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PREDICTIVE SIMULATION FOR IMPROVED OVERHEATING CONTROL IN LARGE SOLAR THERMAL FIELDS

Summary

Due to the intermittent and variable nature of solar energy, solar thermal plants need fast and reliable control to adjust their trajectory to the constant change in conditions. Predictive simulations can rapidly explore and compare various control strategies to ensure efficient real-time operations. It exploits a simulation model which accurately represents the system's complex dynamics while keeping computational effort low. It is used in the following work to determine the best overheating handling strategy in the LACTOSOL (Verdun, France) solar thermal plant. The operating modes commanding the activation of a dry cooler are assessed during a 20-day period, with a rolling time window of 48h refreshed every 24h, under uncertain weather and thermal load. The aim is to maximize the plant's economical profit while maintaining all components under their design operating range. The profit is increased by 43% compared to the standard rule-based control. This is due to a rise in production, a strong decrease in dissipated energy and higher temperatures in the storage tank.

Keywords: Solar Heat for Industrial Processes, Improved operations, Predictive simulation, Thermal Storage management

Field of application for the findings: Real-time operations of solar thermal plants

Addressed audience: Solar thermal plant operators

1. Introduction

1.1 Context:

Solar thermal plants are promising solutions for the decarbonation of industrial heat. However, their implementation can be challenging due to the intermittent nature of the solar resource and its non-concomitance with consumer's load. The addition of a thermal energy storage enlarges their operating range but further increases the need for an efficient and dynamic control to improve performance and ensure the plant's integrity under all working conditions. As performances are highly dependent on the temperature levels, the most recent advancements in enhancing operations for large-scale solar thermal plants are based on the formulation of a Nonlinear Programming (NLP) optimization problem. While this approach has been identified as promising at the laboratory scale, it still lacks the scalability and robustness required for industrial implementation. The use of commercial optimization solvers, high computational costs and complex initialization strategies, combined with convergence uncertainty, can be identified as the main drawbacks of NLP approaches.

1.2 Objective of the present work

The present study proposes to use a simpler approach based on predictive simulations. It allows for a fast determination of an adequate control strategy by simultaneously testing a large number of possible control scenarios in a simulation model. Therefore, it offers a more accurate description of the system dynamics compared to simplified optimization models, while keeping calculation effort low and eliminating the risk of non-convergence. Combined with a rolling horizon framework, it is suitable for real-time applications under uncertain weather and thermal load.

The novelty of the proposed methods also lies in the direct use of production mode as control variable, making it compatible with the state machine of the plant. Predictive simulation is applied to enhance efficiency in the activation of a dry cooler in a real case study.

2. LACTSOL case study

The thermal plant of LACTOSOL (Verdun, France) operated by NEWHEAT is chosen as an industrial case study, as it features state-of-the-art overheating strategies. The plant is composed of a large flat plate collector solar field and a sensible thermal energy storage tank. It supplies low-temperature heat (<100 °C) to a food-processing factory. Water-glycol mixture is used in the solar field as heat transfer fluid. Its temperature can never exceed 110°C, at which ebullition starts occurring, leading to a pressure rise in the pipe and, ultimately, to the evacuation of the fluid toward the recollection tank. This scenario should never occur, as it provokes a complete shutdown of the plant. Therefore, to ensure adequate cooling during critical days (i.e., with low consumption and/or strong solar radiation), a dry cooler is featured at the output of the solar field. It can be activated in two operating modes described as follows:

- Day Cooling (DC): The dry cooler operates alongside solar field production, to instantly cool down its inlet temperature.
- Night Cooling (NC): The NC forces a discharge of the storage tank at night, first by passive circulation in the solar field, then, if necessary, by activation of the dry cooler. The passive NC allows for cooling at a low electric cost, as only the circulation pumps are activated; however, the heat dissipation is 50% slower than with the dry cooler.

The activation of these modes is assessed to maximize the plant's economic profitability, while ensuring all components are operated safely (<110°C), under all operating conditions.

3. Predictive simulation

3.1 General description

Predictive simulation uses a simulation (i.e., saturated) model to explore various control strategies. The generation algorithm provides a batch of N_{ps} parameter set, each encompassing the trajectories for all control variables during a certain prediction horizon. All scenarios are simultaneous tested on the physical model of the system, then their performances are assessed and compared by the selection algorithm. The scenario allowing for the maximization of a chosen criterion is selected and applied to the plant (or its digital twin) operating under real conditions. The physical state of the plant is then evaluated to provide new initialization, ensuring an adequate selection under current conditions. The connection between the simulation model and the plant sensors may be identified as a potential obstacle for the real time implementation of this method.

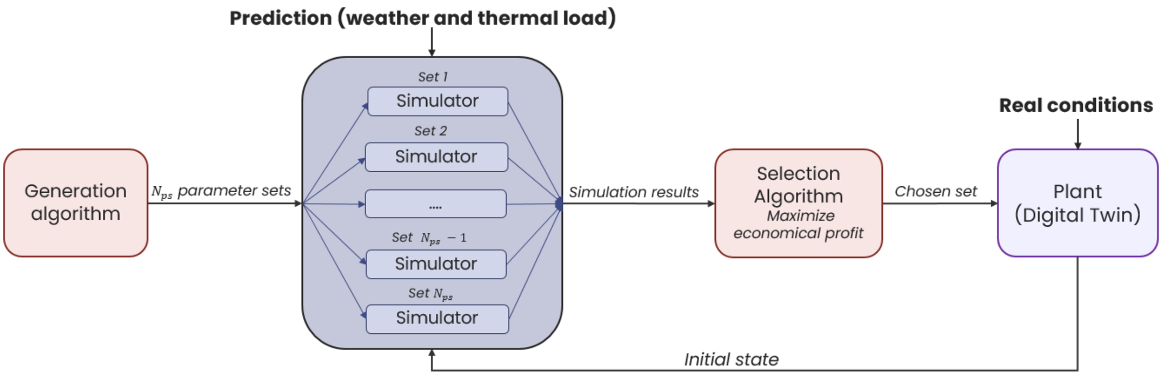

Fig. 1 : General principle of predictive simulation

The same model is used for simulations and evaluations of the scenarios. It was developed in Dymola and validated against experimental data by the plant's operators. The simulation framework was developed in Python using the FMPy library.

3.2 Generation algorithm

The proposed scenarios are based on a priori knowledge of the plant and in-depth numerical parametric studies performed on the same simulation model. The activation of all operating modes (DC, active NC, passive NC) is represented by a binary variable. The following table illustrates the chosen period of activation for the different modes.

Tab. 1 : Possible daily value for all control variables

	DC	**Active NC (with dry cooler)**	**Passive NC (without dry cooler)**
Possible activation period	No activation 12pm – 1pm	No activation 4am – 6am	No activation 2am – 6am

A prediction horizon of 48h is chosen, and all combinations of the cooling modes are evaluated across both days, leading to a total of 7 combinations every 24h. In total $N_{sp} = 49$ parameter sets are tested, considering that NC passive and active cannot be used in the same 24h period.

3.3 Selection algorithm

Economical profit is the chosen criterion for performances evaluations. The solar heat is sold to the industrial consumers at a price of $55€/MWh$. The only operating cost considered is the purchase of electricity at a price of $120\ €/MWh$, to power the circulation pumps and the dry cooler. When the dry cooler is activated, it consumes its nominal power of $68.4\ kW$. The following prices are chosen to illustrate the economic model of the plant but are not issued from the actual historic data.

Beside the preventive cooling mode (DC and NC), an additional reactive mode may use the dry cooler if any temperature rises above 100°C. This constitutes the last security of the plant before the shutdown, and as such should not be used in improved operations. Therefore, a penalty of a double price of electricity is associated with its activation.

4. Results

The following results consider a twenty-day period (27th of June to the 17th of July 2023) with an hourly time step. This time period was chosen, as it presents a serious overheating risk due to low consumption and strong solar irradiance; therefore, it requires appropriate cooling. Weather and thermal load predictions are reconstructed with a variation around historic data.

The preliminary results highlight the impact of integrating predictions into the control strategy. Compared to current state-of-the-art rule-based control evaluated in the same conditions, an increase of 34% (+100 MWh) in produced solar thermal energy can be achieved while reducing dissipated energy by over 78% (-210 MWh). The profit is consequently increased by 43%. With predictive simulation, the storage is operated at higher temperature levels; the energy stored at the final time step rises by 34%.

It is worth mentioning that the rule bases control applied in 2023 was issued immediately after the start-up of the plant. It has been since then revaluated by the operators and might lead to a reduction in the economic benefit presented here. Further comparisons across different overheating periods will be issued in future work.

The NC passive mode is activated three times, for a total of twelve hours. The DC is used only for two hours, in a period when the NC is not sufficient. The NC active mode is used only once in the period. Passive NC seems to be the preferred cooling mode, as its additional electric cost is the lowest since the dry cooler is not activated. It dissipates heat twice as slowly as active NC; however, there is no cooling time constraint in the chosen case study; hence its use.

The CPU time required for the twenty-day simulation is around an hour, meaning that, for a single 24h optimization, the required calculation time is under six minutes. This highlights the scalability of this method for real-time operation of the power plant. In the literature regarding real-time optimization, the time horizon is mostly limited at three days, beyond which the quality of weather reports is insufficient. With the proposed framework, a three-day simulation exploring over 500 scenarios could be performed in less than two hours. The calculation time remains lower than the desired actualization time.