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Abstract

This review provides a deep analysis of the different methodologies to improve the operation of solar thermal plants based on mathematical optimization. The various schemes found in the literature to determine the optimal operational strategy are classified depending on two criteria: time dependence (static or dynamic) and with feedback or not from the plant (real-time or offline). This review shows that offline dynamic optimization is performed on solar thermal plants in research papers but highlights the lack of real-time optimization studies. The analysis work conducted in this review, based on studies of the operation of solar systems but also on process engineering research articles, shows that dynamic real-time optimization seems capable of handling the intermittency of the solar radiation and well suited to improve the operation of a solar thermal plant. Indeed, the daily and seasonal variations of weather and heat demand associated with the uncertainty of their forecasts make the operation of such systems very challenging. This paper details the different ways to implement Dynamic Real-Time Optimization, and the possible improvements to the classical scheme. Perspectives on the application of Dynamic Real-Time Optimization in association with a planning phase to plan a smart use of storage are described. Although it has not been studied in depth in the literature,

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the Dynamic Real-Time Optimization of a solar thermal plant including storage should be investigated in order to maximize the benefits from the heat sold, extend the time period where the heat demand is met and reduce the consumption of back up fossil fuels.

Keywords: Solar thermal energy, Dynamic Real-Time Optimization, Optimal operation, Storage management

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Introduction

More than half of the final energy consumption in the world is in the form of heat (Collier, 2018). The production of heat contributes greatly to the global CO_2 emissions on the planet. Solar thermal energy uses a renewable source, the sun, to produce heat with very low greenhouse gases rejection while operating. According to the International Energy Agency, the use of all the installed solar thermal systems for heat production in 2020 led to savings of 43.8 million tons of oil and 141.3 million tons of CO_2 (Weiss & Spörk-Dür, 2021). Therefore, solar thermal energy acts as a good replacement for fossil fuels used for heat production in various applications and is a key element of a good energy transition.

In 2015, 196 countries signed the Paris Agreement which aims to limit global warming to well below 2°C and to pursue efforts to limit it to 1.5°C compared to pre-industrial levels (United Nations Framework Convention on Climate Change, 2015). Targets are fixed locally for the various sectors of greenhouse gases emissions. In Europe, the Revised Renewable Energy Directive (Renewable Energy Directive, 2018) fixed the target of a 1.3 % increase each year in the share of renewable energy for heating and cooling for every member state. In France, the Energy Transition Law for Green Growth (Loi de transition énergétique pour la croissance verte), adopted in 2015, aims at reaching 38 % of renewable heat in the final heat consumption of the country in 2030 (Loi française, 2015). Similar objectives are fixed in many countries around the world in order to reduce CO_2 emissions and mitigate climate change. In this context, developing efficient solar thermal plants and making the most out of them, through mathematical optimization for example, is crucial to achieve the objectives.

Optimization can be applied to the design of a solar thermal system, in order to size the elements and choose the layout of the process in a way that maximizes revenues while keeping the investments low. It can also be used to determine the best operation strategies given a fixed design for the system. The optimization of the operation of a solar thermal plant including storage is the focus of this work.

It is worth mentioning that heat production for domestic or industrial use is only one purpose of solar thermal plants. Systems with concentration can achieve temperatures high enough for steam and electricity generation and are referred to as Concentrated Solar Power (CSP) plants. This review aims at providing solutions to improve solar heat production for domestic and industrial use. Nevertheless, heat is produced and stored in a solar thermal plant, regardless of the technology used or the final utilization of the heat generated. For this reason, both concentrating and non-concentrating solar thermal plants are considered in this paper, as long as the studies are focused on the solar field operation and storage management. Furthermore, the methodologies described in this paper could benefit to all types of solar thermal plants.

Figure 1 presents the cumulated capacity in operation at the end of 2020, and the energy supplied that year, for solar thermal heat and other renewable energy technologies, including solar thermal power. This diagram shows that solar thermal plants for heat production are already an established technology for renewable energy production. The total collector area in the world is 715 million square meters and China is leading the market, with 48 % of the installed collector area for large-scale systems (Weiss & Spörk-Dür, 2021).

In a solar energy system, both the energy source and demand are time-varying. Thus, it is difficult to find the best operational stategy ensuring best economical performance of the system. A steady-state set point optimization,

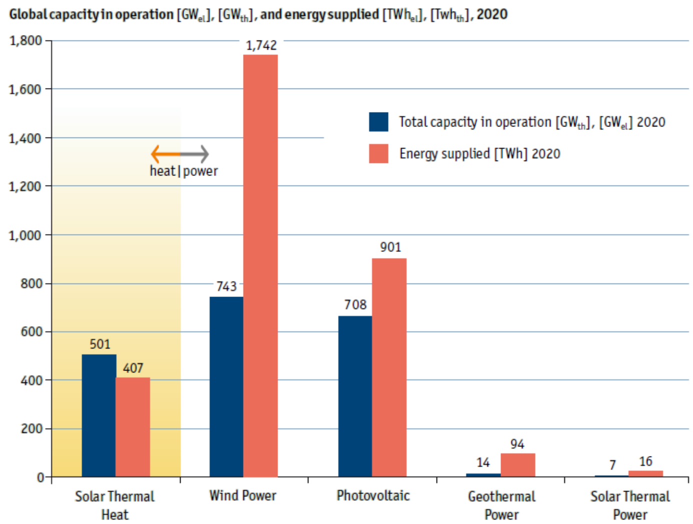

Figure 1: Global capacity and energy supplied for solar thermal and other renewable energy technologies (Weiss & Spörk-Dür, 2021)

computing a constant value for the decision variables, would not be able to ensure optimal operation throughout time. Dynamic optimization computes optimal trajectories for the controlled variables on the complete time horizon chosen, by minimizing an objective function such as cost, and accounting for the dynamic behavior of the system (Biegler & Grossmann, 2004). In order to compute these reference trajectories, inputs such as solar irradiance, ambient conditions, heat demand and the complete initial state of the solar thermal plant are necessary. The values of state variables could be measured directly on the solar plant and the complete initial state would then be inferred from the measurements using estimation techniques. However, the perfect knowledge of the meteorological data over the complete time horizon can not be acquired in advance. Weather forecasts, as well as load forecasts, need to be used even though they contain uncertainties. A way to remedy to these uncertainties is to use Dynamic Real-Time Optimization (DRTO) (Kadam et al., 2002). This methodology, mainly used in process engineering research, could greatly improve the operation of a solar thermal plant. Dynamic optimizations are regularly performed to ensure that the plant continuously operates in optimal conditions (Kadam et al., 2002) to maximize the benefits and meet the heat demand. Before each DRTO run, measurements are performed on the actual plant to determine the initial conditions and the disturbances affecting the system, and forecasts are updated. As the accuracy of forecasts increases when the time horizon shortens, the update reduces the error between the predicted and actual weather and load. On the other hand, a long time horizon ensures a better long term strategy as the solar radiation also varies between days and months.

Therefore, the continuous adaptation of the operation strategy to the current conditions could correct the forecasts uncertainties, and in association with the respect of a plan previously determined, it would help to find the optimal operation strategy for the solar thermal plant.

This paper gives a state of the art on dynamic optimization and control of solar thermal plants. It then provides detailed explanation of the methodology of DRTO with examples from the literature, highlighting the lack of studies focusing on the DRTO of solar systems. Finally, it provides ideas for future work on the DRTO of solar thermal plants. Such a comprehensive analysis of the application of DRTO to solar thermal plants has never been done before to the authors knowledge.

The first Section of this paper introduces the system studied and its modeling and defines the optimization problem considered. Section 2 presents the state of the art on dynamic optimization and control of solar thermal plants. Real-time Optimization is then introduced in Section 3. After a short presentation of the classical scheme for Static Real-Time Optimization (SRTO), the Dynamic Real-Time Optimization (DRTO) schemes are presented in Section 4. Some adaptations to this methodology are provided in Section 5. In Section 6, the three main schemes for real-time optimization are compared and finally, in Section 7, perspectives on the application of DRTO to solar thermal plants are presented.

1. Solar thermal plant modeling and optimization

1.1. Solar thermal plant modeling

A solar thermal plant is composed of several circuits with a Heat Transfer Fluid (HTF) flowing in them. The design of the solar thermal plant is different for each plant, depending on the solar collectors technology, HTF used and the application. Nonetheless, some features are common to all solar thermal plants. In the production loop, the HTF is heated up in the solar field, made of solar collectors, and the heat collected is transferred to the storage circuit through a heat exchanger. Direct storage is also possible when the HTF and the stored fluid are the same. A by-pass pipe allows the HTF to flow through the solar field without supplying the heat in the heat exchanger during a warm up phase. The storage circuit is centered around a Thermal Energy Storage (TES) tank, which can be charged with hot fluid when solar irradiation is abundant and discharged when solar heat cannot be produced in sufficient quantity to satisfy the heat demand. The storage tank can also be by-passed to directly supply the heat produced to the consumer. In some CSP plants, two storage tanks, one for the cold fluid and one for the hot fluid are used (in (Casella et al., 2014) for example), instead of a stratified single one (used in Scolan et al. (2020) for instance). The consumer circuit is generally connected to the storage circuit trough a heat exchanger, but the stored fluid can also be supplied directly. An example of the structure of a solar thermal plant is presented in Figure 2. In order to optimize

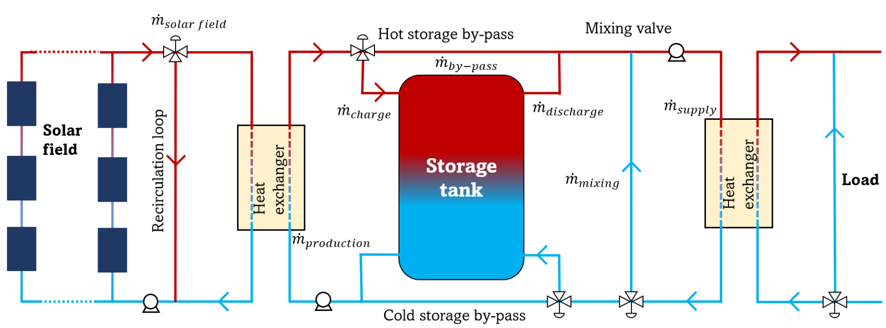

Figure 2: General structure of a solar thermal plant

the operation of a solar thermal plant, a model of the system needs to be developed. In a solar thermal plant, the quantity of energy produced, stored or supplied is as important as the temperature level of that energy. In contrary to electrical system with a fixed voltage, in a solar thermal system the temperature of the energy varies and affects the quality of the energy. For this reason, models of solar thermal plant are nonlinear, with power terms computed with a product between temperatures and flow rates. In order to keep the accuracy of the model, linearization should be avoided. When attempting to linearize the model, the difficulty of various operating points with different dynamics arises (Camacho et al., 2007a). There are two types of models that can be used: first-principle models or data-based models. First-principle models are based on the equations of the conservation of mass and energy, an example can be found in (Pataro et al., 2020b). These models are based on Partial Differential Equations (PDE) that need to be discretised before the resolution. The equations can be developed for each element of a solar thermal plant to build a complete model. Nonlinear detailed models can provide accurate results but require more computational time. Thus, simplifications are often necessary. Data-based models are much faster to solve because they do not incorporate any differential equation or discrete-event based component. Historical data obtained from a real plant or a detailed, physical based, simulation model are used to build the empirical model. There are two categories of data-based models: parametric models and data-driven models (Vasallo et al., 2021). In the literature, data-based models are often used to represent the solar field of a solar thermal plant. In a parametric model, a parameterised function is used to represent the solar thermal plant and the values of parameters are determined with regression techniques. Such models are used in the literature in optimization studies to speed-up the calculations, in (Brodrick et al., 2017) or (Rashid et al., 2019b) for example. Linear models are easier to build with parameter identification. Grey-box models, based on first principles and tuned according to real measurements, can also be built (Gálvez-Carrillo et al., 2009). Data-driven models are based on machine learning. They use historical data and a prediction algorithm to predict the solar thermal plant output, such as the outlet temperature of the solar field or the thermal power produced, based on a few inputs, such as ambient temperature, solar irradiance and inlet temperature. Artificial Neural Networks (ANN) are data processing systems inspired by human brain and have been used in recent years to model the solar field (Ghritlahre & Prasad, 2018). They present numerous advantages such as their simplicity, rapidity, capacity to represent complex and nonlinear relationship among the variables and input data. However, they require a large quantity of appropriate data to train the model, obtained from a real plant or a detailed simulation model. Elsheikh *et al.* reviewed the use of ANN for the modeling of solar energy systems and concluded that ANN models are much simplier and faster than theoretical models and require less experimental data than parametric models (Elsheikh et al., 2019). Moreover, ANN models are able to represent changes such as plant degradation thanks to retraining with appropriate data. Farkas *et al.* trained an ANN model with simulation data from a physical model for flat-plate collectors. During the validation process, an average deviation of 0.9°C was achieved in the outlet temperature. This study shows that ANN model with an appropriate structure and a good training is accurate (Farkas & Géczy-Víg, 2003). A similar study was performed by Heng *et al.* for parabolic troughs collectors. In this paper, a transient model was developed to predict the parabolic trough collector tube exit temperature in Kuala Lumpur, Malaysia. In this location, the solar irradiation fluctuates a lot because of humidity and rarely stays at the same value for more than 1 minute. In such conditions, the accurate prediction of a solar thermal collector system performance is challenging and requires a transient model. The outlet temperature of the fluid during one day is obtained with a mean absolute deviation of 2K with the ANN model, and its calculation lasted only 1 minute on a personal computer, which is short compared to the Finite Element Method achieving the same accuracy (Heng et al., 2019). This study confirms the rapidity of an ANN model to estimate the solar field performances compared to traditional models. Even though data-driven models might be less accurate than detailed first-principle models, the uncertainty in solar irradiance forecasts compensates for this disadvantage (Vasallo et al., 2021). Machine learning techniques are also used to predict the weather conditions affecting solar thermal plants. For instance, Kumari *et al.* reviewed the deep learning models used for solar irradiance forecasting (Kumari & Toshniwal, 2021). Based on these studies, it seems that data-driven models are appropriate to model the solar field of a solar thermal plant in an optimization study. There are no data-based models representing the complete solar plant with the solar field, storage tank, pipes and heat exchangers found in the literature. A solar thermal plant is usually modeled with different sub-models for each element of the system. The remaining parts of this paper focus on the optimization of the operation of a solar thermal plant, independently of the type of model used for the solar field and the other elements of the plant.

1.2. Generalities on optimization

Optimizing means finding the best solution to a problem among all the possible solutions respecting given constraints. The criterion to determine which one is the best solution is expressed through an objective function to be minimized or maximized. Generally, the minimization of cost or maximization of profit are used as objectives for the optimization, although non-economical objectives are sometimes employed, such as energy efficiency or exergy maximization or a target value for a variable (quality target as part of the objective function in (Ravi & Kaisare, 2020) or temperature target in (López-Alvarez et al., 2018)).

The mathematical formulation of a dynamic optimization problem is presented in Equation 1.

$$
\begin{aligned}
& \min_{\mathbf{u},\mathbf{z},\mathbf{y},p,t_f} \quad \Phi(\mathbf{z},\mathbf{y},\mathbf{u},p,t_0,t_f) \\
s.t. \qquad & 0 = f(\dot{\mathbf{z}},\mathbf{z},\mathbf{y},\mathbf{u},d,p,t),\ \ \mathbf{z}(t_0) = \mathbf{z}_0 \\
& 0 = g(\dot{\mathbf{z}},\mathbf{z},\mathbf{y},\mathbf{u},d,p,t), \\
& 0 \geqslant h(\dot{\mathbf{z}},\mathbf{z},\mathbf{y},\mathbf{u},d,p,t);\ \ t \in [t_0,t_f].
\end{aligned} \tag{1}
$$

In this equation, Φ is the objective function to be minimized on the time span $[t_0, t_f]$, in which t_f itself can be an optimization variable. The objective function involves the differential state variables $\mathbf{z}(t)$, with initial conditions $\mathbf{z}_0$, the algebraic state variables $\mathbf{y}(t)$, the controlled variables $\mathbf{u}(t)$ and the parameters of the system p. The number of degrees of freedom in the optimization problem matches the number of optimization variables, which are some of the controlled variables, parameters and t_f if applicable. The minimization is subject to several constraints. Firstly, the process model is represented by the function f, which generally entails partial or ordinary differential equations as well as algebraic equations. In the model, $d(t)$ denotes the disturbances, including external disturbances, plant-model mismatch and measurement noise, and p are the time-independent parameters of the system, which might also be optimized. Finally, g and h contain the design and operational constraints formulated with equalities and inequalities respectively. The complete set of constraints forms a (Partial) Differential Algebraic Equations (DAE) system, in which the only derivatives appearing are those of the differential variables $(\mathbf{z}(t))$.

In Equation 1, the time dependency of the problem denotes a dynamic optimization, which will compute optimal trajectories for the controlled variables. Simplification of this model to steady-state operation would lead to the computation of set-points (constant values) for the controlled variables. Various resolution algorithms may be used to solve a steady-state problem, depending on its characteristics: linear or not, made only of continuous variables or not. In the case of dynamic optimization, solving is more complex, due to the differential terms appearing in the model and constraints. Thus, discretization techniques are needed (Biegler & Grossmann, 2004). One way of solving complex optimization algorithms is to use stochastic algorithms, as opposed to deterministic algorithms. Stochastic algorithms involve randomness and are often based on a biological or physical phenomenon. For example, Genetic Algorithm (GA) is inspired by natural selection and Particle Swarm Optimization (PSO) is inspired by the movement of organisms in a bird flock or fish school.

One advantage of their use is a large search space which avoids local optimum but their main drawback is the need to evaluate the objective function many times until convergence is reached, which leads to long computational time. Stochastic algorithms require objective functions that can be evaluated quickly and are more often used for linear problems. ANN models or other data-based models are well-suited to be used with those algorithms, especially for real-time application (in (Blackburn et al., 2020) for example) because of their fast computational time. Stochastic algorithms are particularly appropriate when the problem studied is complex and its physical modeling is not entirely known (Camacho et al., 2007a), which is the case of a solar thermal plant since it uses an intermittent and hard to predict energy source.

If the optimization uses a deterministic algorithm, the application of the general optimization equation 1 to the operation of a solar thermal plant, would involve the following variables and parameters:

- the differential state variables $\mathbf{z}$ are the temperatures in the system,
- the algebraic state variables $\mathbf{y}$ are the pressures in the system elements,
- the controlled variables $\mathbf{u}$ are flow rates, such as the flow rate through the solar panels $\dot{m}_{solarfield}$, the flow rate to collect the energy from the production loop $\dot{m}_{production}$, the flow rate to supply the energy to the consumer $\dot{m}_{supply}$ and the flow rates to charge, discharge or by-pass the storage tank $\dot{m}_{charge}$, $\dot{m}_{discharge}$ and $\dot{m}_{by-pass}$,
- the manipulated variables, not represented in equation 1 because they are part of the control problem only, and not the open-loop optimization problem, are the valve openings and the pumps rotational speeds. The variable speed pumps and control valves are presented in Figure 2,
- the disturbances d include the weather information (solar irradiance, ambient temperature, etc.), fouling of heat exchangers, plant-model mismatch, etc.,

- the model parameters p include characteristics such as size, heat transfer coefficients, etc. for solar collectors, thermal energy storage, pipes, heat exchangers and other parts of the plant. Some of these parameters are bound to evolve as disturbances affect the system. For example, the fouling of a heat exchanger has an impact of the heat transfer coefficient value.

It goes without saying that this description is highly model dependent and are chosen by the person in charge of developing the optimization scheme. If the system definition changes, so do the previous categories. Using these variables for a fixed design, the optimal trajectories for the flow rates could be determined with an economic objective function, taking into account the revenues due to the heat sold and the operating costs. More complex objective functions including several objectives could also be used (see subsection 5.4). If a stochastic algorithm is used for the optimization, the problem formulation would be adapted. Nonetheless, the variables and parameters involved would remain the same. Thus, this review includes both deterministic and stochastic optimizations, and details are given to explain the cited papers authors' choices.

The main difference between a solar thermal plant and a conventional fossil fuel plant is that the energy source is variable and cannot be manipulated. It then acts as a fast disturbance on the system. Several constraints are associated with the optimization of the operation of a solar thermal plant and are detailed hereafter (Camacho et al., 2007a). The flow rate in the solar field must be above a minimum value to avoid overheating the fluid and to ensure that the pumps are working with a high efficiency. The outlet temperature is also limited to avoid overheating and phase change that would deteriorate the equipment. The temperature difference between the inlet and outlet of a solar field should also be kept under a maximum value to avoid a high pressure variation throughout the collectors. Compared to an electrical system, whose variations are almost instantaneous, there is a transport delay in the field and the pipes of a solar thermal plant. This leads to more complex dynamics. Furthermore, the dynamics of the system changes with the operating point making the optimization and control a solar thermal plant very challenging.

The next section will present a review on optimization and control of solar thermal plants, using a similar description of the system and the optimization problem.

2. Optimization and control of solar thermal plants

Most optimization studies on solar thermal plants aim at optimizing the design of the plant under standard operation strategies. It means that in Equation 1, only the design parameters included in p are optimized. For example, the size of the solar field and its layout, the capacity of the storage tank, the capacity of the pumps, the pipes diameter, can be optimized in order to reduce investments while satisfying the production constraints. Research on the optimization of the design of the elements of solar thermal plants is still active, especially for the integration of solar heat in larger systems. For instance, several studies recently aimed at finding the optimal design for solar thermal systems integrated in District Heating Networks (DHN). Winterscheid *et al.* focused on the integration of solar energy into an existing DHN (Winterscheid et al., 2017), while Hirvonen *et al.* analysed the feasibility of a solar DHN using seasonal storage in Finland (Hirvonen et al., 2018). Furthermore, Tian *et al.* optimized the design of a hybrid solar plant supplying a DHN by minimizing the Levelized Cost Of Heat (LCOH) (Tian et al., 2018). The use of solar heat for industrial processes is also under investigation ((Parvareh et al., 2015), (Jannesari & Babaei, 2018)), the design of the solar system being economically optimized using standard control strategies. The optimization of the design of a solar thermal plant can also be an important step when studying the economic feasibility of a project. For example, Zubair *et al.* optimized the solar multiple and the size of the thermal energy storage of a parabolic trough concentrated solar thermal plant to assess the economic feasibility of a project for international electricity export (Zubair et al., 2021). For the optimization of the design, stochastic algorithms are sometimes used. For example, a GA was used to find the optimal operating point of an evacuated tube solar collector system modeled with an ANN (Dikmen et al., 2014). PSO was used in multi-objective optimization based on a physical model to determine the best design and steady-state operating point ((Awan et al., 2020), (Bahari et al., 2021)). In these studies, no dynamic behavior was considered and the optimization only needed to be conducted once. Therefore, the use of a stochastic algorithm was possible.

Krause *et al.* outlined that the optimization of the design of a solar domestic hot water system greatly improves its performances, leading to a reduction of solar heat cost of about 18 % compared with the conventionally planned and installed system (Krause et al., 2003). The authors concluded that, for a well-designed system, the improvements from the optimization of the operation strategy are smaller, only a few percents, but for a large system, this still leads to impactful savings. Camacho *et al.* explain that, because of the very expensive cost of solar thermal plants, any improvements in their performance, through better operation and control, would help to present them as a viable alternative to fossil fuels (Camacho et al., 2007a). The optimization of the operation of the solar thermal plant is the main focus of this literature survey.

The optimization and control of a solar system can be divided into several levels of decision. The different levels are presented in Figure 3, with the time step decreasing from top to bottom. In this diagram, LP stands for Linear Programming and QP for Quadratic Programming.

The two lower levels correspond to the control level, which aims at tracking a set-point or a trajectory for the controlled variables in the presence of disturbances by adjusting the values of the manipulated variables. The control strategy is an active area of research, especially for Concentrated Solar Power (CSP) plants, which are a particular type of solar thermal plants that produce solar heat at high temperature suitable for electricity or steam generation. In most control studies, the outlet temperature is maintained to a fixed level by adjusting the flow rate through the solar collectors, which presents several avantages (Camacho et al., 2007a). This strategy ensures that the energy is always

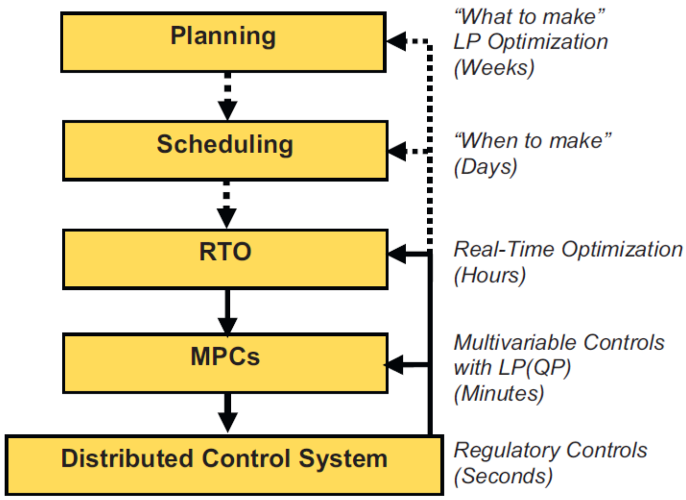

Figure 3: General hierarchy for control and decision making in a plant (Darby et al., 2011)

produced in a usable form with a temperature high enough for the consumer needs. It also avoids frequent shutdowns and startups by keeping the solar field ready for full scale operation if the solar irradiance goes up. Finally, it allows the different parts of the solar thermal plant to work near design conditions with high efficiencies. Nowadays, the outlet temperature of the solar field in actual CSP plants is mainly controlled using basic control approaches to find the appropriate flow rate in the solar field, even though the system characteristics (nonlinear, various dynamics, changing environmental conditions) require a high order nonlinear controller (Camacho et al., 2007a). In the last decades, numerous control methods have been studied and applied to CSP plants (Camacho et al., 2007b), allowing a better disturbance rejection and uncertainties handling. For example, Gálvez-Carillo *et al.* used a nonlinear predictive controller with dead-time compensator to track the outlet fluid temperature from the solar field of a CSP plant in the presence of disturbances (Gálvez-Carrillo et al., 2009). The authors found that this new controller can handle both significant nonlinear dynamics and variable dead-times. Csordas *et al.* compared several control strategies and highlight some drawbacks of the fixed outlet temperature control objective. This strategy leads to dump some solar energy when the solar irradiance is too low to reach the desired temperature. Moreover, if the inlet temperature is high in the solar field, a very high flow rate will be needed to avoid exceeding the target outlet temperature (Csordas et al., 1992). The solar energy unused with this strategy could still be useful. If the consumer needs a precise temperature level, it can be adjusted by mixing the outlet HTF with colder fluid or heated up with a back-up fossil fuel burner. Csordas *et al.* recommended to fix the temperature raise in the solar field instead of the outlet temperature to waste less energy. However, this strategy also presents some drawbacks. The temperature at the outlet of the solar field becomes high when the inlet fluid is already warm. These high temperatures in the solar field lead to high thermal losses, reducing the benefits of avoiding the dumping of energy with a variable outlet temperature. Moreover, constraints on the maximum allowable temperature should be added in order to avoid exceeding the maximum temperature of the components. Some control strategies maximize the output power from the solar thermal plant by adjusting the flow rate in the solar collectors. For example, Amman *et al.* used a control algorithm based on ANN to detect the optimal power operating point of PhotoVoltaic Thermal Panels, maximizing both thermal and electrical powers (Ammar et al., 2013). Ruiz-Moreno *et al.* developed a Model Predictive Control (MPC) to maximize the thermal power of a parabolic trough plant. The MPC needs to be run frequently, every few seconds or minutes. For a large-scale plant with a long time horizon, the computational time might exceeds the sampling time. To remedy to this issue, the authors developed an ANN model to represent the MPC and compute the control output. The computational time was reduced to only 3% of the tradiational MPC calculation time, and smoother outputs were generated with only slight violation of the constraints (Ruiz-Moreno et al., 2021). Thus, control strategies based on ANN are a future direction for research. Allowing the outlet temperature to vary seems to help to meet the heat demand and increase the thermal energy produced. While advanced control strategies help to improve the solar field performances, the operation of a solar thermal plant could further be improved by dynamic optimization with a cost function. This will help to reduce the costs of the complete plant, by making a smart use of storage and running the pumps in order to avoid wasting electricity. This idea will be developed in the next sections.

The higher level of decision for the short term operation of the solar plant is the offline dynamic optimization, also known as planning. In this level, the disturbances and initial state of the system are known inputs for the economic optimization. The time horizon comes from a compromise between long term optimal strategic vision and short term forecasts reliability. The optimal trajectories determined during this planning phase can be tracked by controllers only if the error between the forecasts and the actual measures is small. Delubac *et al.* used a dynamic multi-period approach to determine the best design and also the optimal operation strategy of a DHN using solar energy in association with a biomass plant and backup gas boilers (Delubac et al., 2021). This planning determines the optimum energy mix and particularly the use of the solar thermal plant. It computes the optimal flow rate through the solar field but it does not model precisely the complete solar plant. Offline dynamic optimization has been performed on a non-concentrating solar thermal plant by Scolan *et al.* (Scolan et al., 2020). In this study, the weather and the customer demand in solar heat were supposed to be perfectly known. Under such assumption of perfect forecasts, control was not included in the model since no disturbances were considered. Offline dynamic optimization was then performed to determine the best operation of the solar thermal plant including the heat storage, over a time horizon of 36 hours. Optimal trajectories for the flow rates in each part of the solar thermal plant were computed. The stored energy at the end of the time horizon was added to the objective function, with a weight, in order to give value to the stored energy and thus make the most out of the storage tank. Counterintuitive operating strategies were found to be optimal on this time horizon because of a smart use of storage.In this study, the solar heat provided to the consumer increased by 6.2%, the electricity consumption from the pumps decreased by 62.3% and finally,the economic profits increased by 2.1%.

These gains could further be improved under less favorable weather conditions. This is, to the best of our knowledge, the only study referring to the offline dynamic optimization of the operation of a non-concentrating solar thermal plant, as most studies in this field focus on optimizing only the design of the plant.

The close field of concentrated solar power received slightly more attention recently. Several studies aiming at automatically finding the plant optimal operating point (maximizing the economic profit from electricity selling) can be found in the literature. Wittmann *et al.* developed a methodology to optimize the planning of power selling at the day ahead market for a CSP plant (Wittmann et al., 2011), determining the optimal use of the backup fossil fuel burner and the storage tank. It takes into account meteorological and electricity market price forecasts to optimize the bidding strategy. Thermal Energy Storage (TES) transforms the intermittent solar power into a dispatchable power that can be sold when the electricity price is high and thus, increase revenue. Indeed, it is easier to store heat and then transform it into electricity when needed than to store electricity directly. The time horizon for such an optimization should be between one and two days to compromise between profit gains and forecasts quality. Similarly, Casella *et al.* optimized a Solar Tower Power Plant with TES (Casella et al., 2014). The electricity generation schedule was optimized in terms of the Heat Transfer Fluid (HTF) flow rate to the power block. The other control variable of the problem was the power dumped by heliostat defocusing, which is needed in summer to avoid exceeding the maximum power that can be handled by the receiver. Their paper includes a detailed dynamic model and concludes that optimal control should be taken into account when estimating the potential plant revenue during the plant design phase, as it can increase the revenue of about 7 % for a 10 days case study. Finally, Lizarraga-Garcia *et al.* conducted a similar study but added the possibility to recharge the TES using electric heaters and electricity from the grid (Lizarraga-Garcia et al., 2013). This additional feature further increases the flexibility of the plant and its revenue by taking advantage of the high variability of electricity price. Their optimization variables were the initial temperatures of the hot tank, the cold tank, and the lid, the initial mass of salt in the hot tank, the start-up time, the shutdown time, the mass flow rates between the hot tank and the cold tank, and the electricity purchased from the grid. Offline dynamic optimization was also used by Lopez-Alvarez *et al.* to optimize start up policies of a CSP plant (López-Alvarez et al., 2018). The objective was to reach the target operating temperature (control variable) in the shortest amount of time by manipulating the input water flow rate (water was the HTF used in this solar thermal plant). It is essential for such systems to achieve full operation from shut-down conditions in the minimal amount of time and using minimum energy requirements, in order to meet the power demand. In this study, TES was used after the Rankine cycle to store water warmer than fresh water and recycle it to speed-up the start-up policies of the CSP plant. Wagner *et al.* optimized the timing and rate at which electricity is generated by the power cycle (Wagner et al., 2017) in a concentrated solar power tower plant with TES. They used a Mixed-Integer Linear Program (MILP) to maximize the electricity sales while avoiding frequent cycle start-ups. They used perfect forecasts from historical meteorological data to compute the solar power available, thanks to a simulation tool using design flow rates. Their methodology allows more production during highly priced hours and a smoother generation profile than heuristic control approach. The authors concluded that the Power Purchase Agreement price could improve by 10 to 15% for electricity markets with highly variable electricity prices or narrow windows of high revenues thanks to their optimization. The authors used the same approach in (Wagner et al., 2018) and solved the optimization problem over a time horizon of 48h, applied the hourly dispatch schedule during 24h and then used a rolling horizon of 24h. The yearly results of this optimization show an improvement in the operating cost of the plant over its lifetime, with lower maintenance costs, compared to the standard algorithm that allocates the dispatch to hours of particularly high revenues. Finally, Hamilton *et al.* improved this methodology with a detailed model for off-design conditions for the electricity production (Hamilton et al., 2020). The flexibility of CSP with TES can also help to alleviate negative effects of photovoltaic solar plants. Kong *et* *al.* optimized the scheduling for for a hybrid solar power plant comprising CSP and photovoltaic solar panels. They used a simplified linear model based on energy flows and optimized the day-ahead generation plan of the plant with a time step of one hour. A modified Butterfly Optimization Algorithm (BOA) was used because it is faster compared to GA and PSO. The use of a stochastic algorithm was possible because the system was simplified and the task is performed offline. The operation cost of the integrated system decreased by 10% with this methodology.

In addition to thermal energy storage, hybridization of a CSP plant with a back up fossil fuel system helps to harvest the maximal solar energy. Indeed, the hybrid system considered by Powell *et al.* led to a larger amount of solar energy collected, when optimizing the HTF flow rates through the solar field, through the bypass loop, and from the hot tank (Powell et al., 2014). This is due to the hybrid mode which allows the solar field to operate at a lower temperature, reducing heat losses, the demand being completed by the fossil fuel. Such systems have been improved afterwards by Ellingwood *et al.* who added Flexible Heat Integration (FHI) to the hybrid plant (Ellingwood et al., 2020a). They optimized dynamically a concentrated solar tower connected to a Rankine cycle and including three thermal storages. Brodrick *et al.* optimized the operation of an Integrated Solar Combined Cycle (ISCC), which included a parabolic trough solar thermal field and a gas turbine (Brodrick et al., 2017). The hourly operation, in terms of part load of the gas turbine, solar focus rate and mass flow rate of the solar HTF, of representative days was optimized using different objective functions. A proxy model was used to recreate predicted solar output and no storage was considered in this study. The proxy model is a statistical model with fitting parameters determined thanks to a detailed simulation model. This is a data-based model, thus, the dynamics modeling was simplified compared to the previously mentioned studies based on first-principle models. The design and the operation of the same system were then optimized simultaneously for two conflicting objectives: the net present value (NPV) and the average CO_2 emissions intensity of the power produced (Brodrick et al., 2018). Improvements over published designs were achieved and it shows that optimal operation should be considered when designing a system. Finally, an ISCC with storage was optimized in (Orsini et al., 2021) and the benefits of using storage tanks were presented.

This literature review shows the benefits of using offline dynamic optimization and advanced control strategies to operate a solar thermal plant. There are many ways of implementing the optimization of the operation of a solar thermal plant, with their respective advantages and drawbacks. All of these methods are explored in this review: using a first-principle or a data-based model, employing a deterministic or a stochastic optimization algorithm. The implementation differs from one study to the other. This review is focused on the details of the optimization methodology (decision variables, time horizon, sampling time, hierarchical structure etc.) rather than the model construction or the optimization algorithm. The offline dynamic optimization is based on weather and load forecasts, and thus, cannot adapt the strategy to the current situation. If the uncertainty of the forecasts is too high, the optimal trajectories computed cannot be applied to the real plant. Besides, advanced control strategies are mostly used to track the target outlet temperature of the solar field. Some studies show the benefits of maximizing the output power of the field. Nevertheless, economic considerations are not included in most control strategies even though they might improve the operation of solar thermal plants. An intermediary level between control and planning is Real-Time Optimization (RTO). This method uses measurements of disturbances and state variables of the system to update the optimal set-points (Static Real-Time Optimization SRTO) or trajectories (Dynamic Real-Time Optimization DRTO) online. This ensures that the plant continually operates under optimal conditions, even in a variable and hard to predict environment. All the previously mentioned works would be improved by using a DRTO method, as mentioned in (Powell et al., 2013), to adapt the optimal operation to the plant states, solar irradiation and updated forecasts. It is worth mentioning that data-based models and deterministic algorithms are faster to solve, based on the previous literature survey, and therefore constitute a good perspective for real-time optimizations where computational times are crucial. If DRTO has been widely studied in process engineering research, it is fairly new in the field of solar thermal plants, although it seems well-suited to such systems. The next sections will provide detailed explanations on DRTO, along with the few examples of application of this method to solar systems found in the literature.

3. Generalities on Real-Time Optimization

In the aforementioned mathematical formulation of the optimization problem (Equation 1), the disturbances $d(t)$ and the initial state $\mathbf{z}_0$ are not known in advance. If they are supposed to be perfectly known, offline optimization can be performed to compute the optimal set-points/trajectories until the end of the time horizon. In practical applications, disturbances and initial conditions are always unknown and online optimization, also called real-time optimization, has to be implemented. Measurements are then necessary to access to the initial conditions and disturbances values.

RTO is used in research articles in various fields, from electrical systems (Clarke et al., 2018) to chemical processes. Among the latter category, batch reactors are the focus of many works ((Kadam et al., 2002), (Hua et al., 2004), (Alonso et al., 2013), (Arpornwichanop et al., 2005)). These systems are highly nonlinear, always in transient behavior, their process model is not generally well-known and finally only a few measurements are available (Arpornwichanop et al., 2005). Those systems are then very challenging to optimize, explaining the numerous studies focusing on them. Their characteristics are similar to thermal systems such as solar thermal plants, in which both the energy source and the load are time varying. Solar systems are rarely optimized in real-time in the literature. Hence, batch chemical reactors constitute the major resource for this study. Other fields are seldom found in the optimization literature, such as waste water treatment (Elixmann et al., 2010), thermal building (De Oliveira et al., 2013) or district heating and cooling systems (Cox et al., 2019). The next subsections will highlight the role of measurements in RTO, in subsection 3.1, and the association of RTO and control in a plant, in subsection 3.2.

3.1. Measurements

RTO takes process measurements to update the process model and the initial conditions and trigger a new optimization. Thus, it is able to reject unknown disturbances as they appear in the process. This applies even for large and slow disturbances which can have a high impact on the system, whereas controllers generally reject only fast disturbances because of their short time step.

In a RTO study, measurements are used before each optimization run. The measurements are performed directly on the facility to be optimized (Vettenranta et al., 2006), but for research studies a prototype (Alonso et al., 2013), or more often a simulation model, are used to represent the real process and provide feedback measurements. In the latter case, the simulation model may be different than the model used during the optimization step. For example, Hua *et al.* used a reduced model for the optimization and a detailed model for the simulation of their batch reactor because of their different computational costs (Hua et al., 2004). Also, the measurements on the simulation model can include noise and sampling time delay to represent a real process more realistically (Arpornwichanop et al., 2005). Most of the time, the measurements of the system state variables, although the values usually include noise, provide the initial conditions of the optimization problem. In a solar thermal plant, the temperatures, pressures and flow rates could be measured on the plant and provide a feedback to the optimizer and also define the initial state of the plant. These online measurements allow the system to detect and take into account the disturbances. For a solar thermal plant, ambient temperature, wind speed and solar irradiation need to be measured in order to adapt the optimization and control accordingly. In addition, measurements can correct the plant-model mismatch resulting from simplifications in the model formulation due to computational limitations. Generally, the model used in the optimization algorithm includes uncertain parameters which can be estimated through measurements to limit the impact of the uncertainty on the optimum. The set of uncertain parameters to be estimated online is chosen based on the impact of each parameter value on the objective function. The selection of measurements to estimate those key parameters also has to be based on a sensitivity analysis. Indeed, a change in the measurement must accurately reflect a change in the parameter value. A method to choose the set of key parameters and measurements is presented by Krishnan *et al.* (Krishnan et al., 1992).

There are several ways to take advantage of the measurements to correct parameter uncertainties and plant-model mismatch (Chachuat et al., 2009). Estimation techniques are required to determine the parameters and states values from the noisy measurements. Various techniques exist with different minimization criteria (Zhang, 1997). Parameter and state estimation is an essential but complex topic, that could be the focus of a separate paper.

3.2. Economical and control objectives

Optimization is closely associated to control as both are necessary to ensure best economical performance and feasible operation of a process in the presence of disturbances and uncertainties. The objective of a controller is to track a set-point or a trajectory for the controlled variables in the presence of disturbances by adjusting the values of the manipulated variables. This is called a regulatory objective. Optimization tries to find the set-point (static optimization) or trajectory (dynamic optimization) for the controller to track which leads to the best economical performance for the system.

Tracking relies on the minimization of the quadratic error between the set-points determined by the optimization and the measurements performed on the actual system. The two tasks, economic optimization and tracking, can be done in one layer, called EMPC (Economic Model Predictive Control). However, they are generally performed in two distinct layers. On the upper layer, the economic optimization problem is solved, and the set-points/trajectories are sent to a lower layer controller which tracks them and rejects process disturbances. The lower layer can be composed of simple controllers such as PID (Proportional

Integral Derivative) which are generally able to track the value of one output by adjusting one input. This is the case in a real-time optimization study of an evaporative cooling tower for example (Blackburn et al., 2020). More advanced controllers include Model Predictive Control (MPC). These controllers use a dynamic model of the process inside their formulation in order to predict the future behaviour of the system and track the optimal trajectories more efficiently. The MPC system often constitutes a supervisory controller that communicates with the base controllers (PID for example). Although not always necessary, the MPC ensures a better rejection of disturbances.

To summarize this Section, Figure 4 presents the typical architecture of real-time optimization. State variables, y and z are measured on the system, and their measured values y_m and z_m are sent to the validation part of the algorithm. In the validation part, data reconciliation is performed to eliminate random and gross errors from the measurements and the estimated values for y and z, which are $\hat{y}$ and $\hat{z}$, are sent to the next step. The model updater takes the corrected data to estimate unknown model parameters. The new model is then used to update the optimization. The optimizer computes optimal set-points of trajectories for some variables, following a previously determined schedule or plan. If these new set-points or trajectories represent significant changes in optimization variables, which is tested in the condition part of this framework, the reference set-points or trajectories are sent to the controller. The controller compares the reference values to the measured ones and determines the appropriate control moves to track the optimal set-points or trajectories.

Several schemes exist to implement RTO within the general framework of Figure 4. After a short presentation of the original scheme SRTO, DRTO is explained in the next Section.

4. DRTO schemes

The classical scheme to optimize a process in real-time is based on a stationary model. This scheme, referred to as Static Real-Time Optimization (SRTO),

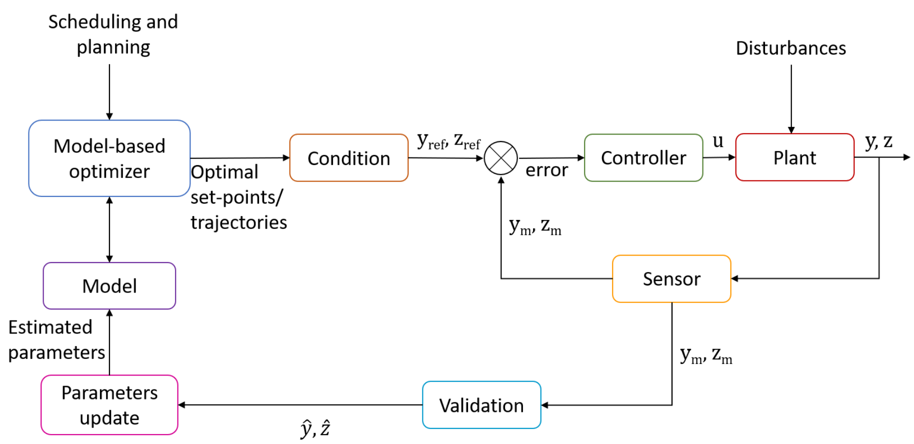

Figure 4: Typical architecture of real-time optimization (based on (Shokri et al., 2009))

allows the re-optimization of the process only when the system reaches steady-state. Measurements are performed at steady-state and the static model is updated before the next optimization is run. The optimal set-points are sent to the lower-level controller, which tracks the optimal constant values of the controlled variables until the next steady-state is reached. A downside of this approach is that the frequency of optimization runs can not be adjusted and is limited to the amount of times the process reaches steady-state. Furthermore, detecting steady state in order to trigger the optimization is not trivial and requires complex detection algorithms (Darby et al., 2011).

Rashid *et al.* performed a real-time optimization of a CSP plant hybridized with a back up fossil fuel burner using a steady-state model (Rashid et al., 2018). The temperature exiting the parabolic trough collector and the split fraction of heat transfer fluid entering the steam generator and the pre-heater were optimized in real-time. The static model used for RTO was an empirical model based on data collected from a one year simulation. The nonlinear model was then complexified in (Rashid et al., 2019a). The detailed model used in simulation and the empirical model used in SRTO were different, introducing plant-model mismatch as in a real application. The data based models were able to predict accurately the total solar power collected for various solar irradiations and ambient temperatures. This nonlinear static model was used in (Rashid et al., 2019b) to optimize the hybrid plant with flexible heat integration. It was shown that SRTO is able to improve the total solar power collected, and hence the solar fraction of the plant, especially when the irradiation is low. Adding Flexible Heat Integration and RTO increases the solar fraction by 18.2%, and the Leverage Cost Of Energy by 3.81% in comparison to the conventional hybrid plant. The CO_2 production also decreases by 4%. In these studies, the solar thermal plant used parabolic trough technology without storage, so the dynamics of the system were all fast (less than 10 minutes). By running the SRTO algorithm every 5 minutes, and adjusting the set-point in the simulation every optimization, the plant was able to stay near optimality.

Hybridization of natural gas with solar energy has also been studied for a Solar Power Tower system. Ellingwood *et al.* showed the improvement in solar energy utilization achieved with hybridization and FHI (Ellingwood et al., 2020b) for a Solar Power Tower system including energy storage. In this study, the operation of the solar thermal plant was based on heuristic control. The preferred mode of operation was determined relative to the incident solar irradiation peaks on the receivers. Dynamic optimization was performed on the same system (Ellingwood et al., 2020a), based on weather forecasts. The methodology is not able to adapt the operation of the plant as disturbances occur in the system, but it provides the optimal operation for known inputs. This study concluded that the heuristic control approach was reliable enough for design and optimization initialization. It also showed that optimization can lead to improved performance of the hybrid plant.

The systems in (Rashid et al., 2019b) and (Ellingwood et al., 2020a) are both hybridized solar-natural gas power plants, even though the solar collectors technologies are not the same. The main difference between the systems from (Ellingwood et al., 2020a) and (Rashid et al., 2019b) was the presence or not of thermal energy storages. TES allows the decoupling between the variable solar resource and the heat supply which aims to be as constant as possible. It can extend the use of solar energy at night and smooth the energy delivery during fluctuating weather conditions. In (Rashid et al., 2019b), no storage was considered, so the dynamics of the different parts of the concentrated solar plant were all fast, allowing the plant to quickly reach steady-state. The use of a static model in a real-time optimization formulation was therefore possible. On the contrary, the three storage tanks in (Ellingwood et al., 2020a), prevent the plant to reach steady-state as the dynamics of the storages are slow while the other systems dynamics are fast. Offline optimization was then preferred, with supposedly perfect weather prediction.

These studies show that SRTO can improve the operation of a solar thermal plant. Since it uses a static model, it needs to be run regularly to adapt the operation to the changes happening in the transient system. A condition to make the use of a static model possible is to have a system with all fast dynamics. Indeed, with fast dynamics, the system will quickly reach steady-state. A disturbance affecting the system's inputs will immediately impact its outputs. Thus, a system with fast dynamics operates in quasi-static conditions with short transitions between steady-states. Computing constant set-point values for the optimization variables is possible. Those values will be optimal until a change occurs in the system or its environment, leading to a different steady-state and requiring a new optimization. On the contrary, if the solar thermal plant includes storage, there is accumulation/inertia in the system. There will be a delay before a disturbance on the system's inputs impacts its outputs. The slow dynamics of the storage and the fast dynamics of the solar collectors, pipes and heat exchangers will prevent the system to ever reach steady-state. It is therefore non-optimal to compute constant values for the controlled variables. Dynamic optimization, which will compute optimal trajectories for the decision variables in the system always operating in transient behavior, is more appropriate. When the inputs, such as solar irradiance, are not known in advance, a real-time scheme is required. Therefore, DRTO seems well-suited to such systems, as it can provide optimal trajectories taking into account process dynamics, while adapting the operation strategy online.

4.1. Single-layer scheme: EMPC

One approach to compute dynamic optimal trajectories in real-time is to perform the economic optimization and regulatory tasks on the same level (Engell, 2007). The economic objective is included into the formulation of the controller. This is generally called Economic Model Predictive Control (EMPC). In this method, the optimization algorithm is run at each sampling time of the controller, which depends on the distubance dynamics present in the system. With this single-layer method, a unique dynamic model is used, ensuring consistency between the economic optimization and the tracking task. The major drawback of EMPC is that the optimization is run very often, which might not be possible for a complete process with a complex model since the computational time would exceed the sampling time of the EMPC. Additionally, the EMPC is not able to handle systems with a wide range of dynamics because its very short sampling time might not be capable of dealing with slow disturbances, such as plant-model mismatch. Finally, stability issues might arise, ensuring best economic performance thanks to the controller is maybe not enough for stability. EMPC are used in some studies, when the process is well-suited for single-layer DRTO, and the model can be simplified without a large loss of accuracy. For instance, Clarke *et al.* used an EMPC to optimize an electrical system containing storage, such as microgrids or hybrid electric vehicles (Clarke et al., 2018). The EMPC performs several tasks: it minimizes the short term economic cost and achieves a reasonable tracking of the storage state trajectories provided by a top-level controller in charge of planning. The use of an EMPC is here feasible because the dynamics of electric devices are very fast and the model used for calculations can be simple. Amrit *et al.* used an EMPC to optimize an evaporation process and a William-Otto reactor (Amrit et al., 2013). The use of a single-layer DRTO was made possible by only considering disturbances with similar dynamics. The sampling time of the controller was then chosen based on this common time constant, 1 minute was used in this study. Finally, Hotvedt *et al.* optimized a CO_2 capture facility with an EMPC (Hotvedt et al., 2019). A reduced model allowed the EMPC to run faster than the sampling time chosen.

EMPC has already been used for solar systems. Serale *et al.* (Serale et al., 2018) and Pintaldi *et al.* (Pintaldi et al., 2019) developed an EMPC for solar systems with storage, with the objective of minimizing backup energy consumption. In (Serale et al., 2018), the performance of a latent heat storage solar thermal system to be used in building is optimized with estimated weather forecasts to represent a real-time implementation. The control time step used in this study is one hour, and the problem is linearized, making the use of an EMPC possible. In (Pintaldi et al., 2019), the system considered is a solar thermal cooling system with storage. A GA is used to solve the optimization problem, based on perfect weather forecasts. The control algorithm was adapted to be used in real-time since the resolution of a nonlinear system is too long. Only the state variables are computed in real-time by the simulation model. The layout of the EMPC is presented in Figure 5, using identical models for the optimization and the simulation.

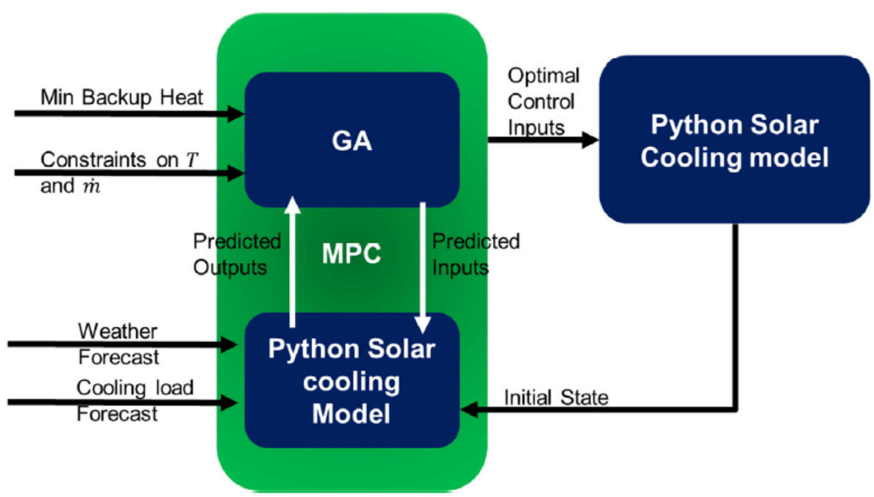

Figure 5: Layout of the EMPC (Pintaldi et al., 2019)

Pintaldi *et al.* highlight the necessity of using a well-tuned EMPC with a system with enough degrees of freedom in order to ensure an enhanced performance of the system thanks to the EMPC control. In their studies, fossil fuel burner energy was reduced by about 10% for the evaluated scenario using EMPC compared to a rule based controller. The authors state that a hierarchical MPC, including a lower layer of controllers, such as PID, to track the set-points, might improve the use of storage. Hierarchical methods with a decoupling of optimization and control will be presented in subsection 4.2.

These were specific examples where the EMPC can solve the optimization problem. In most cases, the complex model involved, the wide range of dynamics in the sub-systems and disturbances and the computational limitations make the single-layer DRTO impractical. In particular, a solar thermal plant including storage presents various time scales and includes highly nonlinear phenomena, so EMPC is not well suited for the optimization of their operation. This observation is bound to evolve with the recent and future computational developments such as methods that take into account the sparsity of the problem and can make the resolution run efficiently.

4.2. Two-layer scheme: DRTO and MPC

Based on the impracticability of the single-layer scheme for complex, large-scale processes, Kadam *et al.* suggested the decomposition of the economic optimization and the regulatory objective on two hierarchical levels (Kadam et al., 2002). This methodology with two layers will be referred as two-layer DRTO in the following parts of the paper. The standalone acronym DRTO is used for the economic optimization on the upper layer. On the upper level, an economic DRTO is performed: optimal trajectories for the process variables are computed to minimize or maximize an economic objective function while satisfying all the process constraints. The DRTO problem is solved repeatedly to update the reference trajectories during the complete time span, taking into account slow disturbances. On the lower level, controllers, often MPC systems, track the reference optimal trajectories. The sampling time of the controllers, noted $\Delta\tilde{t}$, has to be small because the fast process disturbances are rejected at this level. On the other hand, the DRTO does not need to be executed that often and its sampling time, noted $\Delta\bar{t}$, can be larger. The dynamic models might differ between the 2 layers: a detailed model is required for the DRTO to achieve best performance, and a simplified model (sometimes linear) is more suited for the control layer as it has to be executed often and thus needs a short computational time. Since disturbances are rejected on both levels, a time-scale separation needs to be implemented and is schematized in Figure 6, with $\mathbf{z}, \mathbf{y}, \mathbf{u}$ defined in Equation 1. The circumflex accent represents estimates based on the measurements of some state variables $\mathbf{z}_m, \mathbf{y}_m$. The slow-varying and persistent disturbances, noted $\overline{d}$, such as parameter uncertainties, changes in price markets and slow physical disturbances which affect the economic objective are taken into account at the DRTO layer. The controller considers all types of disturbances in its process model, including the fast, stochastic disturbances, noted $\tilde{d}$. The switches in Figure 6 represent the fact that the operations are not performed continuously but at every time step. The estimation of disturbances and parameters from the measurements, and the time-scale separation, can be performed in any order (Würth et al., 2011).

The main advantage of the two-layer DRTO is that the DRTO is executed at a slower frequency, allowing larger computational time and hence, making it practical for real complex processes. A downside is that the models used in the two layers are different and inconsistencies might arise between the two objectives and strategies (Ravi & Kaisare, 2020). Using two layers is the current practice in chemical industries but usually with SRTO on the upper layer. This might change with the future improvements in computational performances.

Such a hierarchical control layout was used in (Gil et al., 2020) to control the start-up procedure of a solar thermal field with storage, with the objective of maximizing the temperature at the top of the storage tank. However, no economic optimization was performed in this study. Berenguel *et al.* also used a hierarchical control architecture to optimize the electricity production of a CSP plant (Berenguel et al., 2005). The set-point optimization layer used a static model and the control layer was based on classic control schemes. An upper layer consisted on a daily and seasonal operation optimization to determine the

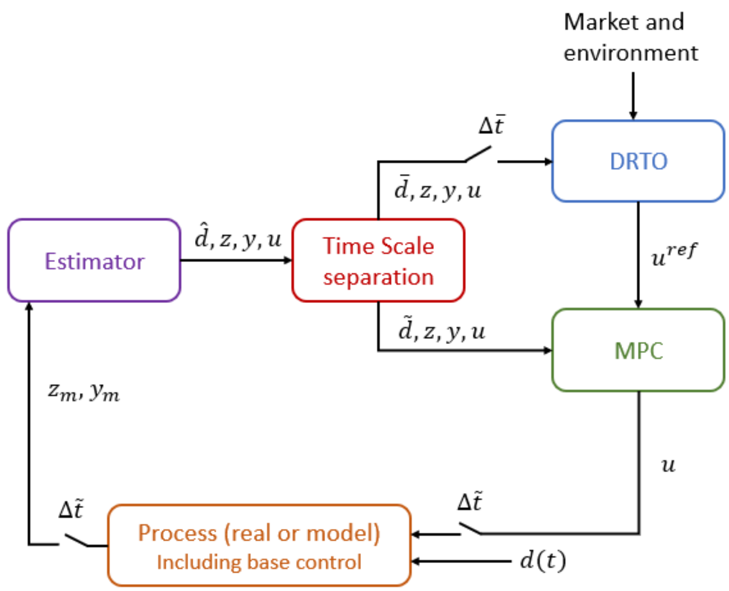

Figure 6: Time-scale decomposition of the disturbances between the DRTO and the control layers (based on (Kadam et al., 2002))

operating periods of the plant based on weather and electricity demand forecasts. These works, although not using an economic DRTO on the upper level, show that the hierarchical structure of the resolution allows the management of storage and a more complex model for the optimization layer. Thus, a two-layer DRTO approach, with a decoupling between the economic optimization and the tracking task, would improve the optimization and control of the solar systems.

Recently, Pataro *et al.* performed a two-layer DRTO of a parabolic concentrator collector field in order to maximize the thermal power energy delivered by the solar field (Pataro et al., 2020b). The economic objective function takes into account the thermal energy produced and the electricity consumption of the pumps. The DRTO algorithm uses measurements of the ambient temperature, solar irradiance and solar field inlet temperature to compute optimal trajectory for the inlet volumetric flow rate. This algorithm is solved repeatedly over a receding time horizon. The results in this paper are promising, the two-layer

DRTO scheme seems to handle correctly disturbances and parameter uncertainties on the irradiance model parameter and the thermal losses coefficient. Even if a complete system with storage and customer load is presented in this paper, only the solar field was optimized in real-time. No other study focusing on the two-layer DRTO of a solar system was found in the literature, but this work confirms the interest of this methodology. The framework presented in (Wagner et al., 2017), and tested in (Wagner et al., 2018), then improved in (Hamilton et al., 2020) seems able to perform the DRTO of the electricity generation in a CSP plant. The methodology was only tested with perfect forecasts but it should be able to adapt the optimal dispatch as disturbances occur in the system. Indeed, the framework already include the CSP controllers and an optimizer, and uses a rolling time horizon. Future work based on these studies could add the possibility to handle uncertainty in weather and electricity pricing forecasts and permit intra-day adjustments to make sure this scheme can be applied on a real facility. For real-time applications, the optimization algorithm needs to run efficiently. One way to achieve that is to use a data-based model, such as in (Brodrick et al., 2017), to model the solar field outputs. This reduces greatly computational time, allowing more frequent optimizations. The model could be adjusted online based on measurements on the real facility or a detailed simulation model.

5. Applications and adaptations of two-layer DRTO

The two-layer DRTO scheme is widely used in chemical engineering research papers and over the last decade, several adaptations have been made to the method presented in the last section, and are detailed in the following subsections 5.1, 5.2, 5.3, 5.4. The last subsection 5.5 shows how to couple a planning phase to the DRTO methodology. This Section focuses on two-layer DRTO since this scheme seems to be the more complete and the more appropriate to optimize the operation of a solar thermal plant. Indeed, the dynamic optimization allows the computation of optimal trajectories, taking into account the various dynamics of the system's components. Additionally, the real-time aspect allows the adaptation of the operational strategy as disturbances occur in the system and can correct uncertainty in weather and demand forecasts. Furthermore, the two-layer scheme allows the rejection of small/fast disturbances that do not necessitate a new optimization. And it also corrects the plant-model mismatch arising from the difference between the simple model used for the frequent optimizations and the detailed model used to replace the real plant for research purposes. Finally, it allows the use of different time horizons and time step sizes in the optimization and the control layers. The methods presented hereafter are a good source of inspiration for future studies on the DRTO of solar systems. The features of the presented algorithms could also be used on studies based on SRTO or EMPC.

5.1. Fast updates and DRTO triggering

Although repetitive DRTO is widely used (in (Hua et al., 2004), (Jamaludin & Swartz, 2016), (Remigio & Swartz, 2020) for example), re-optimization is not necessary at each time step. The previous reference trajectories might still be optimal at the end of the time step if no new significant disturbance appeared and a new DRTO would be computationally expensive and not really useful. A better way to trigger the optimization layer is based on the actual disturbances and is called conditional triggering. When a new optimization is not needed, fast updates of the previous trajectories are sufficient. In the case of small perturbations, linear updates of the solutions are performed and the DRTO is triggered only for large perturbations (Kadam et al., 2003). The DRTO can be triggered based on disturbance sensitivity analysis, which indicates when the Necessary Conditions of Optimality (NCO) are no longer fulfilled ((Würth et al., 2011), (Pontes et al., 2015)). Other studies suggested to re-optimize based on different conditions. Pataro *et al.* state that a new DRTO needs to be triggered when a large perturbation affects the values of the state variables or when a change in the optimization problem such as market prices, operational conditions, etc, appears (Pataro et al., 2020a). Rohman *et al.* ran a new DRTO if the active constraint for the conversion of their final product was violated (Rohman et al., 2019). Ochoa *et al.* listed three different ways of triggering the DRTO: based on a time step, on disturbance analysis and lastly on a value below a threshold for the economic objective function (Ochoa et al., 2009). Finally, some studies mention detecting deviations between the predicted and real variables trajectories and trigger the DRTO when the deviation is too large (Alonso et al., 2013).

5.2. Computational delay

The computational time, noted τ, necessary to obtain the reference trajectories at the DRTO upper level leads to a delay in the real-time implementation of the optimal trajectories by the MPC controllers on the lower level (Pontes et al., 2015). Indeed, during the execution of the DRTO resolution, the state of the system is still under progress. The optimal trajectories computed based on the states measured at time t_n become sub-optimal when implemented in the process at time $t_n + \tau$. Pontes *et al.* suggested to anticipate the need of a new DRTO and predict the state of the system at the time of the new trajectories (Pontes et al., 2015). The DRTO is triggered in advance and when the calculation is finished, the system has reached the predicted state so the reference trajectories implemented are optimal.

When the DRTO is not triggered in advance and there is some computational delay, the previous trajectories are applied during the calculation (Würth et al., 2011). This is the common practice in the literature, but probably not the optimal one.

5.3. Closed-loop two-layer DRTO

Most two-layer DRTO approaches do not consider the presence of the Model Predictive Control (MPC) system in the DRTO problem formulation (Remigio & Swartz, 2020). This traditional scheme can be referred to as open-loop two-layer DRTO. A perfect control is assumed, the hypothesis is that the closed-loop response dynamics will follow the economically optimal trajectories of the

DRTO layer. But it is not always the case, so closed-loop two-layer DRTO was introduced by Jamaludin *et al.* (Jamaludin & Swartz, 2016). In this new formulation, the future MPC control actions are included into the DRTO problem, which means that the control performance is considered when making economic decisions. The DRTO general problem includes MPC optimization subproblems, as presented in Figure 7. In this Figure, a diagram provided in (Remigio & Swartz, 2020), u denotes the inputs of the system while y are the outputs. The entire DRTO prediction horizon N is divided into steps. At each step j, the predicted control moves from the previous step u_{j-1} are fed to the DRTO model in order to compute the actual trajectories for the outputs y_j^{DRTO}. The DRTO plant response provide disturbance estimates for the next MPC calculations. Economic optimization is performed based on these disturbances predictions and new reference trajectories are determined y_j^{ref}. The disturbance estimates from y_j^{DRTO} along with the new trajectories y_j^{ref} are given to the MPC model to compute new corresponding control moves. At the end of the prediction horizon, the last outputs y_N^{DRTO} are used in the economic optimization to compute the set-point trajectories y^{SP} supplied to the plant MPC. The MPC will then determine the control moves to apply to the process u^{MPC}. Finally, the outputs of the process will be measured y^m and sent to the first step of the closed-loop prediction. In Figure 7, scheduling decisions are also included in the DRTO framework.

This closed-loop two-layer DRTO problem can be solved in different ways. In a sequential approach, the optimization determines updated trajectories and then a dynamic simulation generates the closed-loop plant response. These steps are performed iteratively until the minimum of the objective function is reached. This resolution method is used by Pataro *et al.* but they point out some stability and convergence difficulties (Pataro et al., 2020a). The other method adopted in (Jamaludin & Swartz, 2016), (Remigio & Swartz, 2020) and (Li & Swartz, 2019) is the simultaneous approach. The MPC subproblems are transformed into complementary constraints using their conditions of optimality and are moved in the constraints set of the DRTO problem resulting in a single-level

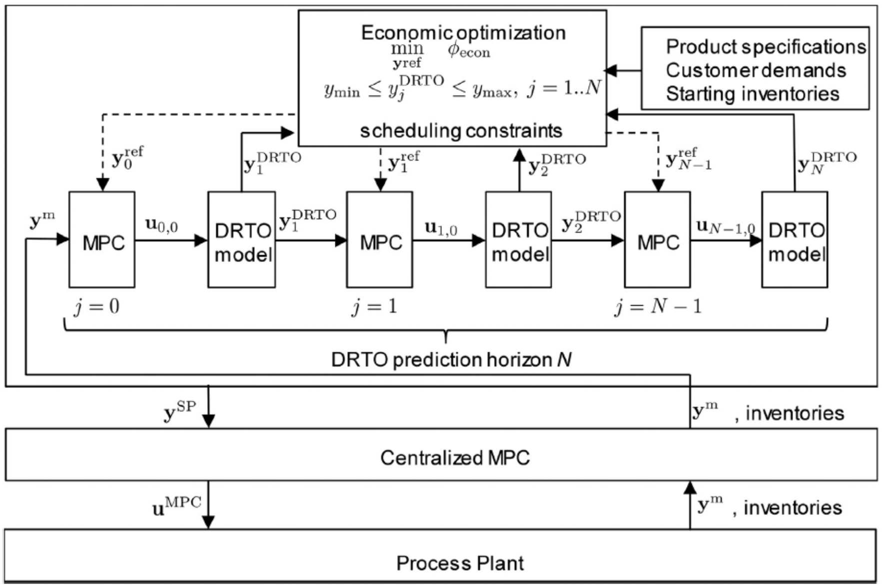

Figure 7: The architecture of a closed-loop two-layer DRTO (Remigio & Swartz, 2020)

mathematical program with complementarity constraints (MPCC). This formulation was improved to include planning decisions (Remigio & Swartz, 2020) or distributed MPC systems for each subsystem of the plant (Li & Swartz, 2019). Although the closed-loop two-layer DRTO scheme performs slightly better than the open-loop two-layer DRTO, it is at the price of higher computational time. This method is still at an early stage of research and its application to a real system has never been tested. Thus, in this review, the focus is made on open-loop two-layer DRTO.

5.4. Multi-objective two-layer DRTO

In a few studies, multi-objective two-layer DRTO is performed. Ravi *et al.* had two hierarchical objectives: the tracking of the quality of their final product and the maximization of the overall profit on plant scale (Ravi & Kaisare, 2020). The tracking objective was formulated in the objective function as the minimization of the squared deviation between the reference and the actual qualities at the terminal point of the time step. The multi-objective problem was solved thanks to the Lexicographic method. The optimal solution for the priority quality objective was retained through an additional constraint for the economic optimization. The Pareto front was generated and the optimal solution was chosen to be the closest to the standalone optimal solution of the respective objective function. Kim *et al.* optimized an energy system with both economic and environmental objectives (Kim, 2020). As in the previous study, the two objectives are here conflicting: an improvement of one objective results in a decline of the second objective. A Tchebycheff weighted metric method was used to find the Pareto optimum without computing the complete Pareto front. Zhang *et al.* optimized the operation of an integrated energy system with several energy carriers (Zhang et al., 2021). Their system included renewable energy sources and the associated uncertainty due to weather conditions. The two levels of optimization had a multi-objective function each: benefits maximization and customer satisfaction for the offline optimization and to limit the deviation from the offline trajectories and to ensure safe operation for the online optimization. An adapted GA was used to solve the multi-objective problems. These works show that it is possible to perform multi-objective two-layer DRTO.

5.5. Coupling between an offline planning and DRTO

The wide range of time scales in a problem sometimes imposes the use of distinct optimization layers. In Section 2, the planning and the RTO levels were introduced. Although both optimization strategies have been applied to solar thermal systems in the literature, there was no coupling between them. Yet, the association of an offline and an online phase could benefit to the operation of a solar system and has been implemented previously for other processes.

For instance, Clarke *et al.* used an upper level planning controller to plan the storage levels of electric systems offline, on a slow time scale, and an EMPC on a lower level controlled the fast dynamics online while performing an economic optimization of the operation of the system (Clarke et al., 2018). The time decomposition was necessary because storage has very slow dynamics compared to the other components of the system and the storage utilization has to be determined on a rather long time horizon to benefit from it. On the other hand, the system presents fast disturbances that need to be rejected on a small sampling time. The architecture of the two layers is presented in Figure 8. In this Figure, $\bar{x}^B$ represents the storage state target set-point and u is the control input.

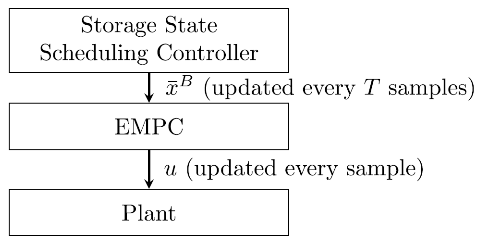

Figure 8: Hierarchical control structure for a system with storage (Clarke et al., 2018)

The upper layer is an offline planning while the lower layer is an EMPC. The storage state targets are the values passed from the offline optimization to the online optimization. Rossi *et al.* also had an offline and an online phases in their optimization of multi-unit batch processes (Rossi et al., 2017). Distinct objective functions were used in the two steps, with an economic objective present in each of the two layers. Some constant key parameters were passed from the offline to the online optimization steps, such as the number of batch cycles. During the second phase, the offline campaign schedule was updated in real-time and optimal control actions were generated. Zhang *et al.* optimized an integrated energy system (WE: We-Energy) including renewable energy sources (Zhang et al., 2021), whose approach is shown in Figure 9. A day-ahead planning was first performed offline, based on the daily energy prices, the renewable energy (RE) forecasts and the energy load. In order to maximize economic profit and customer satisfaction, the shifting of the flexible loads and the amount of energy traded with the networks were determined. Then, real-time optimization balances the renewable energy forecast error thanks to real-time information. A new operation strategy is determined, with some units following the day-ahead plan if they are not flexible enough to be adjusted in real-time. The goal in this step is to minimize the deviation between the day-ahead energy deal plan and the real-time deal.

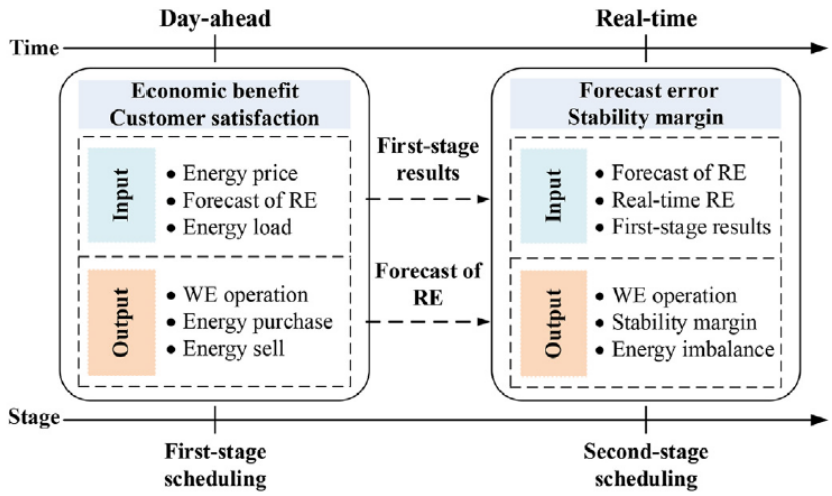

Figure 9: The framework of the optimal planning of an integrated energy system (Zhang et al., 2021)

Here, the uncertainty on the renewable energy forecast is corrected thanks to an online phase. Such a strategy seems perfectly adapted to solar systems.

6. Comparison of the different schemes

The three different real-time optimization schemes presented earlier are summarized in Figure 10, based on a schematic in (Würth et al., 2011), with a possible offline phase. The first scheme, SRTO, will not be studied much further as it only provides constant set-points values and is not well suited to a dynamic system, always in transient state and with various time scales. The advantages and disadvantages of the EMPC and the two-layer DRTO schemes have already been discussed. Caspari *et al.* compared the two schemes for the optimization of a continuous air separation unit (Caspari et al., 2020). The EMPC showed slightly better economic improvements even with a reduced model to decrease the computational requirements. It achieved 0.2 to 2.4 times higher economic

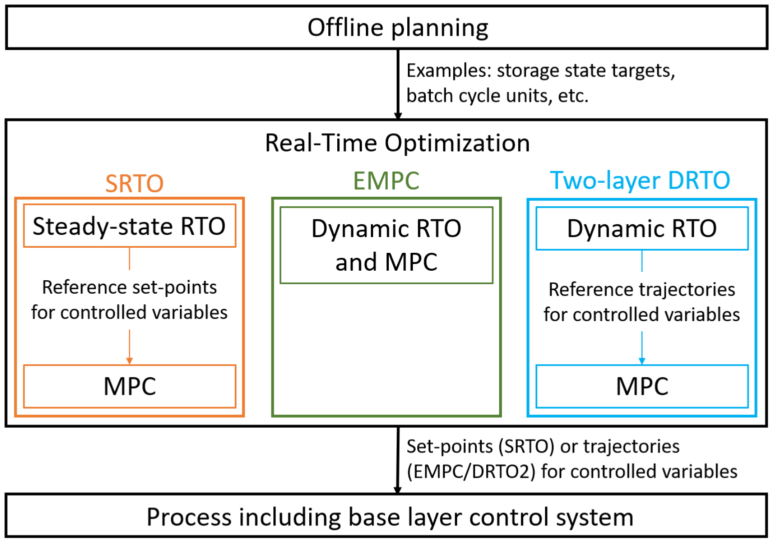

Figure 10: The three different schemes in real-time optimization

performance compared to the improvements of the two-layer DRTO scheme. However, the authors outlined some downsides of choosing the EMPC scheme. First, it requires a new infrastructure to be installed on an existing plant. Also, the EMPC generated more aggressive control moves due to the smaller time step, which can lead to accelerated deterioration of the system components. Furthermore, the two-layer DRTO made a better use of the storage because of its longer time horizon. Given the current computational performances, the two-layer DRTO scheme seems more suitable for the optimization of a large-scale system despite its slightly lower economic improvements.

7. Perspectives on the application of DRTO to solar thermal plants

Based on this literature review, a lack of studies focusing on the DRTO of a complete solar thermal plant is noticed. Most authors performed offline dynamic optimization based on perfect weather forecasts and did not test their methodology online. These papers show the benefits resulting from dynamic optimization, but the methods presented are not readily applicable to a real plant. Indeed, the trajectories are computed based on weather and load forecasts and are not updated online with plant measurements. Thus, the trajectories will probably become sub-optimal and the controllers might not even be able to track them. There are some studies using an EMPC scheme to optimize a solar system, but it required model simplifications and the use of storage was not optimal. A two-layer scheme, composed of a SRTO and controllers, has been used in (Rashid et al., 2019b), but it was applied to a CSP plant without storage. There is only one study in which two-layer DRTO was performed, but it just optimized the operation of the solar field and not the complete solar plant including pipes and storage. Nevertheless, two-layer DRTO seems well-suited to improve the performances of solar thermal plants. Furthermore, if tested using a detailed simulation model, two-layer DRTO should be readily applicable to a real plant since it models both the optimization and the control layers.

The complete optimization strategy that could possibly be used to optimize the operation of a solar thermal plant is presented in Figure 11 and entails a planning phase and a two-layer DRTO methodology. This hierarchical diagram clarifies the different time scales used for each step and the flow of information in the control structure.

The design of the plant and the storage management could be determined offline using weather forecast and planned heat demand (as in subsection 5.5) and sent to the DRTO level (as a market and environment information in Figure 6). The storage planning should be made over a time period ensuring good strategic vision. It might be necessary to compute a new plan before the end of the current one if the forecasts are too inaccurate.

The DRTO layer could take into account the current solar irradiation and load measured on the system and updated forecasts. They would represent the slow disturbances $\overline{d}$ in Figure 6. The optimal trajectories would therefore be adapted to changes in the weather or the load, on an hourly basis for example, or with other triggering methods (see subsection 5.1). The solar irradiation and load forecasts used on the time horizon of the DRTO are updated forecasts. These forecasts will provide accurate but averaged values for the next few hours

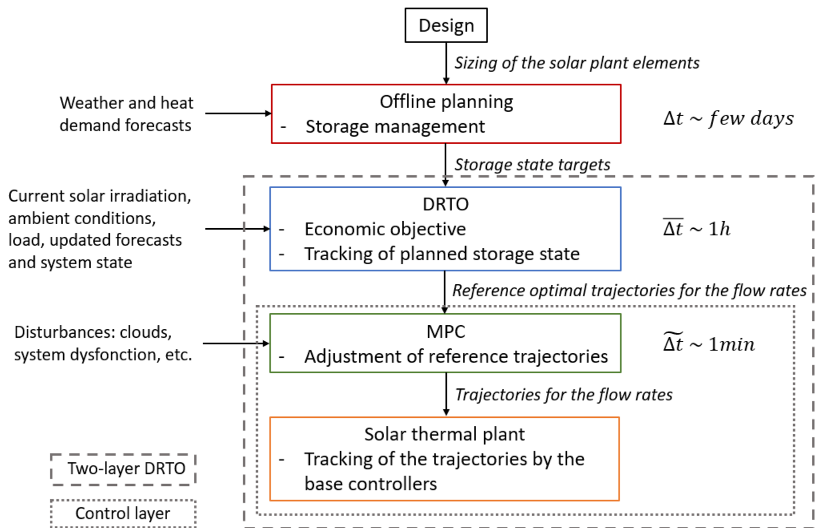

Figure 11: Complete optimization strategy for a solar thermal plant

and they will not be able to predict the actual weather and load with a very precise time step. Finally, the fast disturbances, $\tilde{d}$ in Figure 6, such as cloud movements, would be handled at the MPC level. The averaged solar irradiation used in the DRTO level will be less variable than the actual irradiation, which is affected by clouds moving fast in the sky. Solar thermal plant could benefit from DRTO to correct weather forecast uncertainties and achieve a smoother and enhanced energy supply. To summarize the proposed methodology, Figure 12 is the system diagram from Figure 4 adapted to a solar thermal plant, given as an example of a possible scheme for the optimization of the operation of such systems. The measured outputs are the temperatures and flow rates in the system, as well as some environmental parameters, such as solar irradiation (noted DNI for Direct Normal Irradiation in Figure 12). An example of an estimated parameter in this application is the heat transfer coefficient in the heat exchangers.

Future works should focus on the two-layer DRTO of solar thermal plants and assess the benefits of using this methodology compared to standard control strategies or offline dynamic optimization. Since two-layer DRTO includes con-

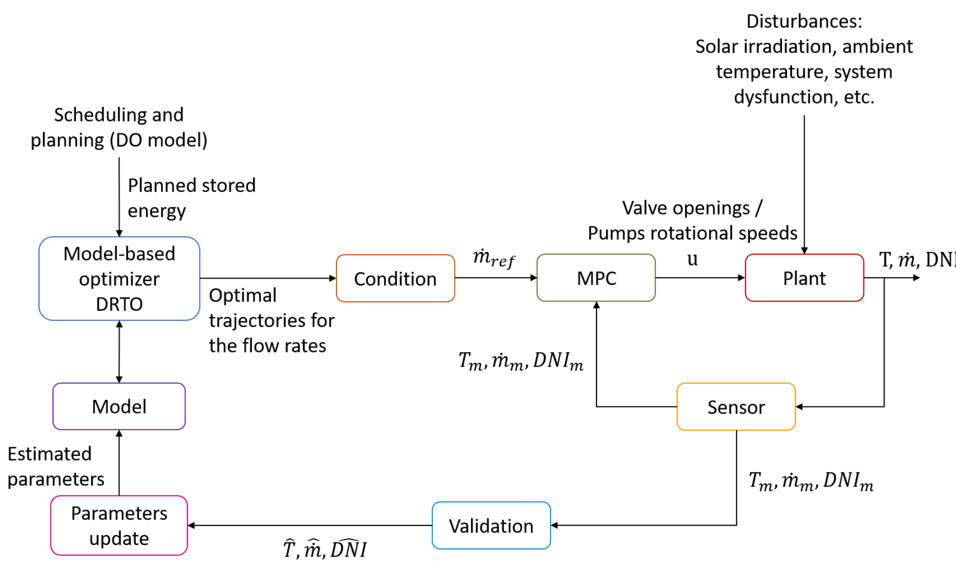

Figure 12: Control diagram for the optimization of a solar thermal plant

trol, work could also be done to improve controllers, which track the optimal trajectories, in terms of uncertainty handling and disturbance rejection.

8. Conclusion

This review is focused on the mathematical optimization of the operation of a solar thermal plant, and particularly on the heat production and storage. It shows that dynamic optimization is often carried out in research papers to minimize the cost of the solar thermal plant operation. Optimal trajectories are computed for the decision variables in the system, taking into account the various dynamics of the components of the plant, such as the solar field and storage tank, and the variable environmental conditions. Improvements in the performance of the solar thermal plant, in terms of solar utilization and costs, are achieved thanks to dynamic optimization. However, the uncertainty in weather and demand forecasts cannot be corrected with an offline optimization. Thus, the dynamic optimization methodologies are not readily applicable to real plants. This review then presents the different schemes of real-time optimization which appears to be a powerful tool to control a process and maximize its benefits. The measurements performed on the actual system allow the optimization algorithm to represent accurately the system and its environment at the current time and thus to provide regularly updated optimal set-points or trajectories. The control layer track these reference set-points or trajectories in the presence of disturbances. The analysis work conducted in this paper shows the potential of two-layer DRTO in association with a planning phase to optimize the operation of a solar thermal plant. The analysis is based on research articles in chemical engineering, where two-layer DRTO is studied in depth. This review provides perspectives on the application of two-layer DRTO to solar thermal plants with details on its possible implementation. Future research should focus on the DRTO of solar thermal plants, including control, in association with a planning phase, to reduce their operating cost, help to meet the heat load and cut down the fossil fuels consumption in heat production.

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