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Revenue Optimization for Dynamic Operation of a Hybrid Solar Thermal Power Plant

Dibyajyoti Baidya, Mani Bhushan*, and Sharad Bhartiya

Indian Institute of Technology Bombay, Department of Chemical Engineering, Powai, Maharashtra, India
* Corresponding Author: mbhushan@iitb.ac.in

ABSTRACT

Solar Thermal Power Plants (STPPs) use solar energy for large-scale electricity production but face significant operational challenges. These include variations in solar radiation, cloud cover, electricity demand fluctuations, and the need for frequent shutdowns if energy storage is inadequate. Deciding an optimal STPP operating conditions is challenging due to these factors. While revenue maximization has been used as an objective in existing literature, current models are often static and fail to capture the dynamic nature of STPPs. In contrast, this work proposes a dynamic model-based revenue optimization approach that accounts for plant dynamics and operational constraints, such as solar radiation variability and changing electricity demand. The objective function is designed to maximize revenue while considering power generation and fluctuating electricity prices. A simulation model of 1 MWe hybrid solar thermal power plant in Gurgaon, India, featuring two solar fields—Parabolic Trough Collector (PTC) and Linear Fresnel Reflector (LFR), is chosen as a case study. The optimization focuses on the oil mass flow rate through the PTC, which influences steam production. The mass flow rate of oil side is optimized at discrete time intervals, forming the decision variables in a nonlinear programming problem (NLP). The results demonstrate the effectiveness of this approach in significantly enhancing the STPP's revenue.

Keywords: Optimization, Dynamic Modelling, Parabolic Trough Collector, Linear Fresnel Reflector

INTRODUCTION

In recent years, there has been a global push to commercialize renewable energy sources as an alternative to fossil fuels. Among these alternatives, solar energy has gained considerable attention due to its abundance, widespread availability, and minimal carbon emissions. Solar energy is a key source for generating electricity, harnessed through photovoltaic (PV) systems and solar thermal power plants (STPPs). PV Systems convert sunlight directly into electricity, while STPP use mirrors or lenses to concentrate sunlight, generating heat that drives turbines to produce power [1]. Specifically, STPP captures the direct normal irradiation (DNI) of the sun, concentrates it onto a receiving surface, converts the absorbed heat into mechanical work, and subsequently produces electricity, typically through advanced thermodynamic power cycles. STPP is an environmentally friendly technology that offers significant potential for energy conservation and environmental protection [2].

To unlock the full potential of an STPP, several studies have focused on optimizing the operation of STPP from various perspectives. Simon et al. [3] explored the techno-economic optimization of low-temperature solar thermal plants ($< 100\,^{\circ}C$). Alix et al. [4] introduced dynamic real-time optimization (DRTO) with an emphasis on improving storage management and reducing operating costs and excess energy delivery. Antonio et al. [5] proposed solutions to boost sales revenue by optimizing turbine inlet temperature and prioritizing energy production during high sales price hours, particularly in low solar radiation months. Luigi et al. [6] focused on maximizing revenue in solar thermal plants with limited storage capacity through optimal control. Sun [7] developed a self operation and low-carbon scheduling optimization model, demonstrating that thermal storage improves power generation capacity and revenue. However, no previous work has specifically addressed revenue optimization based on electricity cost fluctuations in an STPP while incorporating dynamic nature of plantwide operations.

This paper presents a revenue optimization strategy for a dynamic plantwide solar thermal plant, focusing on electricity production in response to time varying electricity demand and solar radiation variability. Thus, unlike traditional methods that focus solely on performance optimization, this approach considers both supply-side factors (solar energy availability) and demand-side factors (market prices) to determine the optimal electricity production levels. Since the operation of STPP is highly complex and nonlinear, finding an optimal operating strategy in presence of the different kind of variations in these factors can be challenging. Therefore, in the current work, an optimization approach is proposed for the same.

In this study, we focus on a 1 MWe (or 5 MW thermal) Hybrid STPP (HSTPP) located at the National Institute of Solar Energy (NISE), affiliated with the Ministry of New and Renewable Energy (MNRE), Government of India (GoI), situated in Gwalpahari, Gurgaon (28°25′N, 77°09′E), India [7, 8, 9]. The HSTPP system employs parabolic trough collectors (PTC) and linear Fresnel reflectors (LFR) as its main energy concentrators, contributing to its hybrid nature. No previous reports on an optimization study exist for this system. However, dynamic models of various components of this HSTPP are available in literature [10], and hence we have selected this plant for our study.

The rest of the paper is organized as follows: PLANT OVERVIEW section provides a description of the various components of the (HSTPP). METHODOLOGY outlines the approach and techniques used to address the problem formulation. RESULTS AND DISCUSSIONS presents the outcomes from the case study, followed by CONCLUSIONS AND FUTURE SCOPE.

PLANT OVERVIEW

Plant components

Figure 1 illustrates the schematic of the Gurgaon HSTPP [9, 11]. This plant has five primary components. These components along with the corresponding dynamic model as available in literature [10] are briefly discussed below:

- Concentrator: Parabolic Trough Collectors (PTCs) are efficient and reliable collectors in STPP systems, utilizing an absorber tube with heat transfer fluid (HTF) flowing through it. The absorber tube is enclosed by a glass envelope to minimize heat losses, while solar radiation is focused by a parabolic reflector [9, 11, 12]. In contrast, Linear Fresnel Reflectors (LFRs) use fixed ground-based mirrors and a water-steam mixture, lowering costs and simplifying maintenance [13]. The PTC model includes three partial differential equations (PDEs) for temperature profiles, whereas the LFR model involves five PDEs for mass, momentum, and energy balances [13].
- Energy storage: Thermal energy storage is crucial for STPPs, enabling power generation during cloudy periods or nighttime by storing heat in fluids such as molten salts or thermal oil [15, 16]. The HSTPP in Gurgaon uses two relatively low-capacity oil storage units namely high temperature (HT) and low temperature (LT) tanks to enable plant operation for 10-15 minutes during low solar availability [9]. Both the tanks are modeled by two ordinary differential equations (ODEs) each.
- Heat Exchanger: The heat exchanger in an STPP transfers thermal energy between fluids, enabling steam generation for turbine and electricity production [17]. The HSTPP at Gurgaon uses multiple heat exchangers such as pre-heater (PH), steam generator (SG) and super-heater (SH), with the PH and SH modeled by two ODEs each for fluid outlet temperatures and the SG described by five ODEs considering various system variables [9].
- Steam Drum: The steam drum (SD) separates the two-phase flow from LFR tubes into liquid water and vapor, with the liquid recirculated and reheated in the LFR receiver, while the steam is pressurized and sent to the SH for turbine operation [7, 9]. The drum dynamics are modeled using five ODEs [9].
- Turbine & Generator: The turbine generates power by utilizing the pressure difference between high-pressure steam from the SG and the low-pressure condenser, driving the turbine blades and generating electricity through the connected generator [8]. The power output is calculated using Willan's line equation, as described in the literature [7, 9].

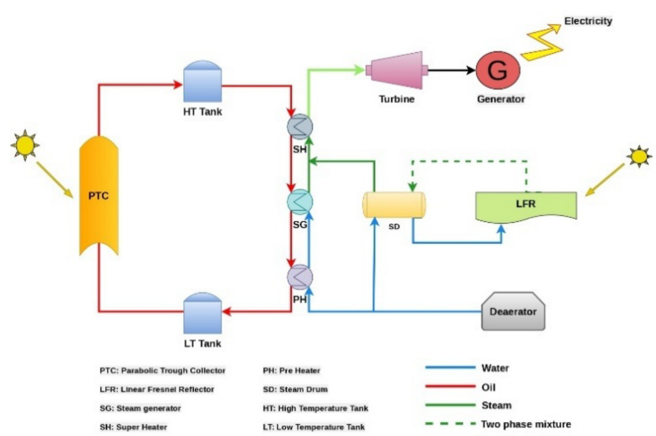

Figure 1. HSTPP block diagram.

The overall HSTPP model is comprised of a total of 58 ODEs (without LFR and SD) after conversion of PDEs to ODEs via spatial discretization. The LFR side (LFR+SD) is modeled by a total of 1,20,005 ODEs but is decoupled from the PTC loop. The dynamic model has been preliminarily validated using field data [10] and is considered in the current work.

HSTPP standard operating procedure

Apart from the differential equations representing the dynamic behaviour, the HSTPP operations also involves discrete decisions corresponding to connections between various components. These are necessitated due to the daily startup and shutdown requirement of the plant. For example, at startup, when the PTC oil outlet temperature is lower than the HT oil temperature, the HT is bypassed, and the oil flow path follows LT-PTC-LT. However, when the PTC oil outlet temperature reaches or exceeds the HT oil temperature, the HT is integrated into the loop, and the flow path shifts to LT-PTC-HT-LT. Similarly, the various heat exchangers (SG, SH, PH) are brought inline when appropriate conditions are met [10].

METHODOLOGY

Proposed approach

The electricity price fluctuates throughout the day based on various factors, particularly market demand, thereby opening up the possibility of increasing revenue by intelligently varying the plant operation. In this context, the oil flow rate through the PTC in an HSTPP emerges as a critical decision variable since it ultimately affects revenue generation as shown in Figure 2.

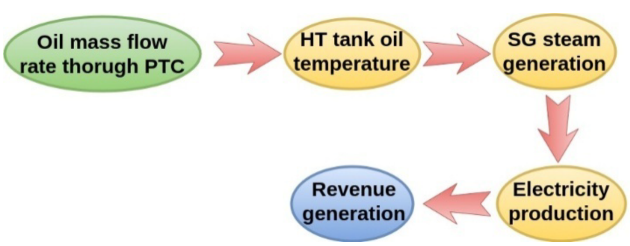

Figure 2. HSTPP block diagram.

This work focuses on developing a strategy to maximize revenue by dynamically adjusting the oil flow rate in response to market price fluctuations and solar radiation variations. For the current study, plant operation in a 10-hour window (8 AM - 6 PM) is considered. The corresponding electricity price is assumed to be proportional to the reported electricity demand [16] on a typical day, and is depicted in Figure 3(a). It is seen that the price varies across 15 minute intervals. Also, the real-time solar insolation data has been taken from a typical summer day at the plant site in Gurgaon, India, specifically from May 14th, 2014 [12] for our simulation as shown in Figure 3(b).

Proposed formulation

The objective in our work is to determine the optimal oil mass flow rate through the PTC loop during daytime operation of HSTPP, so to ensure maximum revenue from electricity generation while adhering to the operational constraints of the HSTPP. This revenue optimization

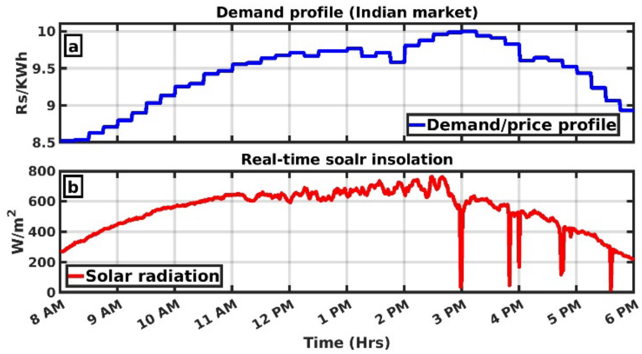

Figure 3. (a) Realtime electricity demand profile [16]. **(b)** Realtime solar insolation profile [10].

problem is defined as Formulation 1:

Formulation 1:

$$\max_{u(t),\ t_0 \le t < t_f} \int_{t_0}^{t_f} W_{PB}(t)P(t)\ d(t) \tag{1a}$$

$$\text{s.t.} \quad \dot{\tilde{x}} = \tilde{f}\big(\tilde{x}(t), u(t), s(t)\big) \tag{1b}$$

$$u_L \le u(t) \le u_U, \quad \forall\, t_0 \le t < t_f \tag{1c}$$

where the objective function (Equation (1a)) represents revenue generated by HSTPP in a day, and Equation (1b) represents the dynamic model of the HSTPP. Further, W_{PB}: Power generation from turbine (MW), P: Price per unit of electricity generation (Rs/MWh), $\tilde{x}$: State variables of HSTPP, u: Decision variables (manipulated inputs), namely PTC oil flow rate ($\dot{m}_{oil,PTC}$) that can be adjusted to influence the states in the optimization problem with upper and lower bound u_L and u_U, s: Solar radiation profile, and t_0 and t_f correspond to the period over which optimization is performed. Since $u(t)$ is a continuous variable, this is an infinite dimensional optimization problem. Further, the plant model involves a large number of nonlinear differential equations coupled with discrete connection operations. This makes Formulation 1 computationally tough to solve. Thus, we make the following simplifications to make the problem tractable:

- **Control Vector Parametrization:** We approximate the decision variable (DV) profile $u(t)$ by discretizing it over time, such that: $u(t) = u(t_p)$, for $t_p \le t < t_{p+1}, p = 0,1,..,P-1$, where P is the number of discretization intervals. Thus, the manipulated variable trajectory is approximated as a piecewise constant function over each time interval.

- **Decoupling of LFR+SD Loop:** The LFR+SD operation is not affected by the PTC oil flowrate. Hence, we precompute the profile of steam ($r\ (t)$) generated by LFR+SD loop for the given solar insolation profile (Figure 3(b)). The dynamic equations corresponding to LFR+SD are then excluded from the model and instead $r(t)$ profile is used. The resulting dynamic model thus comprises of 58 ODEs with states represented as vector x.
- **Numerical Integration of Model Equations:** The dynamic model equations cannot be solved analytically. Hence, they are integrated numerically within the optimization formulation.

With these simplifications, Formulation 1 is reformulated as follows:

Formulation 2:

$$\max_{u(t_p),\ p=0,1,..,P-1} \sum_{j=1}^{N} W_{PB}(t_j)P(t_j)\Delta t \tag{2a}$$

$$\text{s.t.} \quad x(t_{j+1}) = \int_{t_j}^{t_{j+1}} f\left(x(t), u(t_j), s(t_j), r(t_j)\right) dt + x(t_j) \tag{2b}$$

$$u(t_j) = u(t_p), \quad for \quad (p-1)M \le t_j < pM \tag{2c}$$

$$u_L \le u(t_p) \le u_U, \quad p = 0,1,\dots,P-1 \tag{2d}$$

Equations (2b,2c) are written for $j = 0,1,\dots,N-1$. Equation (2b) corresponds to numerical integration of the HSTPP model other than the LFR+SD component, with step size $\Delta t = 1$ minute. Model-equation integration and objective function evaluation is done at 1 minute interval to capture the significant dynamic variations in the plant. However, if the DV u were to be determined at each 1 minute of time interval, the dimensionality of the problem would increase significantly, making it computationally very complex to solve. To mitigate this issue, the DV u is held constant using zero-order hold over a time period $M = \frac{t_f - t_0}{P}$. Specifically, for each interval of M minutes, $u(t_j)$ remains the same. This approach reduces the dimensionality of the problem while still capturing the dynamic variation of the system over the given simulation period.

Solution strategy

Formulation 2 is a nonlinear programming (NLP) optimization problem. Further, the constraints are not explicit due to the need for numerical integration of model equations within the optimizer. The model equations are nonlinear, and non-differentiable at finite time instants, due to presence of discrete variables within model equations. Genetic Algorithm (GA), a popular meta-heuristic approach, are suited for solving such problems and are used in the current work.

RESULT AND DISCUSSION

Case Study

We consider three cases, each focusing on the revenue optimization problem but with varying number of DVs. These cases aim to explore the impact of adjusting key operational parameter, namely PTC oil mass flow rate ($\dot{m}_{oil,PTC}$) on the overall revenue generation in presence of varying electricity prices (Figure 3(a)) and solar radiation (Figure 3(b)). The study aims to identify optimal strategies for maximizing the HSTPP plant revenue under different levels of operational complexity.

The HSTPP stops electricity generation if the HT tank oil temperature drops below $300^\circ C$ for 5 minutes which leads to plant shutdown [9]. As solar radiation decreases at the end of the day, the temperature of the HT tank begins to fall. Consequently, the total plant runtime will vary for different oil mass flow rates.

The GA relevant parameters are listed in Table 1.

Table 1: GA-relevant parameters for case study.

Parameter	Value
Population size	100
Number of generations	50
Elite count	2
Lower (u_L) and upper (u_U) bound	2,5 kg/sec

Case-1 ($P = 1$):

In this optimization problem, a single DV is used, i.e., representing a simplified scenario for analysis. Throughout the 10-hours simulation period, the oil mass flow rate through the PTC loop is kept constant, regardless of the varying electricity demand. The optimizer determines the optimal mass flow rate as $\dot{m}_{oil,PTC} = 2.7\ kg/sec$, with corresponding revenue being $Rs. 25{,}636$ for the $8.8\ hrs$ of plant run. In contrast, the designed oil mass flow rate $\dot{m}_{oil,PTC} = 3\ kg/sec$ as reported in literature [9], would correspond to revenue of $Rs. 24{,}462.5$ for $7.2\ hrs$ of plant run (results not shown here). This revenue value is taken as the base case for comparison.

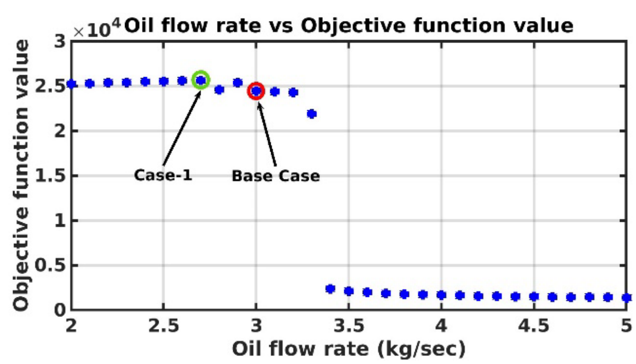

Figure 4. The validation of optimal value for Case-1

Validation of Case-1:

To validate the optimizer results, we computed revenue for 30 different constant mass flow rate values in the range $2-5\,kg/sec$ (Figure 4). The Figure demonstrates the optimality of the GA obtained solution, despite the highly nonlinear and non-differentiable nature of the model equations.

Case-2 ($P = 10$):

This case considers 10 DVs, offering more degrees of freedom. Here, while the mass flow rate is held constant for each hour starting from 8 AM to 6 PM for the 10 hrs of simulation, the flow rates across different hours can be different. The optimizer generated mass flow rate profile for this case is shown in Figure 5. The corresponding generated one-day revenue amounts to $Rs.\,25730.2$ for the daytime plant run of $8.76\,hrs$.

Comparison of Case-1 and Case-2:

The power generated for these cases are depicted in Figure 6(a). It is seen that power generation profile for Case-2 is marginally higher (see Figure 6(a) inset) during the day. However, it is significantly higher during the beginning (9-9.30 AM) which leads to larger revenue. To understand this difference, consider Figures 6(b), 6(c).

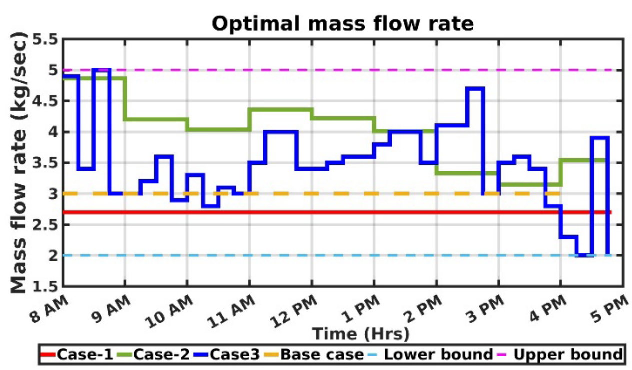

Figure 5. Optimal mass flow rate of oil for the three cases

The plant operation for both cases corresponds to warm startup where the plant has been operating for several days prior to the simulation. The corresponding starting temperatures are: HT tank: $306^\circ C$, LT tank: $240^\circ C$, and the PTC oil temperature: $30^\circ C$. During the initial start-up phase, only the PTC and LT tanks are connected since PTC oil outlet temperature is lower than HT tank oil temperature. In Case-1, the mass flow rate of the oil is $2.7\,kg/sec$ while it is $4.9\,kg/sec$ for Case-2 in the initial period. This leads to faster rise of PTC oil temperature in Case-2 due to injection of higher flowrate from the LT tank which is at higher temperature than the PTC oil temperature. This way of operation, namely injecting higher flowrate in the beginning, is non-intuitive but has been discovered by the optimizer to result in higher revenue generation. Further examination of Figure 6(b) and Figure 6(c) reveals that Case-2 maintains a lower HT oil outlet temperature ($T_{(o,o,HT)}$) throughout the 10-hours simulation but exhibits a higher oil mass flow rate (Figure 5) compared to Case-1. This increased flow rate results in a higher steam flow rate from the SH to the turbine in Case-2 compared to Case-1 leading to higher power generation. This demonstrates that optimizing the DVs can enhance the performance of HSTPP.

Case-3 ($P = 40$):

We also considered a case with 40 DVs where oil flow rate change is allowed every 15 minutes. This led to revenue of $Rs.\,25895.7$ (8.75 hrs of plant operation) which is higher than that obtained in Case-1 and Case-2. Thus, an increase in the number of DVs offers greater opportunity to increase revenue generation. However, optimizing this case is considerably more complex. For the sake of brevity, detailed results for Case-3 are not presented here.

For our problem we also tried the gradient-based method 'fmincon' (MATLAB inbuilt function). However, the results were inferior to those obtained by GA.

Performance metrics

Various performance metrics for the three cases are listed in Table 2. From this Table, it is seen that Case-3, with larger number of DVs, demonstrates the best performance in terms of both energy output and economic benefit. Specifically, considering a single, 10, and 40 DVs optimization strategy yields a revenue increase of $4.80\%, 5.18\%,$ and 5.86% compared to the base case. These findings highlight the critical role of optimizing key operational variables to enhance the revenue generation of STPPs. Also, the significant computation times for the three cases indicate that the problem is computationally intensive to solve.

Table 2: Performance metrics for case study.

Parameters	Base Case	Case-1	Case-2	Case-3
Steam generation from SG (kg)	9548.5	9989.4	10134	10488
Steam Generation from LFR (kg)	17535	18660	18645	18632
Total steam produced (kg)	27083	28649	28778	29120
Electric energy produced (MWe)	2.54	2.66	2.68	2.69
Duration of power generation (hrs)	7.2	8.8	8.76	8.75
Revenue (Rs.)	24462	25636	25730	25895
% revenue increase (over base case)	-	4.80	5.18	5.86
Computation time (days)	-	6	6.5	7

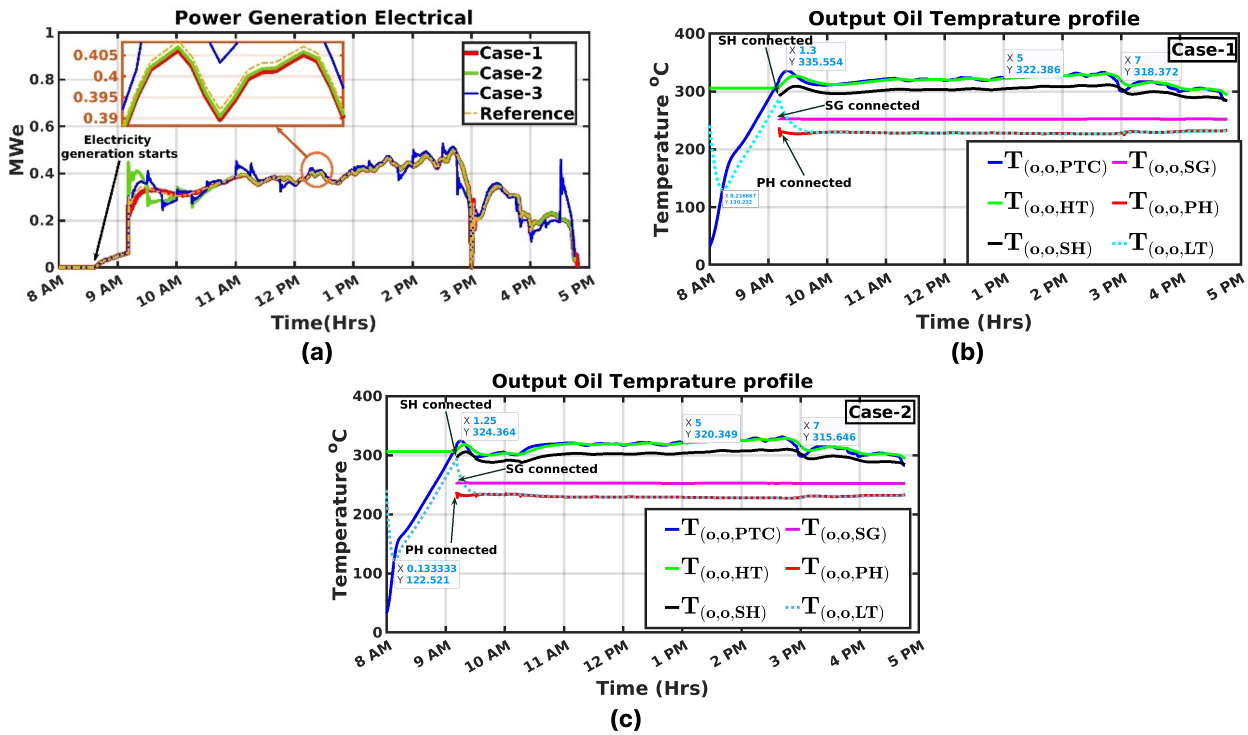

Figure 6. (a) Electricity generation profile for various cases, (b) Case-1 HSTPP oil profile, (c) Case-2 HSTPP oil profile. Here $T_{(o,o,K)}$ is represent the oil outlet temperature (ºC) of component K, K ∈ {PTC,HT,SH,SG,PH,LT}.

CONCLUSION AND FUTURE SCOPE

This paper presents an NLP revenue optimization approach that accounts for plant complexities such as solar radiation variability, fluctuating electricity demand, and process dynamics. The results demonstrate that increasing the number of decision variables (PTC oil flowrate variations) offers greater flexibility in plant operation, which in turn enhances performance and revenue for the HSTPP. The results underscore the importance of integrating dynamic models and optimization techniques to increase profitability of HSTPP by improved operation without any capital investment. In future, other operating variables such as mass flow rates from the HT tank and SD, can also be optimized to further increase revenue generation. Further, the current optimization approach servers as proof-of-concept and can be scaled up by applying it to STPPs with much larger production ratings.

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