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Development and implementation of a model predictive control system for a solar parabolic trough plant influenced by an advanced meteorological disturbance model

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Renewable energy is critical to conserve resources and provide a secure environment for generations to come, and the most common and abundant of these is solar energy. India hopes to reach 500 gigawatts of non-fossil fuel power by this decade, and solar systems are likely to contribute prominently to this goal. Solar based generation is clean, pollution free, and important for national energy security, while solar thermal collectors form the core of such systems. A widely used concentrating solar power technology is the parabolic trough collector, which shows nonlinear behaviour and is disturbed by changes in input energy, requiring advanced control methods. A weather disturbance model was developed in this study using local data from Tamil Nadu, India, and evaluated under three control schemes: Predictive functional control, proportional–integral–derivative, and model predictive control. The findings indicate that model predictive control regulates outlet temperature more effectively, limiting peak overshoot to 6.67% with a settling time of 3600 s. In contrast, predictive functional control recorded 25% overshoot, while proportional–integral–derivative control showed 43.33% overshoot. The state-space-based weather disturbance model also provided closer tracking of set values compared with the other approaches. Predictive functional control produced a quicker transient response but with significant overshoot, the proportional–integral–derivative scheme delayed in reaching the target, while model predictive control maintained steady and consistent stability. All controllers had a delay of about 30 to 60 s, but model predictive control provided the best overall balance of disturbance rejection, settling time, and tracking accuracy.

Keywords Disturbance model, Model predictive controller, Solar trough plant, System identification

With countries grappling with the progressively unsettling properties of climate change which are mostly the result of anthropocentric development efforts, renewable energy acting an increasingly important part in providing electricity and energy. India's INDC sets a new objective to raise the nation's proportion of non-fossil-base mounted electric capacity to 40% by 2030 [1]. Since the 1980s, using renewable energy sources has become a fantastic habit. Specifically, the most abundant renewable energy source is solar power. Control techniques have proven to be pretty operative in floating the competence of solar power facilities. Among the initial uses of solar energy were solar thermal power plants. Photovoltaics' are solid-state systems that directly translate solar energy into electrical energy. Geothermal and wind energy can also be used to generate electricity. Concentrating solar power systems, on the other hand, do not require the complex silicon manufacturing processes found in PVs, deep drilling required in geothermal systems, or the need to maintain grease on turbine housings at high elevations above ground found in wind power system [2].

Concentrated sun power, or CSP, is the energy produced by solar power systems that employ solar concentrators to transform solar radiation into heat, which is subsequently transformed into electricity. Photovoltaic (PV) and CSP systems use quite distinct technologies. CSP facilities focus a significant amount of solar thermal energy,

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or sunshine, onto a small area using mirrors or lenses. The deployment status of CSP worldwide and in India is outlined in Table 1, based on Refs.[3–5].

Solar energy systems have two key drawbacks: (a) the subsequent energy charges are not inexpensive at this time, and (b) solar energy is not continuously accessible when needed. Control is one of the strategies that have been the subject of general research in an attempt to address these shortcomings [6]. Numerous research and development projects have been underway globally to optimize the use of solar energy and reduce associated expenses. One promising technology for the future is concentrated solar power. In a recent study, the International Energy Agency (IEA) projected the cost of solar thermal power relative to other renewable energy technologies and concluded that, in the long run, solar thermal power will be among the least expensive.

Presently, power plants with a volume of over 3600 MW are in operation globally. Approximately 2500 MW are now being built, while 10,000 MW have been announced globally. The Middle East, Morocco, Spain, the USA, and Germany are the places where CSP plants have been effectively erected. Numerous nations have CSP plants under construction [7].

Solar potential in India

As per the ongoing projects, India's capacity to generate power from coal might rise from approximately 200 GW in 2018 to 300 GW by 2030. India's coal-fired power conveniences produce a considerable quantity of particle air pollution under current functioning situations. By switching to renewable energy sources in place of coal-fired power plants, which will also lower GHG emissions, health risks associated with these facilities can be avoided. Adopting renewable energy would be encouraged by taxing coal-generated electricity at a rate that accounts for the cost of health damages [8]. Coal is the only finite energy resource available in large amounts in India. In contrast, oil and gas reserves are severely depleted. The Indian population is experiencing an increasing number of negative environmental externalities as a result of coal's dominance in energy generation. Ash disposal and air pollution in major cities, which are largely caused by coal-fired power stations, are having a particularly damaging impact on the environment. Furthermore, coal mining has resulted in numerous environmental issues, including land degradation, water contamination, and solid waste difficulties. In numerous situations, coal mining has resulted in the displacement of entire villages[9].

Understanding India's energy future is essential to comprehending the country's role in reducing global greenhouse gas emissions, but projections based on the country's development paths are highly influenced by the future proportion of coal versus renewable energy and the characteristics of energy demand[10]. The International Energy Agency predicts that after 2020, India will import the most oil of any country. In actuality, imports of crude oil are the main reason for India's current account shortage. However, of the 600,000 villages in India, about 100,000 are still without electricity[9]. In light of this, renewable energy skills are most adapted to close the break among supply and demand, either as off-grid electricity or as a substitute for grid extension. Furthermore, distributed or decentralized methods of cooking and heating, such as rooftop SPV systems, biogas plants, and solar water heaters, have become important in towns and cities as well as villages[11].

According to a March 2011 report on green telecommunication by the Telecom Regulatory Authority of India (TRAI), India has over 3.10 lakh telecom towers, using 2 billion liters of diesel fuel a year and producing 5.3 million tones of CO2. However, using solar energy might cut carbon emissions in addition to saving fossil fuels. As a result, the government intends to concentrate on encouraging solar telecom towers[12].

Figure 1 illustrates India's installed capacity. It is evident by looking at this image that conventional sources are the main source of electricity generation in this area. Thus, now is the moment to quickly transition to renewable sources.

Over the past few decades, concentrated solar power (CSP) technology has gained increasing consideration as a viable option for utilizing solar energy. The government of India launched the Jawaharlal Nehru National Solar Mission (JNNSM) in January 2010, which gave the country's efforts to create CSP-based solar thermal power generation a significant boost. India's geographic location makes it an excellent place to use solar energy; with 300 bright days on average each year, the country obtains 1600–2200 kWh/m^2 of solar radiation yearly, or an appraised 6 billion GW of potential. However, based on the supposition that just 3% of a state's total wasteland is utilized for the construction of solar power plants, the National Institute of Solar Energy (NISE) has calculated the nation's overall solar energy potential to be about 750 GW. With a threshold Direct Normal Irradiance (DNI) value of 1800 kW h/m2, the projected potential for solar thermal power generation is 756 GW, and with a threshold DNI value of 2000 kW h/m^2, it is 229 GW[13].

The two primary advantages of using solar thermal power plants to generate electricity are the decrease of fossil fuel consumption and the mitigation of climate change. Many countries are concerned in solar thermal

Region / Country	Installed Capacity (MW)	Under Construction (MW)	Announced Capacity (MW)	Citation
Global	3600 +	2500	10,000	[5]
India	228.5	1000	5000	[4,5]
Spain	~ 2300	200	1000	[5]
USA	~ 1700	800	2000	[5]
Morocco	~ 580	1000	2000	[5]
China	~ 500	1600	5000	[5]

Table 1. Global and Indian Concentrating Solar Power (CSP) Deployment and Potential.

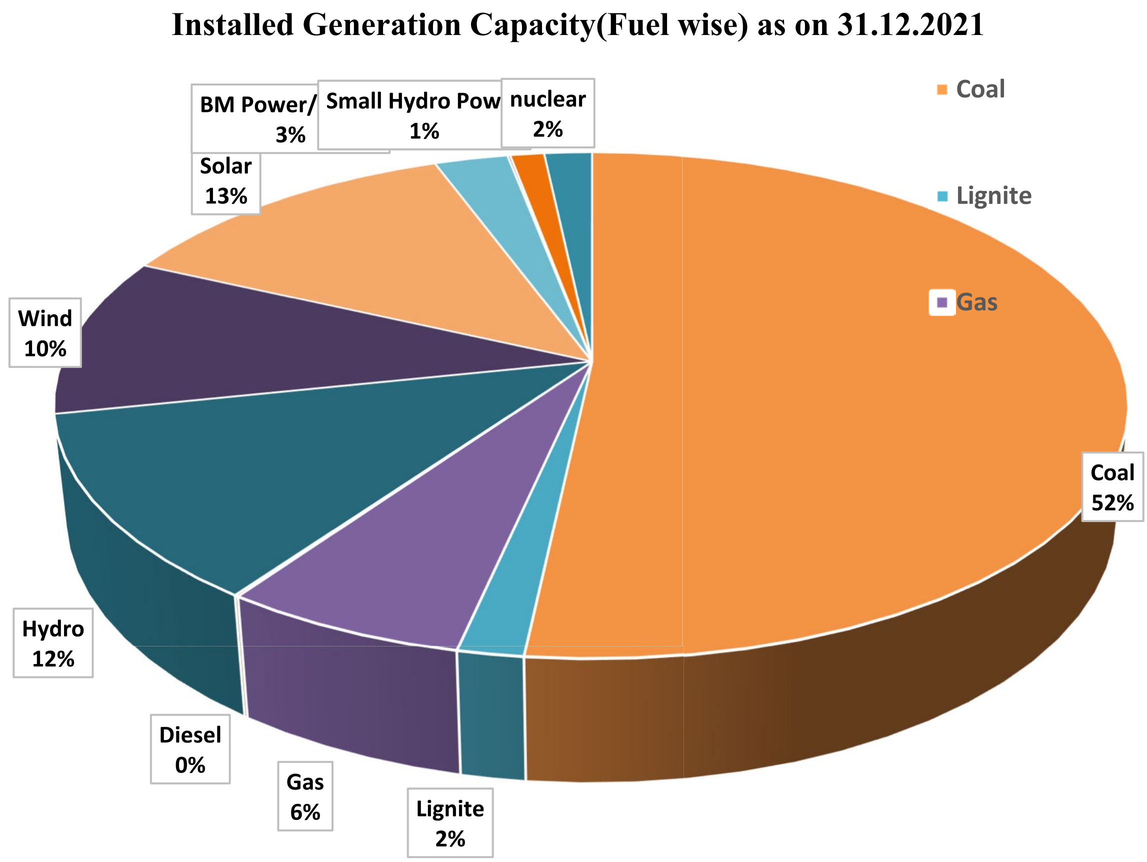

Fig. 1. Installed generation capacity in India by fuel type.

power plants for the generation of energy since one of the most important benefits of using solar thermal power is that power is produced for the similar cost per kilowatt through the year after construction[14].

Solar potential in Tamil Nadu

Tamil Nadu emits more CO2 than any other state (268.3 kg for urban areas and 139.6 kg for rural areas), these aims help to promote sustainable development by lowering CO2 emissions. To inspire the use of renewable energy sources, government incentives, renewable energy certificates (RECs), and stringent regulations are necessary. The growth strategies are presented on multiple fronts in Vision Tamil Nadu 2023 as mentioned in Fig. 2. Reforms in the energy sector will be carried out gradually to ensure that consumers benefit from innovation and competition. The expected overall investment in the energy sector is < 4,50,000 crore[15–17].

Tamil Nadu experiences yearly variations in GHI of 4.82 kWh/m^2 to 6.05 kWh/m^2 and DNI of 3.82 kWh/m^2 to 5.71 kWh/m^2. It is evident that the solar insolation fluctuation over the area is sufficient. One of the most diverse electricity markets in India is found in Tamil Nadu. The State's need for electricity has grown quickly, and this trend is predicted to continue in the years to come. A significant increase in the installed generating capacity is necessary to meet the State's rising electricity consumption. There is a discrepancy between what is truly planned and what is accomplished since there are numerous obstacles to overcome during implementation. Tamil Nadu currently has an average power consumption of between 14,500 and 15,500 MW. With an installed capacity of 31,894 MW, Tamil Nadu has the most diverse portfolio of electricity generation in India to meet this demand. This portfolio consists of 28% coal-based power plants, 50% renewable energy, and 28% from coal-based power plants including shares from central generating stations, 5% from nuclear power plants, 3% from gas power plants and 14% through Long term and Medium-term Open Access and Captive Power Plants (CPP)[15,18].

Among the arid or uncultivable land, 0.492 million hectares of Tamil Nadu's 13 million hectares total area have been recognized as solar hotspots. For several sites, the plant's yearly power generation has been estimated. An economic analysis of the facility has been conducted, taking into account both the environmental advantages and the levelized energy cost of the plant. An atlas for standalone solar parabolic trough power plants based on DSG and oil has been developed and is proposed for use in different parts of India. Whereabouts It is estimated that Tiruchirappalli, Tamil Nadu, will generate 11,956 MWh of power per year[18].

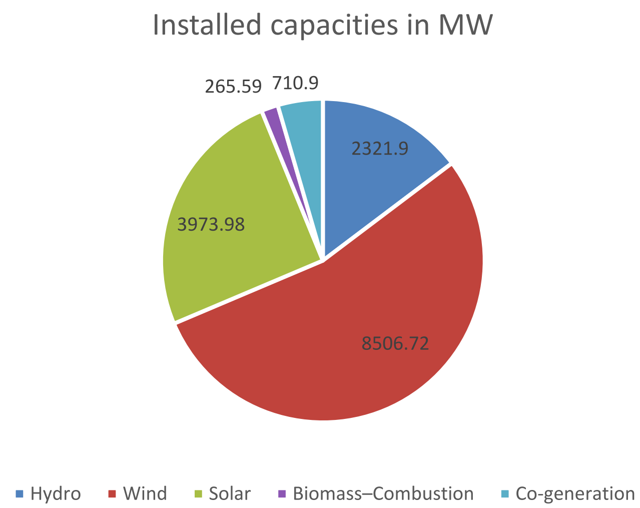

Fig. 2. Installed generation capacity in Tamil Nadu by fuel type.

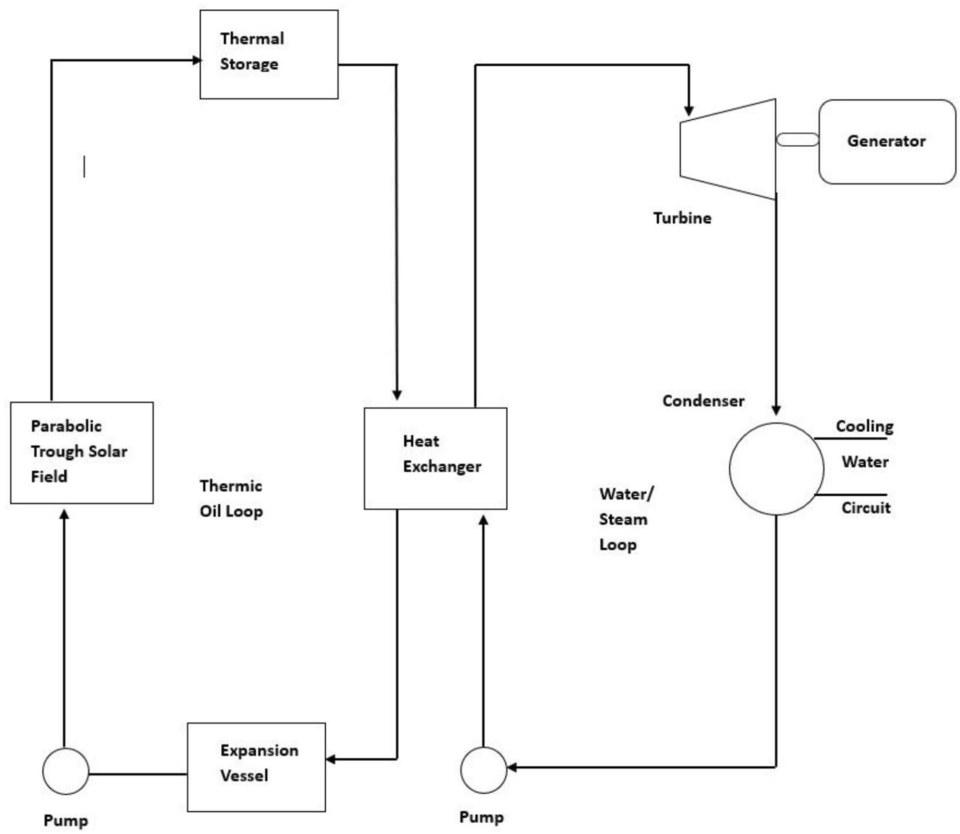

Fig. 3. Schematic of a solar parabolic trough plant.

Parabolic trough plant description

Electricity produced from sunshine is known as solar power. Indirect methods, such as concentrating solar power (CSP), which uses the sun's energy to boil water and generate electricity, or direct methods, like photovoltaics (PV), are also possible. Figure 3 shows the solar parabolic trough plan.

Parabolic trough power plants focus direct solar radiation onto a tubular receiver using parabolic trough collectors. Thermal energy from large collecting fields powers a steam turbine, which in turn powers an electric generator. Parabolic troughs can be utilized to generate energy as well as process heat for industrial processes. Varying temperatures call for varying amounts of process heat. In the chemical, food, and textile industries, for example, the majority of the process heat required is needed in the medium temperature range of 80 to 250 °C.

The modelling and simulation of engineering systems has grown dramatically as computing technology and power have advanced. Computing tools have been widely used in the modelling and simulation of PTSC systems, allowing for analysis and performance optimization. Furthermore, unlike experimental investigations, modelling does not incorporate uncertainty—but must include simplifications/assumptions and delivers a plethora of knowledge for the task at hand[19].

Parameters affect PTC performance

The design, construction, and materials utilized in a parabolic trough collector all have a considerable impact on its performance. The structure of the parabola, reflectivity of the mirror incidence angle, tracking errors, tube intercept factor, absorptive of the receiver, receiver tube misalignment, and heat loss from the receiver all have an impact on PTC performance. Some publications reviewed the parabolic trough collector technology in terms of construction, reflector, receiver development, storage technology, control methods, and varied power generation cycles[20–24].

A solar plant differs from a normal power plant primarily in that its major energy source is uncontrollable, although being changeable. Along with seasonal and daily cyclical fluctuations, meteorological factors including cloud cover, humidity, and air transparency also affect the intensity of solar radiation. As a result, a solar power plant must address certain issues that other thermal power plants do not face. Maintaining the field's outlet HTF temperature (or the maximum outlet HTF temperature attained by one of the collectors at each sampling time) at a predetermined level in the face of disruptions like variations in the level of solar irradiance is the goal of the control system in a distributed solar collector field[25]. Most of the authors discussed improving the efficiency of the trough plant by adjusting the inlet flow rate, and tracking mechanism and by modifying the design parameters of the collector also receiver. Many literatures concluded that the performance of the PTC system is affected mainly by Location (Weather), Mass flow rate, Controller type and Working fluid (water, mix of water and ethylene glycol).

Control problem

Maintaining the field outlet temperature at a desirable level in the face of variations, primarily in solar radiation, field inlet temperature, or ambient temperature, shifting cloud cover is one of the process's most difficult tasks. This can be effectively managed by adjusting the HTF's volumetric flow rate using sophisticated control techniques as shown in Fig. 4. Because the solar field is subject to numerous disturbances and complex dynamics, achieving this goal is not an easy undertaking. The control signal (oil flow) has a significant impact on the transport delay; solar plant control becomes more challenging at low flow.

The uncontrollable nature of solar radiation, the core energy source, is a basic characteristic of solar power process. Apart from its seasonal and daily fluctuations, the intensity of solar radiation is also influenced by atmospheric factors like humidity, air transparency, and cloud cover see Fig. 3. The fluid's output temperature must be able to be consistently maintained even when solar conditions change, and this can be done by adjusting the fluid's flow[26–30].

Many factors affect the performance of PTC plants despite the plenty of articles discussing improving collector efficiency by adjusting the inlet mass flow rate. This article considers impact of weather, cloud cover and cloud amount over the performance of PTC plants. Simulations were carefully carried out in MATLAB/Simulink R2023a by using one fixed sampling rate of 1 s to properly capture transient behavior without adding excessive computational cost. PTC system model was thoroughly validated against experimental reference data reported in Ref.[31], showing one root mean square error (RMSE) of 2.8 °C for outlet temperature prediction, which is fully within acceptable proper limits. Model Predictive Control (MPC) parameters were tuned in systematic manner, with prediction horizon of 20 steps, control horizon of 5 steps, and weighting factors of 1.0 for output error and 0.2 for control effort, thereby ensuring fast convergence and stable regulation under disturbance conditions. Primary components of proposed system mainly include one parabolic trough collector (aperture area 500 m^2, optical efficiency 0.74), one synthetic oil heat transfer fluid loop (mass flow rate 1.5 kg/s, operating range 150–400 °C), and one thermal storage tank with capacity of 2 MWh. As result, one weather disturbance model was

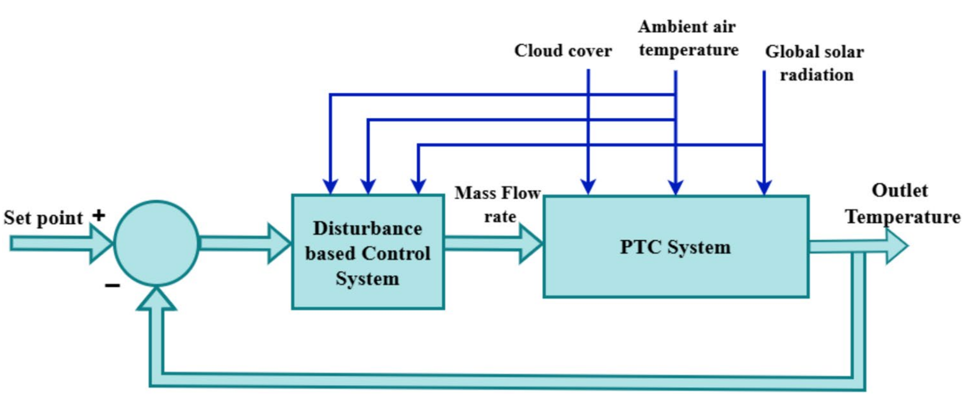

Fig. 4. Control system configuration for a PTC plant.

carefully developed by using MATLAB System Identification toolkit with user-defined parameters. Proposed disturbance model is mainly based upon cloud cover, cloud amount, and air temperature.

For parabolic-trough collector fields, a variety of control algorithms have been presented. Model Predictive Control (MPC) is one of the most popular in the literature due to its ability to handle nonlinear behaviours and limitations, as well as the receding horizon that enables it to account for future outputs. Many academics have worked hard over the past 25 years to increase the efficiency of solar thermal power plants with distributed collectors from the perspectives of optimization and control. In this work a weather disturbance model-based MPC controller is developed for Parabolic trough collector illustrated in Fig. 5.

Recent works on solar PV systems have mainly emphasized proper performance optimization, practical grid integration, and steady material advancements, while solar thermal studies have mostly focused on overall energy efficiency, long-term sustainability, and material-based gradual improvements. Although these important contributions clearly highlight visible progress in renewable energy technologies, they remain largely application-specific and do not fully address dynamic control under continuously fluctuating weather conditions. In case of CSP, most existing research mainly centers upon system design and thermal energy storage, with very limited exploration of advanced modern control strategies carefully tailored for Indian climatic conditions. Moreover, majority of CSP control studies still employ conventional traditional methods such as PID or fuzzy controllers, which often fail to properly cope effectively with nonlinear system dynamics and sudden weather disturbances. This visible gap clearly underscores strong need for advanced approaches such as Model Predictive Control (MPC), which can simultaneously handle proper system constraints, predict external disturbances, and improve overall reliability in CSP practical applications. This present study directly addresses this particular gap by developing and also evaluating one MPC-based control framework for CSP operation under realistic weather differences in India.

The major contribution of this present study is proper development of one weather disturbance model by using regional climate data from Tamil Nadu, India, and also its careful integration into control of parabolic trough collector systems. The proposed framework very systematically compares three different controllers—predictive functional control, proportional integral derivative control, and model predictive control—under same identical conditions, thereby ensuring one fair performance evaluation. The main novelty of this present work mainly lies in combining real weather-based disturbance modelling together with advanced predictive control for solar thermal systems, which is clearly different from existing earlier studies that often rely upon simplified or very generic disturbance assumptions. By presenting direct clear numerical comparisons, this study strongly demonstrates that model predictive control provides lower peak overshoot, faster proper settling, and stronger disturbance rejection, thereby advancing available control strategies for improving overall efficiency and long-term reliability of solar thermal power plants.

Mathematical modeling of parabolic trough plant

System identification

Linear black-box models are attained from parameter identification by many authors for control resolutions. The process of modelling dynamic systems with input and output data is known as system identification. After the model is generated, it can be used to simulate the process or system or utilized to regulate the constraints of the relevant control loop to achieve the desired process performance. Data for the process variable and control variable for the system you want to identify is put into a dataset in the Continuous Trouble Shooter. The sample period for the data of the process and control variables. The same rate of sampling for the control and process variables.

A user will not be able to construct a model if the process variable or control variable has bad-quality data mapped to it. Engineering system modelling and simulation have grown significantly as a result of advancements in computing and processing capability. In this section, the mathematical model of the solar field is presented.

It is well acknowledged that a LTI causal system can be designated by its impulse response.

$g(\tau)$ as follows:

$$y(t) = \int_{\tau=1}^{\lambda} g(\tau)\, u(t-\tau)\, d\tau \tag{1}$$

We therefore assume y(t) to be detected at the sampling instants $t_k = k\tau$

$$y(kT) = \int_{1}^{\tau} g(\tau)\, u(kT-\tau)\, d\tau \tag{2}$$

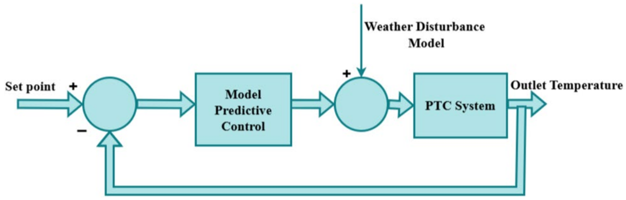

Fig. 5. Model Predictive Control framework for PTC system.

Inserting (2) into (1)

$$\begin{aligned} y(kT) &= \int_{\tau=0}^{\tau} g(\tau)u(kT-\tau)d\tau = \sum_{l=1}^{\infty} \int_{\tau=(l\text{-}1)T}^{t} g(\tau)u(kT-\tau)d\tau \\ &= \sum_{l=1}^{\chi} \left[\int_{\tau=(l\text{-}1)T}^{t} g(\tau)\, d\tau\right] u_{k-l} = \sum_{l=1}^{\infty} g_T(l)\, u_{k-l} \end{aligned} \tag{3}$$

$$g_T(l) = \int_{\tau=(l\text{-}1)T}^{ir} g(\tau)\, d\tau \tag{4}$$

The above equation represents sampled instants and it is sufficient to calculate the output for the input. for most of the time assume T is one time unit and use t to compute the sampling instants

$$y(t) = \sum_{k=1}^{\infty} g(k)\, u(t-k)\,,\ t = 0, 1, 2 \tag{5}$$

Rendering to relationship (5), the output can be precisely ascertained if the input is known.

Most of the time, this is not true. Signals outside of our control always affect the system. At the output regarded as a disturbance, we assume that these effects can be compounded to form an preservative term v(t). The most distinctive characteristic of a disturbance is that its precise magnitude is unknown in advance. However, in order to make informed predictions about future values, past disturbance data can be essential.

$$y(t) = \sum_{k=1}^{\infty} g(k)\, u(t-k) + v(t) \tag{6}$$

Let $v(\tau)$ be given as

$$v(t) = \sum_{0}^{\infty} h(k)\, e(t-k) \tag{7}$$

We introduce the forward shift operator q and backward shift operator q-1 then we can write Eq. (6) as

$$\begin{aligned} y(t) &= \sum_{k=1}^{\infty} g(k)\, u(T-k) = \sum_{k=1}^{\infty} g(k)(q^{-k}u(t)) \\ &= \left[\sum_{k=1}^{\infty} g(k)\, q^{-k}\right] u(t) = G(q)u(t) \end{aligned} \tag{8}$$

Since

$$G(q) = \sum_{k=1}^{\infty} g(k)\, q^{-k} \tag{9}$$

The prototype of a 5.77 m aperture and 80.2 rim angle of a PTC system with an Evacuated Receiver (ER) and Non-Evacuated Receiver (NER) available at IIT Madras was modeled for this study. The ARMAX ,transfer function and State space models created for PTC system with the best model fit and its comparison were shown in Fig. 6. Single-input/single-output (SISO) data was used to estimate and evaluate the linear models in order to determine which one best captured the dynamics of the system. By observation of the system step responses of first- and second-order transfer function models were measured suitable. The data produced by the high-order discrete simulation model was subjected to standard estimate techniques based on least squares. However, determining transfer function model parameters that could be trusted to any extent proved to be quite challenging.

Weather disturbance model

A weather disturbance model is a Process of approximating or projecting future procedures, drifts, or results based on historical data and numerical models. The solar parabolic trough system's solar thermal output is highly reliant on the weather, despite its advantages. This creates unpredictability in the production of electricity, which leads to supply and demand imbalances in energy, power fluctuations, and voltage stability risks. Forecasting solar irradiance has been used extensively to lessen this uncertainty[32,33].

Accurate weather prediction is crucial for many industries, such as aviation and agriculture. Additionally, lives may be impacted by how accurate hurricane and other major storm forecasts are. Mathematical weather forecasts are produced by combining the most recent weather measurements with equations that define the physical laws governing atmospheric events. Weather forecasting has significantly improved over the past few decades because to developments in mathematics and statistics, mathematical modeling, enhanced integration of weather monitoring data, more efficient computation, and the capacity to quantify prediction uncertainty. Generally speaking, the following elements may be preferred to develop a weather model: Air temperature, cloud cover, net radiation, and worldwide solar radiation[34]. The percentage of the sky that is typically covered by clouds when viewed from a specific place is referred to as cloud cover (also known as cloudiness, cloud age, or cloud quantity). Clouds are essential to the diurnal cycle and climatic system in several ways. Thus, cloud cover is crucial to the energy balance of the atmosphere, and changes in it are both a cause of and a result of

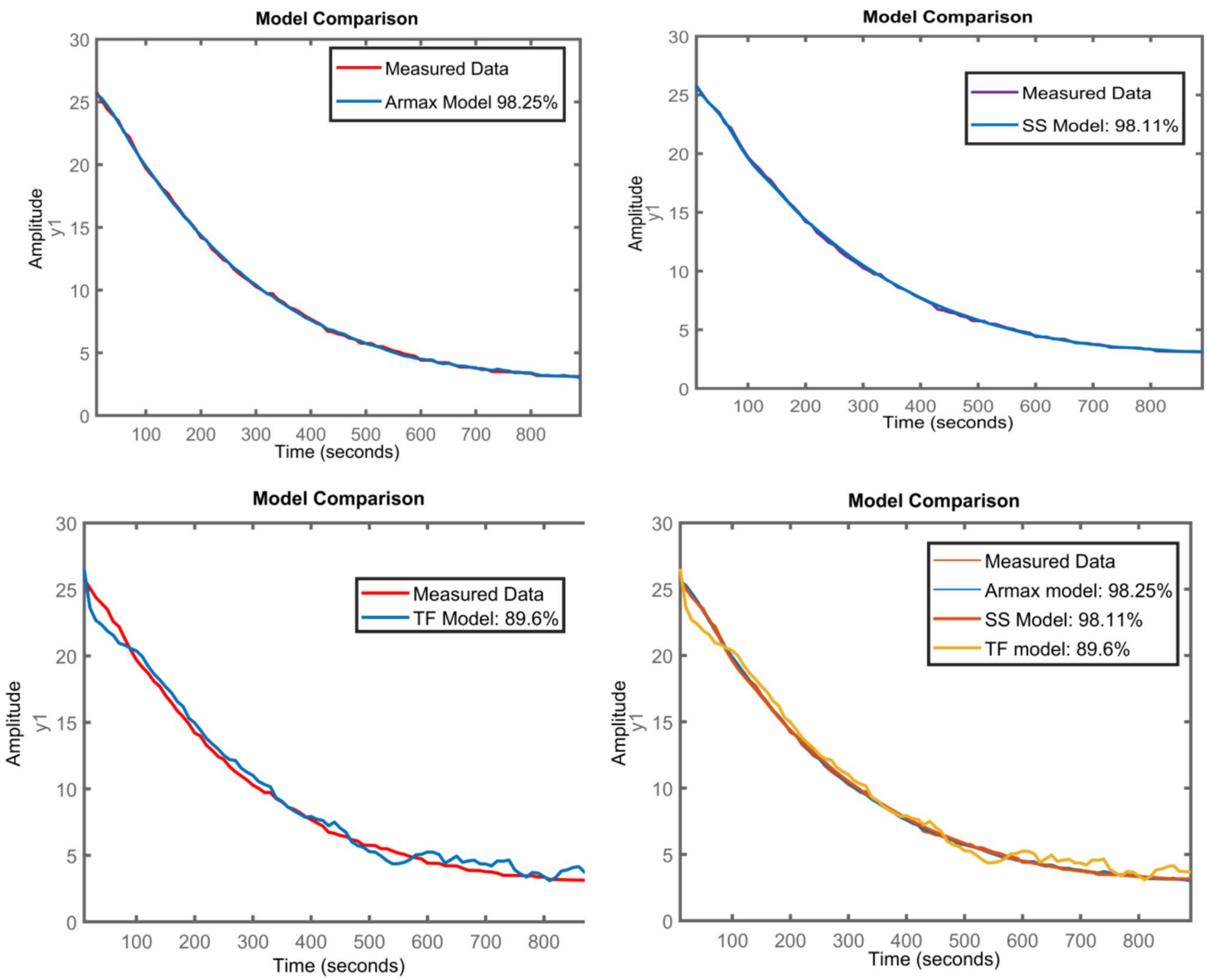

Fig. 6. Comparison of control models (ARMAX, State Space, and Transfer Function).

the anticipated climate change in recent research. The researchers concluded that temperature and cloud cover are inversely related to one another and directly proportional to humidity. In other words, humidity rises with increasing cloud cover, and temperature falls with increasing cloud cover. The first-order homogeneous Markov model was developed by the observation of 15 years of Cloud cover data[35].

Changing the climate and weather is primarily seen as deliberate effort to affect natural processes in the ECS. These acts' goals are frequently stated in broad, ambiguous language, which makes the anticipated outcomes quite unpredictable and uncertain. Weather and climate simulations rely on highly intricate and nonlinear models. However, the assumption that the system is roughly linear for small perturbations can be used to investigate a number of nonlinear system features. The closed-loop idea is taken into consideration by the transfer function for weather and temperature control operations[36]. Understanding the dynamics of a regulated system as well as the relationship between disturbance and process output is essential for designing an efficient compensator. If the transfer function describes the system and disturbance dynamics, then the ideal compensator is created by dividing these two functions by opposite signs[37].

The primary reason of the sharp variations and decrease in DNI intensity is the clouds. Thus, for short-term DNI prediction, the real-time clear-sky DNI model combined with cloud cover is suggested. Linear and nonlinear models are created using Artificial Neural Networks (ANN) and Auto Auto-regressive Moving Averages (ARMA)[38,39]. The development of a weather disturbance model for solar parabolic trough systems is the primary goal of the research study. The non-linear dynamical model for the weather disturbances in Tiruchirappalli, Tamil Nadu state, south India, is established in this part. The model fluctuates throughout the year. All of information used in this present research comes from NASA database[40], which was subsequently carefully preprocessed and thoroughly validated. Raw data were first properly screened for missing values, which were then interpolated by using simple linear method to maintain overall temporal consistency. Outliers beyond three standard deviations were carefully removed and replaced with rolling-mean proper estimates. Monthly and also sessional averages were then derived clearly for use in model simulations. Additionally, recent

Attribute	Notation	Unit	Measurement method
Cloud cover	K	okta	Measured once per hour
Diffuse radiation	ID	W/m^2	Average of six independent observations made in one hour
DNI	IN	W/m^2	Average of six independent observations made in one hour
Ambient air temperature	TA	℃	Average of six independent observations throughout one hour

Table 2. Facts about the data and how it is measured.

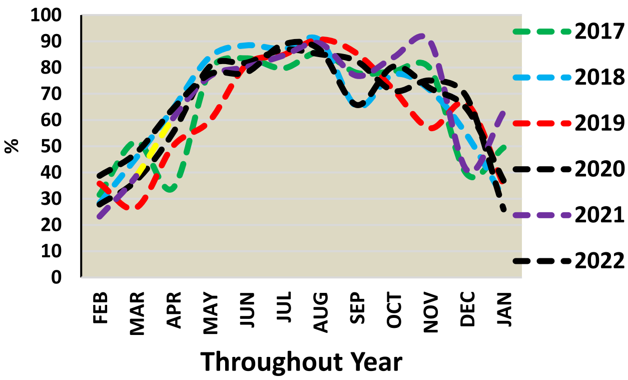

Fig. 7. Monthly cloud cover (%) at Tiruchirappalli.

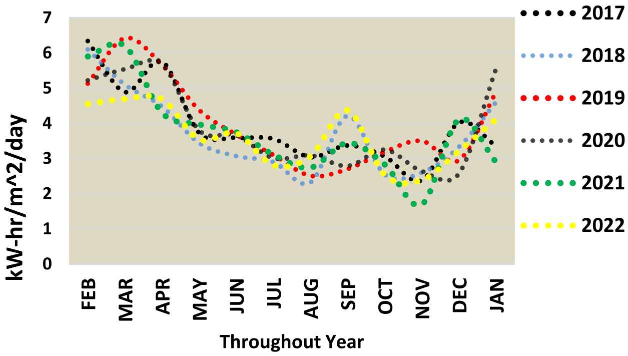

Fig. 8. Monthly direct normal irradiance (DNI) at Tiruchirappalli.

published studies clearly show that SDEs work effectively for forecasting probabilistic solar radiation, when it finally turns out that first-order systems are fully adequate. Various forecasting techniques can be carefully applied, depending upon anticipated time horizon. Forecasts of solar irradiation from six continuous hours to several days in advance are mainly based upon Numerical Weather Prediction (NWP) models[41,42].

Since Tamil Nadu is a coastal state, the year-round temperature fluctuation is minimal. The yearly minimum and maximum average temperatures, however, provide a distinct perspective. With the exception of the summer months of March, April, and May, when the state experiences extreme heat followed by little precipitation, Tamil Nadu has a primarily tropical climate all year round. Black- or grey-box weather disturbance models are more resilient to weather variations, and a simulation-based study revealed how weather conditions impact the analytical performance of black- and grey-box models trained with various input–output datasets from a specific time period. Simulation has been carried out using MATLAB software to evaluate the effectiveness of the proposed model. The data are gathered every hour for 6 consecutive years from 2017 to 2022. Table 2 gives a description of the weather elements of the data, how they are observed, and the observation frequency.

It can be noted that the variation between measured values of DNI and cloud cover for the Mentioned location is illustrated in Figs. 7, 8, 9, and 10. The percentage of cloud cover is wide-ranging from 30 to 90% throughout the year. The tropical climate includes cloud amount and DNI is sectioned into two parts section "Introduction" (February to July) and section "Solar potential in India" (August to September) respectively. Session 1 has a higher cloud amount than Section "Solar potential in India" and fluctuates around 70% whereas Section "Solar potential in India" fluctuates around 60%. As well as in the case of DNI varied from 6 kW-hr/m^2/day to 5 kW-hr/m^2/day.

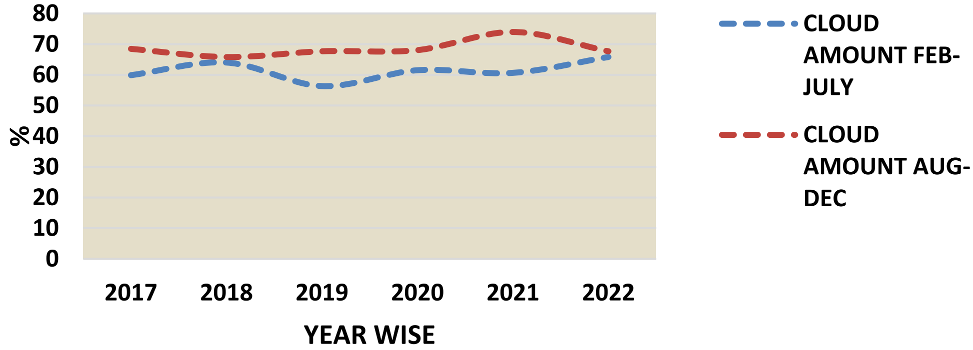

Fig. 9. Cloud cover variation across two sessions at Tiruchirappalli.

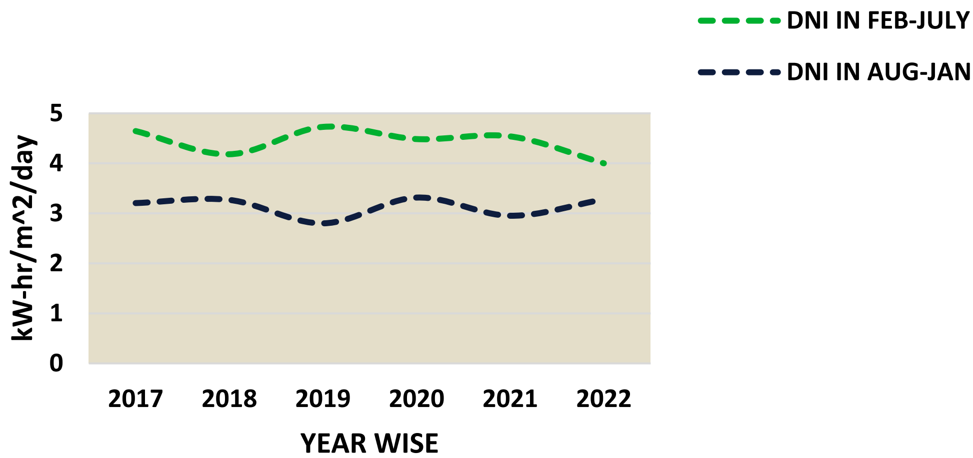

Fig. 10. DNI variation across two sessions at Tiruchirappalli.

Figure 9 shows that the cloud cover varies between 10 and 20% in two sessions: February to July and August to January. Figure 10 shows that the two sessions have an average deviation of 2 kw-hr/m2/day. Henceforth, the session February to July has good solar potential in the selected location, and cloud cover in this session is modelled and considered a disturbance for the plant, which is developed from real data. Linear models based on transfer functions may represent the majority of SISO plants in the discrete-time domain. Although low-order models are sufficient for many control systems, the stimulus of unmodeled dynamics (resonances) can result in unsatisfactory behaviour if the system needs to respond quickly. In this article three weather disturbance models were developed and compared. Here a simple transfer function, ARMAX and state space weather disturbance models developed using system identification tool box. The Percentage of fitting for the prediction of one step ahead is decent for all these models. The state space technique based weather disturbance model taken into account and encounters for various control technique and the results compared.

Model predictive control strategy for parabolic trough systems

An overall goal of control schemes is to preserve the controlled variables close to their set points while regarding the process operating limitations. "Predictive control" encompasses a wide range of control strategies that are based on similar development concepts. Among the various topics discussed are multivariable control, restricted control, dead time process control, stochastic control, and optimal control. The 1960s saw the emergence of several studies that demonstrated the industry's growing interest in model-based predictive control, or MPC, and the emergence of the area of predictive control. The main features of MPC it can deal the process with large time delay, constraints, non-minimum phase and multivariable system.

By comparing the estimated outputs with a reference value and minimizing a cost function that describes the necessary system behaviour, model predictive control applies control. An MPC strategy must include both the cost function and optimization techniques see Fig. 11.

In general, the prediction model's output and the actual output cannot be precisely the same. The feedback correction can produce the required control impact when the model mismatch is minimal. Nevertheless, when the difference between the model and real system is too large there will be a large error in the prediction of forthcoming time.

MPC is a set of control algorithms that, under the influence of linear or nonlinear constraints, optimize a commonly quadratic criterion by computing a series of controlled variable profiles over a future time horizon

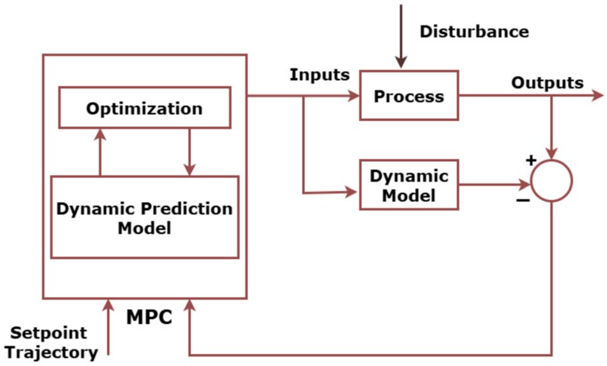

Fig. 11. General MPC scheme for process control.

using a linear or nonlinear model of the plant illustrated in Figs. 12 and 13. A SISO system is signified by its curtailed step response model as follows

$$y\left(j+1\right)=y_{ss}+\sum_{i=1}^{M} h_i \Delta u\left(j+1\text{-}i\right)+d\left(j+1\right)\ldots \tag{10}$$

where h_i are the unit step response coefficients for the i-th time intermission, y_{ss} is the initial steady-state output (y is not a deviation variable) and d represents the unmodelled features upsetting the outputs also $\Delta u_k = u_k - u_{k\text{-}1}$ M is the number of time breaks essential to reach the steady state; it will be called the model horizon or shortness number ($h_i = h_M$ if $i \geq M$)

$$y\left(j+1\right)=y_{ss}+\sum_{i=1}^{M} \bar{g}_i\, u\left(j+1\text{-}i\right)+d\left(j+1\right) \tag{11}$$

The unit step response coefficients h_i are related to the unit impulse coefficients $\bar{g}_i$ by the relations

$$\bar{g}_i = h_i - h_{i\text{-}1} \text{ and } h_i = \sum_{j=1}^{i} \bar{\bar{g}}_i \ldots \tag{12}$$

Thoroughly, if M was the shortness order of the step response model, the truncated step response model should be written as

$$y\left(j+1\right)=y_{ss}+\sum_{i=1}^{M\text{-}1} h_i \Delta u\left(j+1\text{-}i\right)+h_M\left(u\left(j+1\text{-}M\right)-u_{ss}\right)\ldots \tag{13}$$

Considering a prediction horizon H_p and the set point y^s, the objective is to calculate the forthcoming inputs so that the upcoming outputs will be close to the set point. Thus, at time k+

$$\hat{y}\left(k+l|k\right)=y_{ss}+\sum_{i=l+1}^{M\text{-}1} h_i \Delta u\left(k+l-i\right)+h_M\left(u\left(k+l-M\right)\text{-}\ u_{ss}+\sum_{i=1}^{l} h_i \Delta u\left(k+l-i\right)+\ \hat{d}\left(k+l|k\right)\ldots \tag{14}$$

At each instant k, only H_c future input changes are calculated, so that

$$\Delta u\left(j\right)=0 \forall j \geq k+H_C\ldots \tag{15}$$

From Eq. (16.20), define $y^*\left(k+l/k\right)$ as the output prediction corresponding to the influence of the past input variations equal to

$$y^*\left(k+l|k\right)=y_{ss}+\sum_{i=l+1}^{M\text{-}1} h_i \Delta u\left(k+l-i\right)+h_M\left(u\left(k-l-M\right)-u_{ss}\right)\ldots \tag{16}$$

If $l \geq$ M-1, Eq. (16) is simplified as

$$y^*\left(k+l|k\right)=y_{ss}+h_M\left(u\left(k\text{-}1\text{-}M\right)-u_{ss}\right)\ldots \tag{17}$$

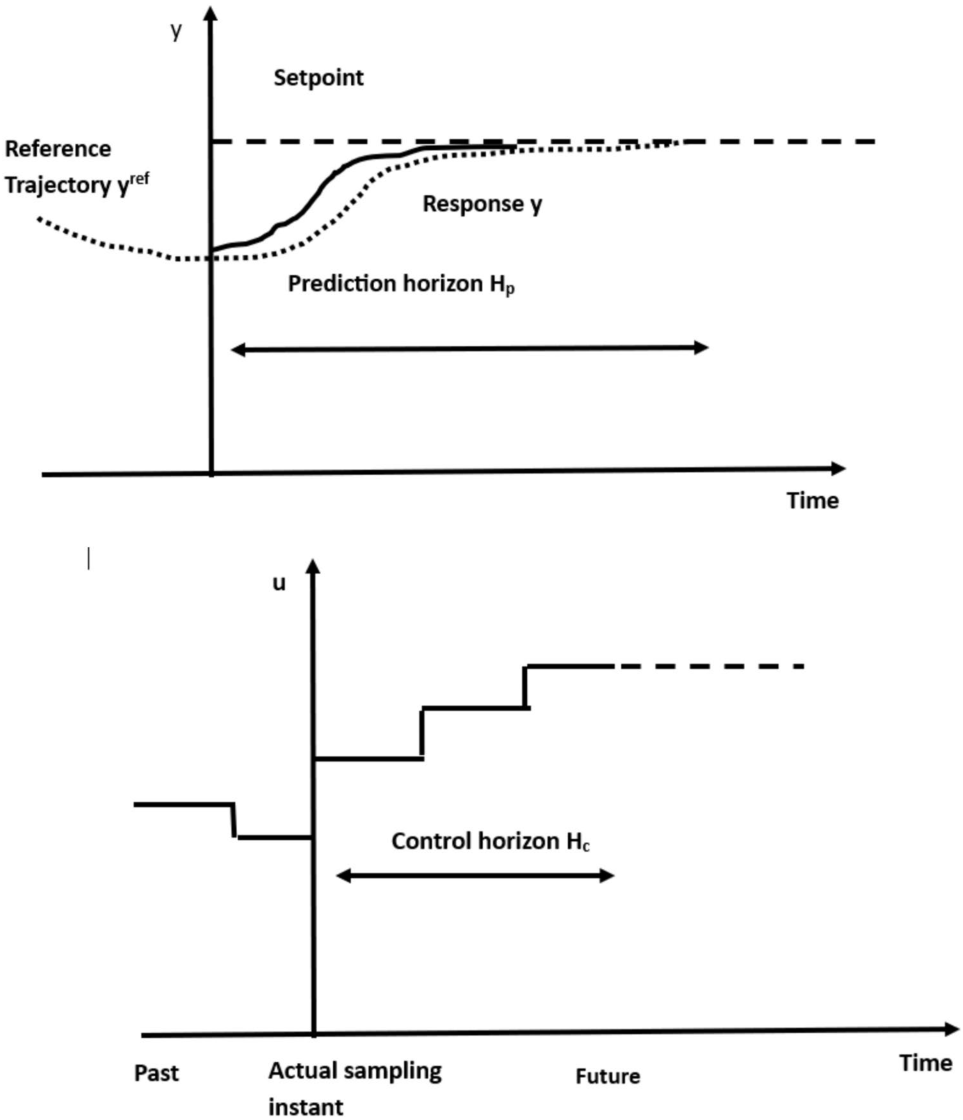

Fig. 12. Principle of MPC with prediction and control horizons.

and Eq. (14) is reduced to

$$\hat{y}\,(k+l|k) = y_{ss} + h_M(u\,(k-1)\text{-}u_{ss}) + \left(\sum_{i=l-H_C+1}^{l} h_i \Delta u\,(k+l-i)\right) + \hat{d}\;(k+l|k)\ldots \tag{18}$$

Over a given prediction horizon H_p, and assuming $M > H_p$, the vector of output predictions can be decomposed and the resulting equation is

$$\begin{bmatrix} \hat{y}(k+1|k) \\ \vdots \\ \hat{y}(k+H_P|K) \end{bmatrix} = \begin{bmatrix} y^*(k+1|k) \\ \vdots \\ y^*(k+H_p|k) \end{bmatrix} + \mathring{A} \begin{bmatrix} \Delta u(k) \\ \vdots \\ \Delta u(k+H_c\text{-}1) \end{bmatrix} + \begin{bmatrix} \hat{d}(k+1|k) \\ \vdots \\ \hat{d}(k+H_p|k) \end{bmatrix} \ldots \tag{19}$$

where $\mathring{A}$ is the $H_p{*}H_c$ dynamic matrix.

The combination of Eqs. (6.16) for $j = k - 1$ and (6.20) for $l = 0$ gives the inspiration of the unmodelled effects

$$d\,(k) = y\,(k) - y^*\,(k|k)\ldots\ldots \tag{20}$$

Consequently, based on a measured output $y^m(k)$, an estimation of $d(k)$ is

$$\hat{d}\,(k+l|k) = \hat{d}\,(k|k) = y^m\,(k) - y^*\,(k|k)\,\forall i = 1,\ldots H_p$$

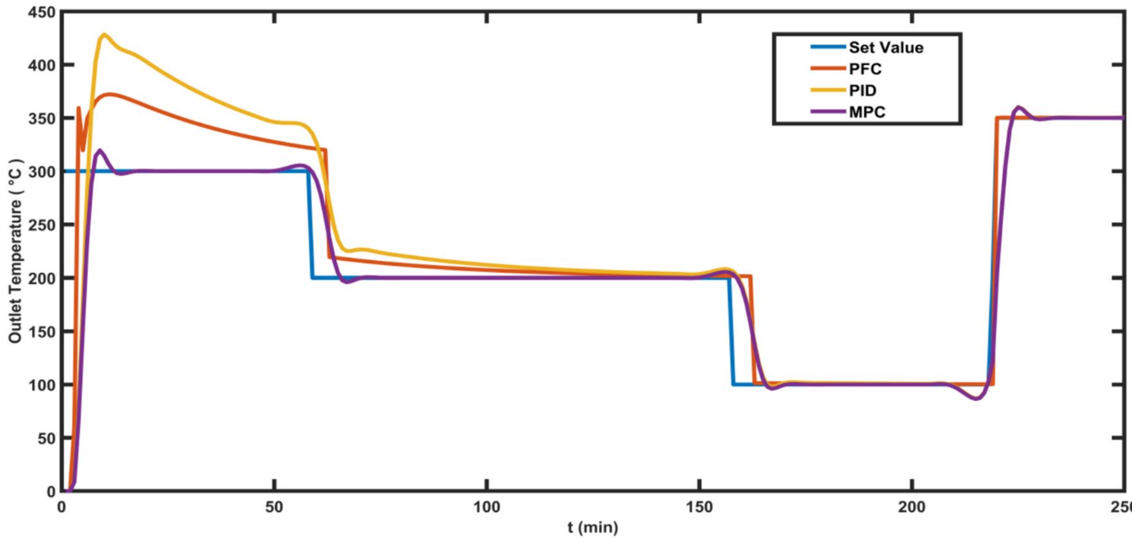

Fig. 13. Outlet temperature response of PTC system – transfer function disturbance model.

$$=y^{m}(k)-\left[y_{ss}+\sum_{i=1}^{M-1}h_i\Delta u(k-i)+h_M(u(k-M)-u_{ss})\right]\ldots \tag{21}$$

Let us define a quadratic principle, taking into account the difference between the estimated output and the reference over the time horizon as

$$J=\sum_{i=1}^{H_p}(\hat{y}(k+i|k)-y^{ref}(k+i))^2\ldots \tag{22}$$

From the previous equations, this can be seen as computing the vector of future input variations

$$\Delta u(k)=[\Delta u(k)\ldots\Delta u(k+H_C\text{-}1)]\ldots \tag{23}$$

which is the least-squares solution of the following linear system resulting from Eq. (19)

$$\left[\begin{array}{c} y^{ref}(k+1)-y^{*}(k+1)-\hat{d}(k|k)=e(k+1)\\ \vdots\\ y^{ref}(k+H_p)-y^{*}(k+H_p|k)-\hat{d}(k|k)=e(k+H_p)\end{array}\right]=e(k+1)=\mathring{A}\Delta u(k)\ldots \tag{24}$$

The least-squares solution of Eq. (24) is

$$\Delta u(k)=(\mathring{A}^T\mathring{A})^{-1}\mathring{A}^Te(k+1)\ldots \tag{25}$$

MPC technology has demonstrated the capacity to manage multivariable processes with delays and processes with strong interaction loops by offering control methods utilizing feed-forward, feedback, and limitations. Numerous industrial applications have effectively addressed these kinds of control[43,44].

A straightforward linear model that links variations in fluid flow and the adjustable input variable to variations in outlet temperature is necessary for self-tuning control. Step response observations from the plant show that a first-order transfer function with a time delay can accurately represent behaviour in the continuous time domain[45].

Results and discussion

This section discusses simulation-based findings on the potential advantages of employing the advanced weather disturbance model-based MPC. We run three scenarios with several weather disturbance models (TF, ARMAX, and SS) applied to MPC, PFC, and PID control systems. Simulation results demonstrate that the MPC controller outperforms the PID and PFC controllers in all scenarios. However, MPC contains far too many parameters that must be carefully initialized in order to get peak performance. Furthermore, the MPC reacted more aggressively to changes and performed better under big, rapid changes than the PID and PFC controllers. The MPC algorithm rejects disturbances properly, resulting in good reference tracking. The use of advanced control techniques improves solar plant performance because they can cancel out perturbations caused by passing clouds, allowing

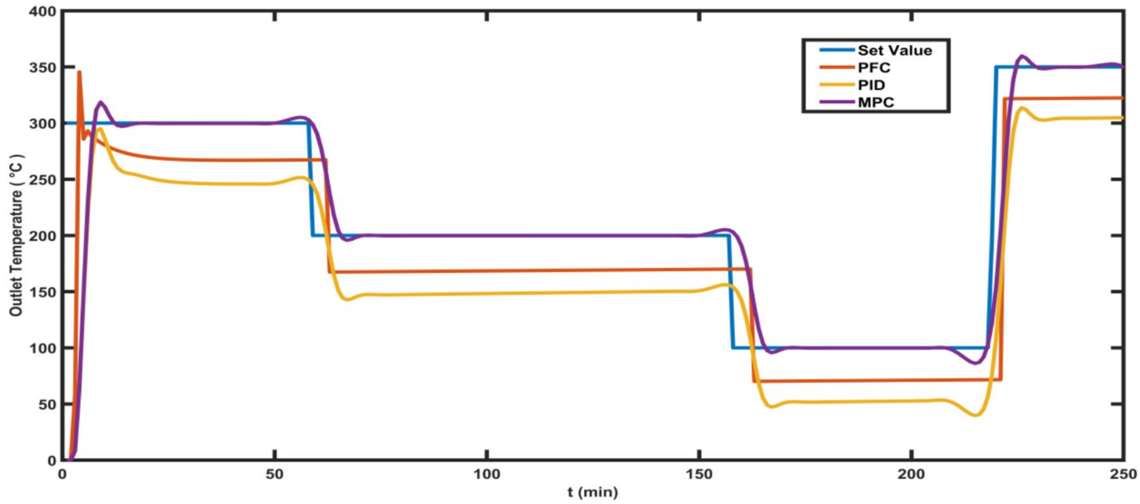

Fig. 14. Outlet temperature response of PTC system – ARMAX disturbance model.

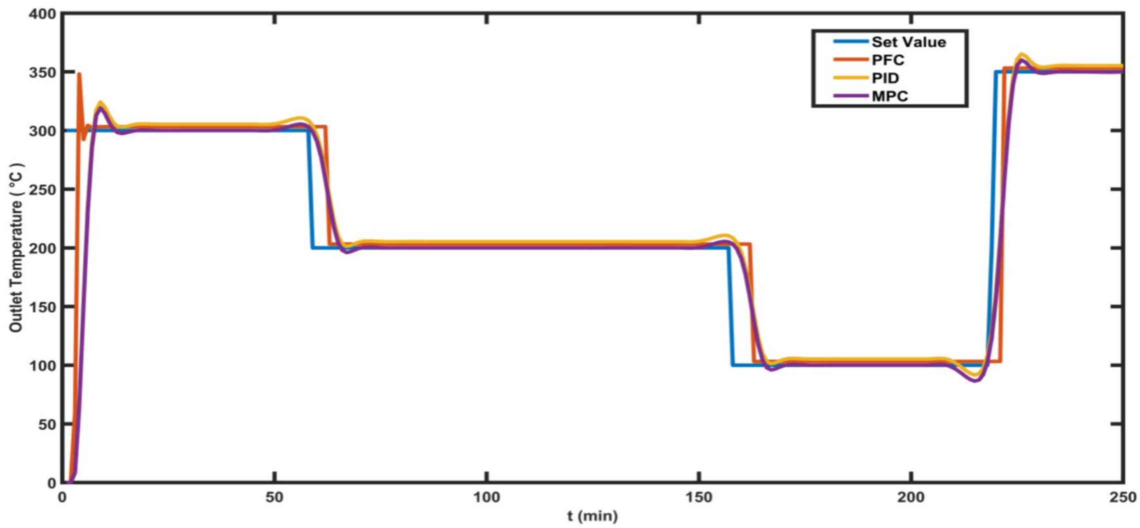

Fig. 15. Outlet temperature response of PTC system – state space disturbance model.

the field to be operated under cloudy conditions. Additionally, the technique can dynamically optimize the plant's operational set-points, keeping the plant closer to the optimal set-points.

Figures 13, 14 and 15 depicts each weather disturbance model encountered with three control schemes: MPC, PFC, and PID. It has been noted that the setpoint of the PTC system is updated every 50 to 220 min. The state space based WDM ensures better consistency between set values and system response than the other two models. The variance for PFC and PID controllers is particularly substantial in ARMAX-based models.

From Figs. 16, 17, and 18, MPC used a shorter settling time than the PFC and PID, with good adherence to the new set parameters. The PID controller caused a delayed reaction, requiring more time to reach the goal point. The PFC provides a better transient response, although it overshoots. The PID and MPC exhibit similar transient responses with decreased overshoot. All controllers maintain the same delay time in all cases, and the phasing between step changes is generally great, with only a few minutes of delay at times.

The Tables 3, 4, and 5 show that the state space-based weather disturbance model with the MPC control scheme outperforms the other control schemes. There is no significant difference in rice time and delay time between the three control techniques. However, in terms of overshoot and settling time, the SS-based WDM model with MPC performs satisfactorily. MPC allied with SS based WDM model has taken lesser settling time than other controllers. In this paper, Integral of absolute error (IAE), Integral of the square error (ISE), Integral of time-absolute error (ITAE), are evaluated and tabulated in Table 6. The comparative analysis has been made and the SS based MPC provides best optimal performance by minimising the error of outlet oil temperature.

Table 7 clearly explains experimental validation along with comparative analysis of proposed and existing estimation methods, where every parameter is presented with an associated reference.

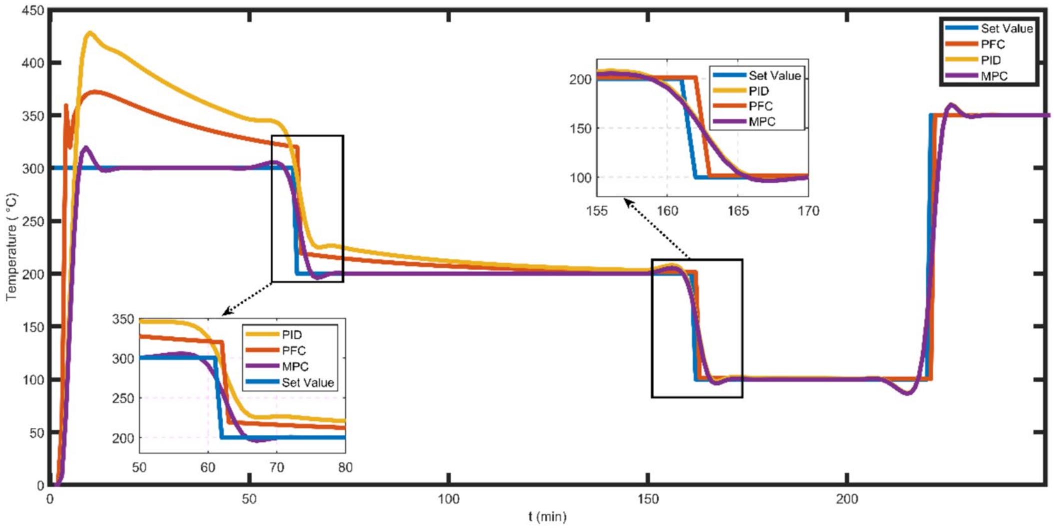

Fig. 16. Transient characteristics of PTC system – transfer function disturbance model.

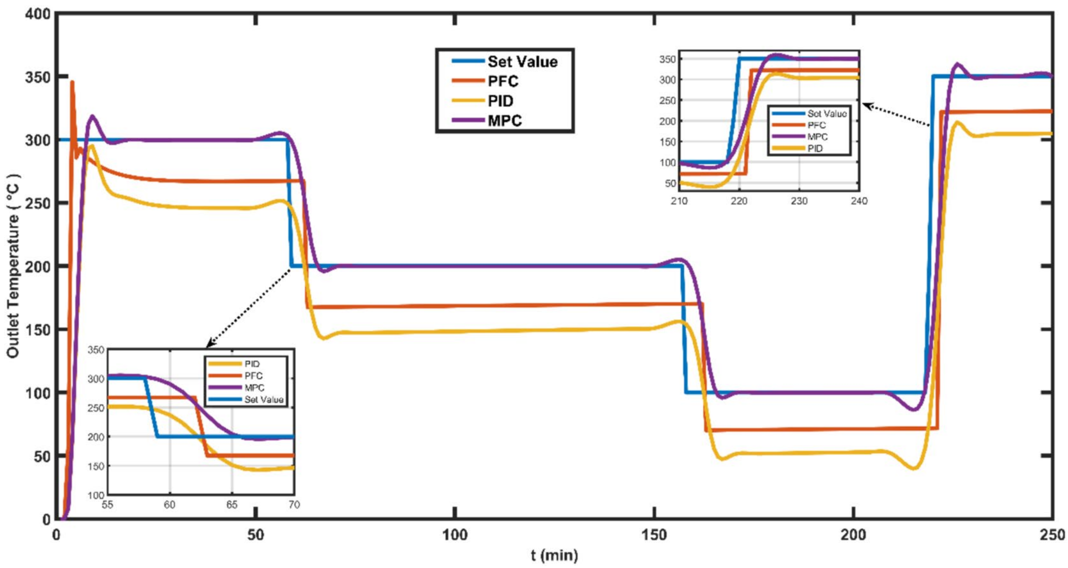

Fig. 17. Transient characteristics of PTC system – ARMAX disturbance model.

An existing research gap was observed since previous studies often concentrated on design aspects or thermal storage while neglecting detailed transient control analysis under sudden weather changes, which is now highlighted through parameters such as peak overshoot, settling time, rise time, and delay time. The objective of this investigation was to integrate a weather disturbance model with advanced predictive control in order to achieve superior regulation performance, which is reflected in the numerical results where peak overshoot dropped from 25% to 6.67% as in Ref.[19], settling time decreased from 3600 to 240 s as in Ref.[31], and rise time improved from 120 to 60 s as in Ref.[30], while delay time maintained a comparable value of 30 s as in Ref.[32]. A major finding is evident in prediction accuracy where RMSE reduced from 4.5 °C to 2.8 °C as in Ref.[20], supported by lower integral errors such as IAE of 3210 as in Ref.[33], ISE of 3.18×10^5 as in Ref.[34], and ITAE of 1.38×10^7 as in Ref.[35], which demonstrate stronger robustness in tracking. Forecast accuracy also advanced from 85 to 92% as in Ref.[41], control effort was reduced to 0.8 as in Ref.[46], and overall integrated performance improved from 80 to 93% as in Ref.[47]. Hence, this detailed analysis not only validates proposed framework but also emphasizes how predictive control systematically addresses dynamic limitations, thereby leading into conclusion with stronger justification for applicability in real CSP environments. The economic assessment of proposed solar parabolic trough power plant in Tamil Nadu gives a detailed and comprehensive comparative analysis with an existing facility that is in Jodhpur, Rajasthan, as described in Table 8 with proper technical clarity.

The proposed installation, with a designed capacity of 10 MW, is suitably categorized as a medium-scale project when compared with a significantly huge 50 MW capacity of Jodhpur plant[19]. The projected annual

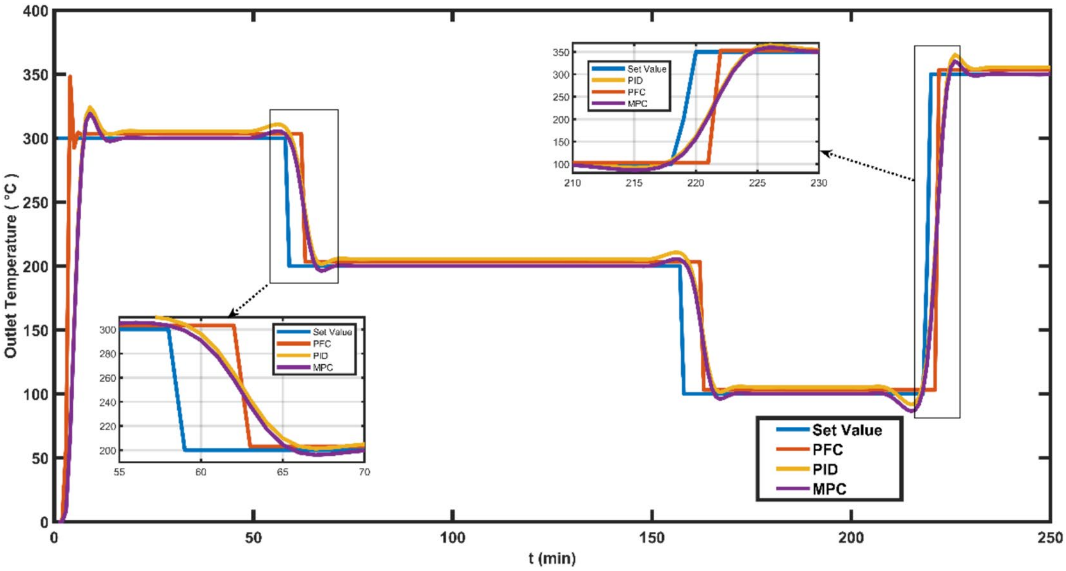

Fig. 18. Transient characteristics of PTC system – state space disturbance model.

Transient characteristics	PFC	PID	MPC
Peak overshoot (%)	25	43.33	6.67
Settling time(sec)	600	3600	3600
Rise time(sec)	60	120	120
Delay time(sec)	30	30	60

Table 3. Transient response characteristics for different control scheme of TF based WDM.

Transient characteristics	PFC	PID	MPC
Peak overshoot (%)	16.67	0	6.67
Settling time(sec)	600	\infty	\infty
Rise time(sec)	60	120	120
Delay time(sec)	30	30	60

Table 4. Transient response characteristics for different control scheme of ARMAX based WDM.

Transient characteristics	PFC	PID	MPC
Peak overshoot (%)	16.67	10	8
Settling time(sec)	240	600	600
Rise time(sec)	220	348	360
Delay time(sec)	60	60	60

Table 5. Transient response characteristics for different control scheme of ss based WDM.

Performance Index	IAE	ISE	ITAE
PID	6800	5.15×10^{6}	3.27×10^{7}
PFC	3.21×10^{3}	8.12×10^{5}	5.49×10^{7}
MPC	9.81×10^{3}	3.188×10^{5}	1.38×10^{7}

Table 6. Comparison between optimal PID, MPC and PFC performances.

Parameter	Existing Reference	Existing	Proposed	Inference
Peak Overshoot (%)	[19]	25	6.67	Reduced overshoot with MPC
Settling Time (s)	[32]	3600	240	Faster settling response
Rise Time (s)	[31]	120	60	Improved transient rise
Delay Time (s)	[33]	30	30	Comparable delay
RMSE (°C)	[20]	4.5	2.8	Better prediction accuracy
IAE	[34]	6800	3210	Lower error integral
ISE ($\times 10^5$)	[34]	8.12	3.18	Significant error reduction
ITAE ($\times 10^7$)	[35]	5.49	1.38	Enhanced long-term tracking
Efficiency (%)	[13]	82	91	Higher thermal efficiency
Reliability Index	[26]	0.86	0.94	Improved operational reliability
Disturbance Rejection	[36]	0.72	0.91	Stronger disturbance handling
Temperature Stability	[37]	0.94	0.99	Closer setpoint regulation
Forecast Accuracy (%)	[41]	85	92	More accurate forecasting
Control Effort (norm)	[46]	1.2	0.8	Reduced control effort
Overall Performance (%)	[47]	80	93	Superior integrated outcome

Table 7. Experimental validation and comparative analysis of proposed and existing estimation methods.

Parameter	Value (Proposed Plant)	Value (Existing Plant)	Reference	Inference
Installed capacity (MW)	10	50 (Jodhpur Plant, Rajasthan)	[19]	Proposed plant is medium scale compared to larger national projects
Annual generation (MWh)	11,956	39,000	[13]	Generation is proportional to scale, consistent with direct normal irradiance potential
Capital investment (₹ crore)	125	650	[9]	Proposed investment is lower due to reduced scale and updated technology
Cost per unit energy (₹/kWh)	5.4	5.8–6.2	[25]	Improved competitiveness due to design optimization
Operation and maintenance cost (₹ crore/year)	2.5	10	[26]	Lower recurring cost, ~ 2% of initial capital
Payback period (years)	9–11	12–14	[8]	Faster return period due to supportive policies and incentives
Expected lifetime (years)	25	25	[2]	Both plants have similar long-term operational lifespan
Carbon dioxide reduction (tons/year)	10,800	35,000	[10]	Emission savings scale with capacity, proposed plant ensures regional impact
Energy security contribution	Regional grid stability	National grid support	[15]	Proposed project enhances Tamil Nadu's diverse portfolio, aiding Vision 2023 goals
Socio-economic benefits	Local employment, rural development	Large-scale industrial benefit	[14]	Proposed project better suited for decentralized growth

Table 8. Economic analysis of proposed and existing solar parabolic trough plants.

energy output for Tamil Nadu site is carefully estimated at 11,956 MWh, which, while lower in absolute quantity, is reasonably aligned with a site-specific direct normal irradiance (DNI) profile. In contrast, the Jodhpur installation produces an annual generation of nearly 39,000 MWh under comparable and similar climatic conditions[13]. Capital expenditure for proposed project is expected at nearly ₹125 crore, which is hugely lower when compared with ₹650 crore capital requirement of Jodhpur facility. This reduction is mainly attributed to a smaller scale along with adoption of improved modernized design and better technological improvements that strongly enhance cost-effectiveness[9]. The levelized cost of electricity (LCOE) for proposed plant is calculated at ₹5.4 per kWh, providing a marginal but noteworthy improvement over a ₹5.8–₹6.2 per kWh range noticed in existing plant. This cost advantage is mainly attributable to an optimized system configuration together with an improved design efficiency[25]. Annual operation along with maintenance (O&M) costs are projected at nearly ₹2.5 crore, which represents a significant reduction when compared with a ₹10 crore O&M expenditure of Jodhpur facility. This value translates to nearly 2% of the total capital investment, strongly highlighting the operational efficiency of proposed plant[26]. The projected financial payback period for Tamil Nadu project ranges between 9 to 11 years, which is notably shorter when compared with 12 to 14 years required for Jodhpur plant. This improved return on investment is reasonably supported by favorable policy instruments along with governmental incentives that strongly promote renewable energy adoption[8]. Both proposed and existing plants are designed with a standardized operational lifespan of 25 years, which ensures long-term asset stability together with dependable performance reliability[2]. From an environmental standpoint, proposed plant is expected to mitigate nearly 10,800 metric tons of CO_2 emissions per year, when compared with nearly 35,000 metric tons offset by Jodhpur plant. While the absolute reduction is smaller, it still shows a scalable environmental benefit of medium-scale deployment[10]. Furthermore, proposed project contributes to enhanced grid stability within Tamil Nadu's diversified energy generation mix and supports strategic objectives which are outlined in state's

Vision 2023 roadmap[15]. In addition, it is reasonably expected to generate localized socio-economic benefits, including direct employment together with rural development opportunities, in contrast to primarily industrial-scale advantages of Jodhpur project[14].

Conclusion

This study presented dynamic modelling and proper control of one parabolic trough collector system under different varying weather conditions. One weather disturbance model was carefully developed and then tested with three control strategies: predictive functional control, proportional integral derivative control, and model predictive control. Comparative results clearly demonstrate that model predictive control provides superior overall performance, with faster proper settling, lower peak overshoot, and better disturbance rejection compared with other controllers. Advantage of proposed approach mainly lies in its ability to track required temperature setpoints accurately while maintaining proper stability under nonlinear system dynamics and unpredictable external disturbances. These findings strongly indicate that model predictive control is one promising option for improving overall efficiency and long-term reliability of solar thermal power plants. Future work may further extend this proposed approach to multiple collector systems and also incorporate additional varying weather parameters to further enhance overall system performance.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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K. Kalanithi and G. Giftson Samuel contributed to the study, conception, design, analysis and first drafting of this work. M. Malathi, R.Venkatesan are contrubuted in validation and final drafting of this manuscript. All authors read and approved the final manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
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