{nom} \tag{3}$$

$$TPR = \dot{Q}_{EH}^{nom}/Q_{MSR}^{nom} \tag{4}$$

$$AR = (A_{PV} + A_{BESS})/A_{CSP} \tag{5}$$

$$IR = \sum_{n=1}^{N} GHI_n \,/\, \sum_{n=1}^{N} DNI_n \tag{6}$$

In addition to the aforementioned KDIs, MoSES incorporates several important KPIs. The Annual Energy Yield (AEY) is a key indicator calculated as the cumulative electricity production of the CSP, PV, and BESS components over the course of a year, as represented by equation (7). The Hybrid Capacity Factor (HCF) is another significant metric that measures the ratio between the AEY supplied to the grid and the total annual electric load, which is considered as the maximum injectable energy to the grid. This ratio is derived from equation (8). To assess the contribution of CSP to the total electricity production of the hybrid plant, the Electricity Production Ratio of CSP (EPR_{CSP}) is defined by equation (9). This metric quantifies the impact of CSP production on the overall electricity generation of the hybrid system. Furthermore, the Storage Electricity Fraction (SEF) is introduced as the ratio between the electricity production discharged from the TES and BESS and the AEY, as presented in equation (10). This KPI offers an indication of the portion of electricity production supplied by the storage systems in relation to the total annual energy yield. Lastly, the electric heater utilization factor (UF_{EH}), defined by equation (11), measures the ratio between the annual thermal energy production of the electric heater and the maximum energy that could have been produced if it operated continuously at nominal capacity.

$$AEY = \sum_{n=1}^{N} P_{CSP,n}^{net} + P_{PV,n}^{grid} + P_{BESS,n}^{dis} \tag{7}$$

$$HCF = AEY / \sum_{n=1}^{N} P_{load,n}^{grid} \tag{8}$$

$$EPR_{CSP} = \sum_{n=1}^{N} P_{CSP,n}^{net} / AEY \tag{9}$$

$$SEF = \left(\sum_{n=1}^{N} \dot{Q}_{TES,n}^{dis} \cdot \eta_{PB,n} + P_{BESS,n}^{dis}\right)/AEY \tag{10}$$

$$UF_{EH} = \sum_{n=1}^{N} Q_{EH,n}^{out} \,/\, \sum_{n=1}^{N} Q_{EH,n}^{nom} \tag{11}$$

The LCOE serves as an indicator of the hybrid plant's relative profitability and is influenced by the investment cost (CAPEX), operational cost (OPEX), and the AEY.

$$LCOE = (CAPEX \cdot CRF + OPEX)/AEY \tag{12}$$

where CRF is the Capital Recovery Factor, calculated in (13) as a function of the real discount rate (r) and the lifetime of the plant (N). The real discount rate is defined in (14) for a nominal discount (d) and an interest rate (i).

$$CRF = r \cdot (1 + r)^N/((1 + r)^N - 1) \tag{13}$$

$$r = (1 + d)/(1 + i) - 1 \tag{14}$$

3.5 System optimization setup

This section presents the methodology employed for optimizing a hybrid PV-CSP system. Figure 8 illustrates the workflow, where the optimizer receives user-defined inputs such as the ranges of design variables and the objective function(s) to be maximized or minimized. The objective function(s) can be selected from a set of predefined KPIs, including LCOE, HCF, and CAPEX, among others. To solve the single- or multi-objective optimization problem, a Genetic Algorithm is utilized. This algorithm, inspired by natural selection and genetics, employs evolutionary strategies to obtain a set of tradeoff optimal solutions (J.F. et al., 2010). The optimization problem is implemented using either the *scipy.optimize.differential_evolution* algorithm, which is a simple and efficient heuristic for global optimization (Storn & Price, 1997) or the *Pymoo* framework (Blank & Deb, 2020). The algorithm follows a modified survival selection approach based on the general outline of NSGA-II (Deb & Sundar, 2006). The optimizer iterates through a loop, interacting with the system model. It provides a set of single values for the design variables and obtains the corresponding plant design, cost, operating parameters, and KPIs for each input combination. The system model incorporates user-defined financial and design parameters. Based on the user-specified objective function(s), the optimizer delivers the optimal configuration of the hybrid PV-CSP system as the output of the optimization.

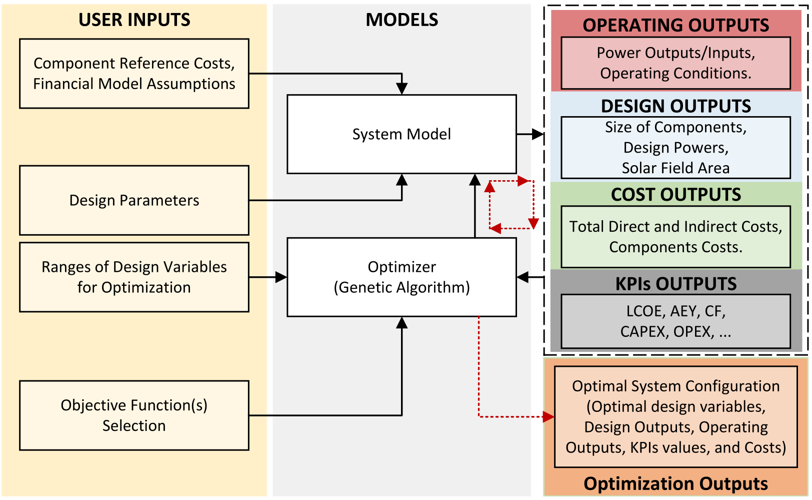

Fig. 8: Schematic representation of the definition of the key performance indicators

4. Techno-economic analysis results - case study

This section presents an example of the results achievable through the utilization of MoSES on the system outlined in Section 2. The design of the molten salt based hybrid PV-CSP plant was identified by solving a multi-objective optimization problem, with the goal of minimizing the LCOE and maximizing the HCF of the plant. To begin with, the hybrid solar plant was optimized adopting as location Evora, Portugal (38.5°N, -8.0°E), with a CSP capacity of 100 MW_e, serving as the base-case scenario. Evora is characterized by an annual DNI of 2000 kWh/m^2/year and an annual Global Horizontal Irradiance (GHI) of 1800 kWh/m^2/year. Then, to explore the scale effect on the techno-economic performance, a CSP capacity of 10 MW_e was implemented at the same location (Evora). This specific size was chosen to emphasize the inherent scalability potential of sCO_2 power blocks and evaluate their ability to enhance the cost competitiveness of CSP, even at smaller scales. Lastly, the impact of location was analyzed for a 100 MW_e plant situated in Likana, Chile (-22.7°N, -68.6°E), with an annual DNI of 3500 kWh/m^2/year and an annual GHI of 2600 kWh/m^2/year.

Figure 9 shows the results of the techno-economic optimization conducted on the hybrid PV-CSP plant for the two different scales and locations. The figure represents the optimal tradeoff between the minimum LCOE and the maximum HCF. The color bar shows the impact of the NPR. The results reveal that higher NPR ratios correspond to greater HCFs, surpassing 70%, albeit with a slight increase in LCOE. Conversely, smaller NPR ratios result in relatively lower HCFs and higher LCOEs. This underscores the significance of hybridizing these technologies: low-cost PV systems enhances the cost-competitiveness of CSP, while the dispatchability of CSP enables achieving high capacity factors and firm electricity production.

For the Portuguese location, the NPR range that minimizes the LCOE of the 100 MWe plant is between 1.9 and 2.1. The optimized configuration achieves a minimum LCOE of 66 EUR/MWh with an HCF of 78%. When considering the smaller scale of 10 MW, the hybrid plant is characterized by a minimum LCOE of 96.6 EUR/MWh (50% higher compared to the larger-scale scenario), alongside a HCF of 70%. This minimum LCOE is obtained at NPR around 2.5, indicating that the integration of PV becomes even more impactful at smaller capacities due to economies of scale. Indeed, despite the reduction in overall plant size, which lowers the total CAPEX, the specific costs associated with central tower CSP rise due to the scale effect and fixed expenses related to non-modular components such as the tower, heliostat field, TES, and power block. These findings underscore the competitive cost of hybrid PV-CSP systems, even at small scales and in a favorable European location. Moreover, at 10 MWe, higher NPR ratios are preferred, signifying a more relevant role of the electric heater in the system.

Regarding the impact of location, Figure 9 illustrates how higher solar resource availability leads to improved system performance, characterized by elevated HCFs and reduced LCOEs. The minimum attainable LCOE reaches 46.5 EUR/MWh, aligning with an 85% HCF. In Likana, owing to enhanced solar availability and a higher DNI/GHI ratio of 1.3, the optimal systems exhibit lower NPRs compared to the base-case scenario situated in Evora. This higher DNI/GHI ratio signifies that in Likana, CSP becomes more efficient than PV in harnessing the solar resource. The NPR ratio that minimizes the LCOE is less than one (0.9), resulting in CSP contributing to 71% of the total production share, without an excess of PV generation. Consequently, the electric heater is not a part of the optimal design. In comparison to the Evora-based plant, CSP assumes a more prominent role in Likana, both in terms of capacity and electricity generation.

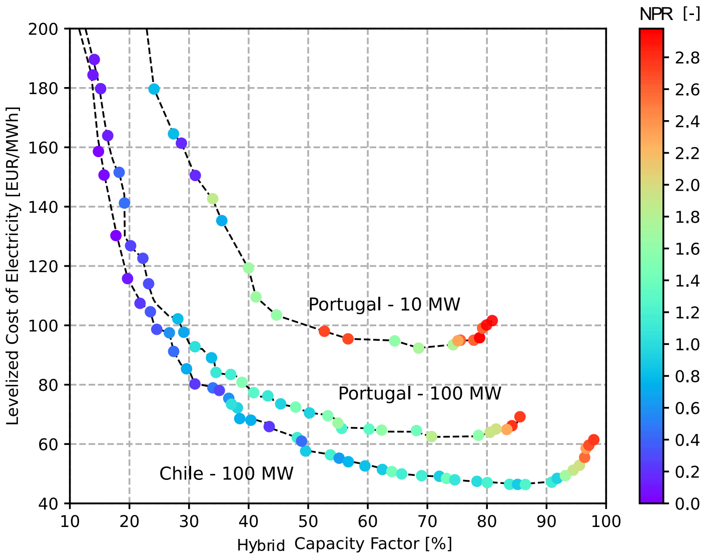

Fig. 9: Techno-economic optimization results for two locations (Portugal - Chile) and scales (10 - 100 MW$_e$)

5. Conclusions

In this study, a new tool called MoSES (Modeling of Solar Energy Systems) has been introduced. This tool aims to facilitate the evaluation and advancement of innovative solar power plants with energy storage for firm electricity production through simulation activities. MoSES offers a comprehensive platform for designing, optimizing, and benchmarking various solar plant configurations tailored to different locations, sizes, and electricity markets. The tool incorporates pre-defined system models, including sCO_2 power blocks and hybridization with state-of-the-art PV plants and BESS, enabling users to perform techno-economic optimizations, sensitivity analyses, and annual performance simulations. MoSES allows also for the integration and interconnection of existing component models, thereby expanding its capabilities. The modeling approach employed to simulate and optimize the performance of solar hybrid systems has been described, with a specific focus on system design, costs, and expected performance. Furthermore, new KPIs and KDIs specifically designed for hybrid solar power plants have been introduced, providing users with flexibility in selecting objective functions for system optimization. The inputs that can be customized by the user and the expected outputs for the design, operation, cost, and optimization of the system model have been presented.

As a case study, a techno-economic optimization has been conducted using MoSES on a hybrid PV-CSP system layout with molten salt thermal energy storage and a sCO_2 power block. The results demonstrate that integrating sCO_2 power blocks and actively hybridizing with PV can make CSP cost-competitive at both large (<66 EUR/MWh) and small scales (89 EUR/MWh). The study revealed high hybrid capacity factors (>70%), underscoring the role of such hybrid plants in the energy market by providing dispatchable and flexible generation. For European locations with a DNI of 2000 kWh/(m^2-yr), small-scale systems exhibited significant gaps between PV and CSP capacities (NPR > 2.3), allowing for the integration of electric heaters. In locations with abundant solar resources (3500 kWh/(m^2-yr)), electricity production was primarily driven by CSP, with system designs featuring an NPR ratio below 1. Under these conditions, the integration of electric heaters was unnecessary.

The MoSES tool shows to be promising in its early stages of development for simulating hybrid PV-CSP solar power plants. However, to ensure its reliability and effectiveness, there is a need for further refinement and validation efforts. To hinder the accessibility and user friendliness of MoSES, future efforts need to concentrate on the development of a Graphical User Interface (GUI) and the provision of comprehensive documentation. Indeed, the absence of a GUI may discourage some users from engaging with the tool, potentially limiting its adoption and applicability. Moreover, MoSES is slated for additional improvements, including the incorporation of innovative system models designed to evaluate the benefits of next-generation hybrid PV-CSP plants and explore avenues for enhancing CSP's cost-competitiveness. Validation of conventional component models of the hybrid PV-CSP plant has been accomplished through cross-referencing with established models verified against actual power plants. However, emerging technologies such as sCO_2 power block components, high-temperature electric heaters, storage, and receivers still in experimental stages, introduce uncertainties due to the lack of real-world data for validation. To counteract this, correlations derived from inputs provided by industrial partners in different research projects have been formulated and implemented for these low Technology Readiness Level (TRL) components not yet integrated into real power plants. The validation and refinement of these pivotal component models will be executed using real-world data gathered from demonstrations and research projects that underscore the feasibility of these components. While MoSES boasts accessibility and transparency as an open-source Python-based tool, its necessitates ongoing updates to accommodate new language versions and associated libraries. Neglecting to ensure compatibility with the latest versions of included libraries could result in performance glitches.

In conclusion, the MoSES tool holds promise as a valuable resource for simulating hybrid PV-CSP solar power plants. Addressing these challenges will be instrumental in enhancing the tool's reliability and its ability to provide accurate insights for the advancement of hybrid solar power systems.

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7. References

Bell, I. H., Wronski, J., Quoilin, S., & Lemort, V. (2014). Pure and pseudo-pure fluid thermophysical property evaluation and the open-source thermophysical property library coolprop. *Industrial and Engineering Chemistry Research*, *53*(6), 2498–2508. https://doi.org/10.1021/ie4033999

Blank, J., & Deb, K. (2020). Pymoo: Multi-Objective Optimization in Python. *IEEE Access*, *8*, 89497–89509. https://doi.org/10.1109/ACCESS.2020.2990567

Deb, K., & Sundar, J. (2006). Reference point based multi-objective optimization using evolutionary algorithms. *GECCO 2006 - Genetic and Evolutionary Computation Conference*, *1*, 635–642. https://doi.org/10.1145/1143997.1144112

Gilman, P., Janzou, S., Guittet, D., Freeman, J., DiOrio, N., Blair, N., Boyd, M., Neises, T., Wagner, M., & USDOE Office of Energy Efficiency and Renewable. (2019). *PySAM (Python Wrapper for System Advisor Model ‘SAM’)*. USDOE Office of Energy Efficiency and Renewable Energy (EERE). Renewable Power Office. Solar Energy Technologies Office. https://doi.org/10.11578/dc.20190903.1

Guccione, S., & Guedez, R. (2023). Techno-economic optimization of molten salt based CSP plants through integration of supercritical CO2 cycles and hybridization with PV and electric heaters. *Energy*, *283*, 128528. https://doi.org/https://doi.org/10.1016/j.energy.2023.128528

Hirsch, T., & et al. (2017). SolarPACES Guideline for Bankable STE Yield Assessment. In *IEA Technology Collaboration Programme SolarPACES, Tabernas*.

IRENA. (2020). Renewable Power Generation Costs in 2020. In *International Renewable Energy Agency*.

J.F., K., K., W., C.L., N., & M.J, S. (2010). Genetic Algorithms and Their Application to In Silico Evolution of Genetic Regulatory Networks. In *Computational Biology. Methods in Molecular Biology (Methods and Protocols), vol 673*. Humana Press. https://doi.org/https://doi.org/10.1007/978-1-60761-842-3_19

National Renewable Energy Laboratory (NREL). (2022). *System Advisor Model Version 2022.11.29 (SAM 2022.11.21)*.

Scott, P., Alonso, A. D. L. C., Hinkley, J. T., & Pye, J. (2017). SolarTherm: A flexible Modelica-based simulator for CSP systems. *AIP Conference Proceedings*, *1850*(June 2017). https://doi.org/10.1063/1.4984560

Stein, J. S., & et al. (2017). PV Performance Modeling Methods and Practices. In *Report IEA-PVPS T13-06:2017, IEA Photovoltaic Power Systems Programme*.

Storn, R., & Price, K. (1997). Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. *Journal of Global Optimization*, *11*(4), 341–359. https://doi.org/10.1023/A:1008202821328

Turchi, C. S., Boyd, M., Kesseli, D., Kurup, P., Mehos, M., Neises, T., Sharan, P., Wagner, M. J., & Wendelin, T. (2019). CSP Systems Analysis - Final Project. *Nrel/TP-5500-72856, May*.

Zurita, A., Mata-Torres, C., Valenzuela, C., Felbol, C., Cardemil, J. M., Guzmán, A. M., & Escobar, R. A. (2018). Techno-economic evaluation of a hybrid CSP + PV plant integrated with thermal energy storage and a large-scale battery energy storage system for base generation. *Solar Energy*, *173*(July), 1262–1277. https://doi.org/10.1016/j.solener.2018.08.061