

Solar Energy Prediction Based on Intelligent Predictive Controller Algorithm

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ABSTRACT

The technological advancement in all countries leads to massive energy demand. The energy trading companies struggle daily to meet their customers' power demands. For a good quality, disturbance-free, and reliable power supply, one must balance electricity generation

and consumption at the grid level. There is a profound change in distribution networks due to the intervention of renewable energy generation and grid interactions. Renewable energy sources like solar and wind depend on environmental factors and are subject to unpredictable variations. Earlier, energy distribution companies faced a significant challenge in demand forecasting since it is often unpredictable. With the prediction of the ever-varying power from renewable sources, the power

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generation and distribution agencies are facing a challenge in supply-side predictions. Several forecasting techniques have evolved, and machine learning techniques like the model predictive controller are suitable for arduous tasks like predicting weather-dependent power generation in advance. This paper employs a Model Predictive Controller (MPC) to predict the solar array's power. The proposed method also includes a system identification algorithm, which helps acquire, format, validate, and identify the pattern based on the raw data obtained from a PV system. Autocorrelation and cross-correlation value between input and predicted output 0.02 and 0.15. The model predictive controller helps to recognize the future response of the corresponding PV plant over a specific prediction horizon. The error variation of the predicted values from the actual values for the proposed system is 0.8. The performance analysis of the developed model is compared with the former existing techniques, and the role and aptness of the proposed system in smart grid digitization is also discussed.

Keywords: Energy demand, future response, model predictive control, performance analysis, prediction, renewable energy, smart grid, system identification

INTRODUCTION

The growing awareness of green energy is moving the global power sector towards renewables. The variability in renewable-based power generation with respect to time needs to be predicted in advance to plan the power distribution properly. This universal transformation headed for renewable energy sources (RES) has motivated the progress of photovoltaic (PV) panels. As per the prediction by (Khalil, 1981), the opportunities for solar photovoltaic applications are growing exponentially. For instance, the production costs of generating electricity from solar PV panels have dropped drastically, but the energy conversion efficiency is increasing. In particular, between 2010 and 2017, the electricity cost of large-scale PV panels decreased by 73%, as described by (IRENA, 2018). The industries also seek carbon-neutral energy purchase plans (Jin et al., 2018). The increasing efficiency and decreasing cost have made PV panels a competitive alternative for non-renewable energy sources in many countries (Andrade & Bessa, 2017). Energy footprints have become essential in manufacturing systems (Jeon et al., 2015).

The energy output from the PV panel ultimately depends on weather conditions like cloud envelopes and solar radiation. It makes the energy output produced by the PV panels unpredictable and uneven (Suresh et al., 2013). So, forecasting the power output of solar power plants has become crucial for energy traders, who get attracted to long-time horizons, typically day-ahead forecasting, since most electric power is traded on the day-ahead marketplace (Marimuthu & Kirubakaran, 2014). As a result, the profitability of these operations depends on the capability of forecasting the fluctuated solar PV panel

energy output precisely. Though the demand for accurate and well-organized solar PV panel output power prediction is evident, the consequence is far from trivial. There are many technical hitches in the existing research. One apparent trouble is the inherited deviation of weather, making accurate weather forecasting challenging (Sassi & Oulamara, 2017). Many technologies are available for forecasting, including mathematical calculations based on weather data, artificial intelligence-based techniques, and a combination of both methods (Gopinath et al., 2014). This paper has attempted to employ a controller to predict power output. The primary objectives of this paper are to design an intelligent predictive control technique for solar power generators and simulate and conduct performance analysis for the same.

Literature Review

Power forecasting has become a crucial component of the electricity sector. It helps load scheduling, electricity price-fixing, and other related decision-making processes. Solar energy, a predominant source in tropical countries like India, is of more importance. Hence, the time ahead prediction is very vital. This process of prediction can be done either directly or indirectly. The direct method involves systems that predict the power for a given solar thermal or photovoltaic system (Accenture, 2016). The indirect process involves predicting solar irradiance or insolation, which is the necessary input to the power generating systems (Khosravi et al., 2018; Ozoegwu, 2019; Zendehboudi et al., 2018). These systems predict the global horizontal irradiance and diffuse horizontal irradiance falling on the earth at a particulate latitude and longitude (Guermoui et al., 2018). The electrical power can be predicted based on the pre-predicted solar irradiance.

Also, the parameters involved in power prediction for solar thermal-based power generation systems differ from those of the photovoltaic system (Prabhu et al., 2015). In a solar thermal system, heat is of prime importance because the system generates heat from sunlight, which is then applied to the heat engine to generate power (Rodat et al., 2016). Whereas in photovoltaic-based power generation, sunlight is directly converted into electricity. Different methods are in practice to predict the output power of a solar photovoltaic system, and they can be classified as numerical methods based on regression, correlation, and other mathematical calculations, intelligent methods like neural networks, fuzzy logic, model predictive controller, and hybrid methods which are the combination of the two mentioned above (Moon & Park, 2014).

Firstly, the numerical calculation methods are found to be in use widely. The regression-based systems use the relationship between atmospheric parameters like weather, temperature, irradiance, and output power to manipulate the prediction (Kuhe et al., 2021). Multiple linear regression is applied to predict power by fitting the variables into the linear equation derived from the historical data (Abuella & Chowdhury, 2015). Wavelet transform

is a mathematical function that analyzes time series categorization and pattern recognition in machine learning. It significantly impacts solving the non-linearity of solar photovoltaic systems and predicts the output power based on time series analysis (Mandal et al., 2012).

Secondly, intelligent systems are emerging at a rapid pace due to the advantages they offer. Artificial neural networks simulate the functions of the human brain to perform a task. ANN-based prediction models work by studying the input-output relationship (Zafarani et al., 2018). The network automatically adjusts its weights and biases in line with the input and output parameter relationships. This method involves a vast amount of historical statistics for better training the network. They can be designed efficiently in MATLAB through codes or built-in applications (Ehsan et al., 2014; Mandal et al., 2012). Fuzzy logic-based prediction works on IF-THEN rules designed by manipulating how the system works (Ncane & Saha, 2019). The system requires translating the input variables into fuzzy, understandable form and retranslating the output again. So, the power prediction in this model needed precise rule database design (Chugh et al., 2015).

Thirdly, the models can be combined to fit the needs of the required system. Hybrid models used for solar power prediction combine one or more methods or technology to do the task (Das et al., 2023). The combination can be intelligent—hybrid or numerical intelligent hybrid (Aliberti et al., 2018). The first case of combining two or more intelligent techniques is discussed below. The artificial neuro-fuzzy inference system groups artificial neural networks and fuzzy controllers (Raja et al., 2023). In this hybrid, the artificial neural networks determine the fuzzy controller's rules, making the design process less complicated. The forecasting system with ANFIS has combined advantages of both Artificial Neural Networks (ANN) and fuzzy logic (Frei, 2008).

However, the Adaptive Network-based Fuzzy Inference System (ANFIS) can be integrated with previous soft computing techniques such as particle swarm optimization or genetic algorithm for forecasting (Guermoui et al., 2018). The particle swarm optimization method is a population-based optimization algorithm stimulated by nature. It works by computing the movement of particles in a given space at a time and velocity (Yadav et al., 2019b). A genetic algorithm is an evolutionary algorithm that produces or determines high-quality outputs and works like human gene selection strategies like selection, mutation, and crossover (Padmanathan et al., 2019). This technology can be combined with ANFIS predictors to optimize the data sets for ANFIS training (Yadav et al., 2019a). Also, the three techniques can be combined for predicting solar photovoltaic power (Semero et al., 2018).

The numerical-intelligent hybrids are the one that combines one or more mathematical and intelligent techniques for task completion. A Binary Genetic Algorithm (GA) through the Gaussian process regression model-based suitability function can also determine a predictor's high-impact input parameters (Kenning, 2016). An integrated hybrid methodology uniting Particle Swarm Optimization (PSO) and GA can optimize an

ANFIS and will contribute more towards the performance enhancement of the predictor (Viswavandya & Mohanty, 2018).

Another numerical-intelligent hybrid forecasting model connects the wavelet transform (WT), adaptive neuro-fuzzy inference system (ANFIS), and also with hybrid firefly and particle swarm optimization algorithm (HFPSO) (Abdullah et al., 2019; Karan, 2019; Lund et al., 2019; Taki et al., 2019), where the wavelet transform reduces noise in both the meteorological and solar power data. ANFIS is the predictor, whereas the HFPSO is the combination of the firefly (FF) and particle swarm optimization (PSO) algorithm, which is engaged in optimizing the input parameters of the ANFIS to enhance the accuracy (Oldewurtel et al., 2012). Season-based models with self-evolving algorithms can be designed by integrating evolutionary seasonal decomposition least-square support vector regression (ESDLS-SVR) (Lin & Pai, 2016). This method combines three technologies: empirical mode decomposition, least square method, and support vector machine. Empirical Mode Decomposition (EMD) processes non-linear series through time-space analysis, and the support vector machine is a discriminative classifier trained by the supervised learning process (Vinayagar et al., 2022).

Finally, this paper proposes a solar output power predictor based on model predictive controllers. Model predictive controllers are widely employed because it is an optimization-based strategy that identifies the control inputs that affect the outputs over a given time frame (Mikhaylidi et al., 2015). The forecasts can be obtained by applying the Model Predictive Controller (MPC) to the solar photovoltaic system (Arnold & Andersson, 2011). The MPCs are extensively employed to control predicted energy demand and supply in-home and micro-grid management systems (Hernández-hernández et al., 2017). A receding horizon MPC Scheme solves the comfort tracking problem by considering solar outputs and thermal inertia as a second-order state-space model designed for a generic building studied and employed in Spain (Enríquez et al., 2016). The other applications of MPCs in the Energy Management System (EMS) include optimal operation schemes, forecasting, cost minimization, and energy optimization (Lee et al., 2018). MPC-enabled EMSs can help in optimal scheduling for end-user smart appliances, heating or cooling devices, local power generation devices for residential needs, weather-dependent generation and demand forecasts, electric pricing, and technical and operative constraints (Parisio et al., 2015). Unlike the methods discussed above, The papers aim to simplify the predictor design and establish an input-output relationship-based prediction model. The comparison of different strategies employed and their findings are reported in Table 1.

Role of Forecasting in Digitization of Smart Grid. Society today depends on a wide range of digital technologies that consume more power. So, the heavily industrialized nations accommodate renewable energy to meet the growing power needs, infrastructure security,

Table 1
The comparison of different methods employed and their findings

Reference	Method	Findings
Yadav et al., 2019b	PSO ANFIS	PSO is employed to optimize the parameters and rules for ANFIS
Ehsan et al., 2014	ANN	ANN is trained with the back-propagation algorithm.
Semero et al., 2018	GA- PSO-ANFIS	The design involves three soft computing techniques, adding to the computational complexity.
Viswavandya and Mohanty, 2018	Fuzzy Logic & ANFIS	Fuzzy shows better performance than ANN in the case proposed.
Abdullah et al., 2019	HFPSO – WT ANFIS	The HFPSO is used to optimize the training data, and the WT is availed to optimize the ANFIS parameters.
Chugh et al., 2015	Fuzzy Logic	The predictive system has less design complexity and better performance.
Yadav et al., 2019b	PSO -ANFIS	Particle swarm optimization is applied to optimize the performance of ANFIS.
Abuella and Chowdhury, 2015	MLRA	Multiple linear regression analysis involves complex calculations, and the performance is low compared to intelligent techniques.
Mandal et al., 2012	WT-BPNN & WT-RBFNN	Two ANN-based models are compared, and the wavelet transform is used for data set optimization.
Ncane and Saha, 2019	Fuzzy & ANN	Fuzzy logic and neural network-based models are compared.
Yadav et al., 2019a	GA-ANFIS	A genetic algorithm is used to enhance the performance of the ANFIS predictor.
Lin and Pai 2016	ESDLS-SVR	The method evolves according to seasonal variations and performs better in forthcoming years.

and balancing climate problems. However, this integration process has more challenges in the control paradigm of the grid and transmission activities (Yaniktepe et al., 2017). It demands a robust and automated grid technology with a bidirectional flow of electricity and information. Many countries are on the verge of modernizing their existing grids into smart grids and deploying micro-grids for decentralized power generation and distribution (Taticchi et al., 2015). The need of the hour requires a sound policy for deploying smart grids. These policies shall include regulations for power generation and finance models, such as regulatory targets, and address the data requirements, renewable energy credits, and different interconnection tariffs and utility subsidies (Brown & Zhou, 2013; NEP, 2017).

The smart grid is an “electricity network that can intelligently include the behavior and actions of all consumers connected to it—generators, customers and those that do both—that efficiently distribute sustainable, economical and secure electricity supplies” stated by the European Union for smart grids (India Smart Grid Forum, 2019). Customers are the active players in an electricity system, and forecasting the power generation can help them contribute more towards power savings and peak demands (Vassiliadis, 2000).

Hybridizing renewable energy and energy storage facilities with an existing grid would boost the grid's potential, but control strategies are required (Vigneshwari et al., 2016). The above data includes the forecasted data, which is highly crucial for developing state-of-the-art energy management systems.

The role played by different countries in digitizing the energy sector was reported in 2017. According to it, the USA prefers policies based on environmental implications; China focuses on strengthening policies on the supply side. European Union aims to install smart meters in 80% of houses by 2020, while Japan strives to reduce GHG emissions by 30% by 2030. In contrast, Denmark has demonstrated the advantages of a smart grid for the country's prosperity (Zame et al., 2018).

An extensive study on the Indian perspective of solar photovoltaic (PV) systems has been done to find the acceptability of solar PV systems among the citizens of the nation and the hurdles in retrofitting new energy technologies in the country (Padmanathan et al., 2019). The smart grid within the Indian context and the factors influencing the micro-grid costs, such as distributed generation assets, grid automation, micro-grid optimization software, development and installation charges, and energy storage, were discussed by Kumari (2017). The author also suggests that microgrids will help in decreasing power costs. India's first micro-grid was at UpariBabhan, Rajasthan, with a generation capacity 15.78kW and consumption rates of 10.43kW (Gupta, 2018). The industries to deploy microgrids in the next five years based on Zpryme and IEEE surveys are given in Table 2.

Different Smart grid topologies are discussed by Singh et al. (2015), which include radial grid, mesh grid, and ring grid. The authors have also presented a smart micro-grid model with 300W to 1 KW SPVS, an intellectual bidirectional converter turn out Sinusoidal Pulse Width Modulation (SPWM) AC power of 230 Volt, 50 Hz, and 1800Wh battery storage unit which depicts power savings up to 50% or more. Lampropoulos et al. (2010) discuss how load and generation forecasting could help develop small, decentralized power generation units through data availability, defining user groups, and data process.

Forecasting is now becoming a mandatory power management component as the grids are digitized. It is evident that smart grids make power management easy, transparent, hassle-free, and economical

Table 2
The industries to deploy micro-grids in the next five years based on Zpryme and IEEE survey

Industry	Possibility
Health Care	44%
Military	43%
Government (non-military)	40%
Utilities	39%
Manufacturing	37%
Residential	34%
Agriculture	31%
Education	27%
Transportation	23%
Mining	19%
Construction	14%
Retail	11%
Other	4%

(Sivaneasan et al., 2017). These advantages of the smart grids can be made possible only with the forecast data of the power generation units. Hence, energy forecasting contributes more towards the electricity value chain presumably. Though numerous technologies are available for power forecasting, not all technologies always hold good for all grids (Ramachandra et al., 2005). The model predictive controller discussed here has a good adaptability range and can be reprogrammed easily for different grid specifications at low computation cost and complexity. Hence, this work applies it to forecasting the solar photovoltaic power generation.

MATERIALS AND METHODS

The day ahead forecast model reported in this research is designed for a 1 kW grid-connected solar power plant at Gandhigram Rural Institute (Latitude: 10.277565°, Longitude: 77.936200°), an educational institute in India. The 1 KW plant is designed with 4 Rene Sola JC255m-24/Bb modules connected in series with a conversion efficiency of 15.7% and an area of 6.1 m². The system data acquisition has been done by ZeverCom acquisition systems and stored in the cloud.

Solar energy prediction is becoming a significant problem in the framework of renewable energy sources (RES), so Machine Learning Algorithms are employed more for this process. This paper proposed a consequential methodology based on machine learning algorithms to accomplish realistic and perfect results, which includes system identification and model predictive control techniques. The block diagram of the proposed system is represented in Figure 1.

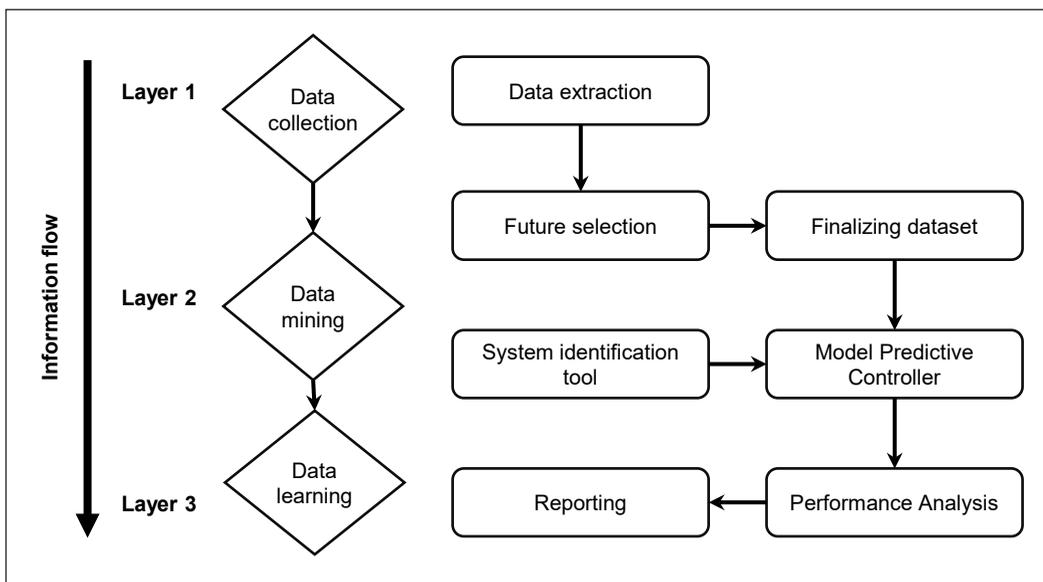


Figure 1. Block diagram of the proposed system

The first step in the process is data collection, which includes recording the raw weather data and the power production at the Gandhigram Rural Institute (GRI) 1 kW grid-connected solar power plant to get significant numeric values. The power data is predicted from the weather data. The second step in the process is data mining. The collected data is processed to fix redundancy errors missing data issues, and remove outcasts. It performs correlation analysis among the weather features and the energy output to get rid of hopeless features.

The third step is to apply the data to the MPC controller. The MPC Controller predicts and analyses the performances of the proposed system with the aid of soft computing algorithms. The system identification tool and model predictive controller (MPC) approach are used to recognize the pattern of collected data and envisage future potential and fluctuations. Hence, the specific features are imported as the input source for MPC, which is to be adjusted and controlled for solar radiation prediction problems.

The final step is to analyze the performance of the designed MPC controller. A steady-state error evaluation determines the performance of the proposed system. The steady-state error is the deviation of the control system's output from the input response in the limit while time goes to infinity (i.e.) once the response has reached a steady state. The steady-state error for the proposed control system is given by Equation 1 (Ramedani et al., 2013).

$$E(\infty) = \lim_{s \rightarrow 0} s E(s) = \lim_{s \rightarrow 0} \frac{s R(s)}{1+G(s)} \quad (1)$$

Where $R(s)$ is the Laplace transform of the reference input signal, $E(s)$ is the error signal, $G(s)$ is the plant of the system, and $Y(s)$ is the Laplace transform of the output signal.

PROPOSED PREDICTION METHOD

System Identification Algorithm

Identifying a system is required to obtain corrective measures to improve the overall system performance. System identification is an approach that provides valuable techniques for analyzing the system properties, performing simulations, understanding the experimental phenomena (machine learning process), predicting events in the future (time series analysis), and obtaining a system model of signal in filter design (signal processing techniques). The ultimate purpose of the system identification process is to build a UPA model from a system's offered input and output data.

Therefore, the procedure is to pick a particular input u , apply it to the system, and then measure the system response y . From this input/output data (u and y), a model, a differential/difference equation, or transfer functions can be obtained. A transfer function correlates a control system's input and output signal for all possible input values. The second-order transfer functions are commonly used in convention for a dynamic system to exhibit oscillations and are usually represented as Equation 2 (Liu et al., 2018).

$$G(s) = \frac{b_0}{s^2 + a_1s + a_0} \quad (2)$$

where $G(s)$ is the transfer function of the system.

Also, the transfer function obtained from the real-time data utilized for the design of the solar power predictor is given by Equation 3.

$$G(s) = \frac{0.5495 s^2 + 1.8 s + 5.766}{s^3 + 2.078 s^2 + 11.31 s + 7.769} \quad (3)$$

This transfer function was obtained from physical modeling and data collection. The data from the controller was taken as an output, and the input was taken from the panel simulation. In a modeling task, the following steps are employed in sequence: (1) collection of prior information of the system, (2) selection of the model set and model structure, (3) experimental design and collection of data, and (4) model parameter estimation and model validation process. The phases of the system identification procedure are shown in Figure 2.

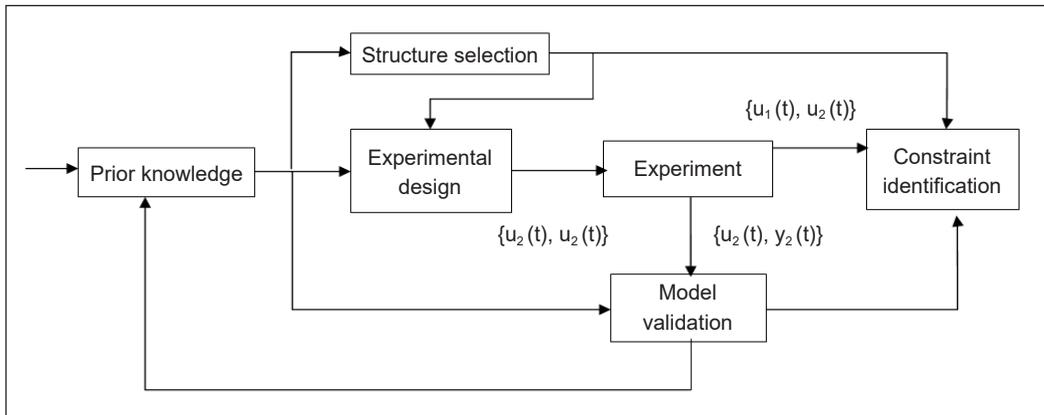


Figure 2. Stages of the system identification procedure

Model Predictive Control (MPC)

A model of process control is available to predict the future progress of the system for optimization of the control signal. The main aim of the MPC is to develop a model of the process to forecast the future response of the system as well as to compute control actions if necessary. The control objective is correlated with an error function based on the deviation between the desired and the actual responses. This objective function is called the cost function J , and the optimal control action is established while minimizing the cost function within the optimization window (Kazem et al., 2016). The MPC structure is shown in Figure 3.

In MPC, future values from the output variables are predicted based on a dynamic model of the system process and with the current measurements. In order to minimize an

objective function, J , the manipulated variables, $u(k)$, at the k -th sampling instant, must be considered. Equality and inequality constraints with the measured disturbances were integrated into the control calculations (Jeon et al., 2015). The designed manipulated variables are realized as a reference value or a set point for lower-level control loop processes.

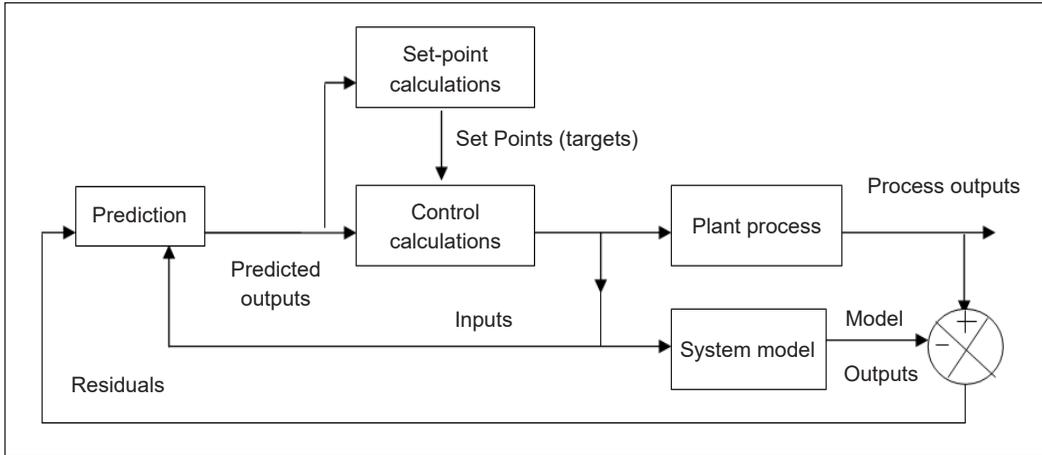


Figure 3. Model Predictive Controller (MPC) structure

Receding Horizon Control (RHC)

MPC is formed with an iterative and finite-horizon optimization of a respective plant model. At time interval t , the state of the existing plant is sampled, and cost-minimizing control strategies are worked out for a sensibly short time horizon in the future behavior $[t, t + h]$. An online method or on-the-fly calculation can also investigate the state trajectories derived from the current state and find a cost-minimizing control strategy until the time $t + h$ (Kazantzidis et al., 2018). The block diagram for the receding horizon and the concept showing the optimization problem are represented in Figures 4 and 5.

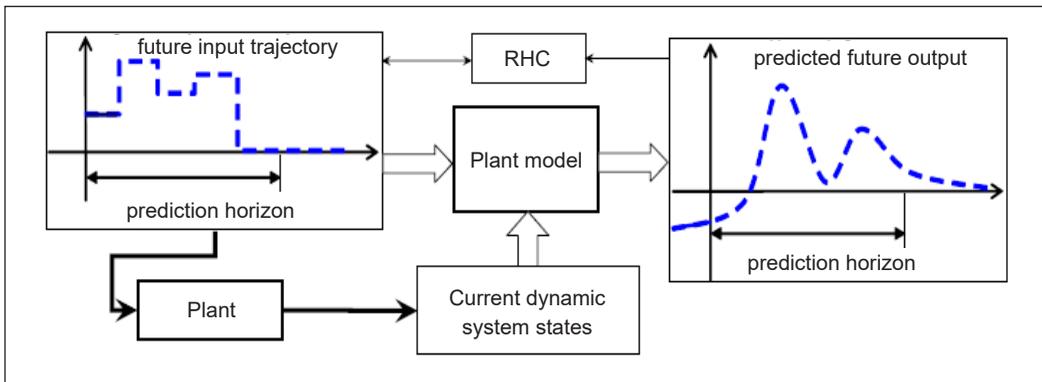


Figure 4. Block diagram for the receding horizon (Gorinevsky, 2005)

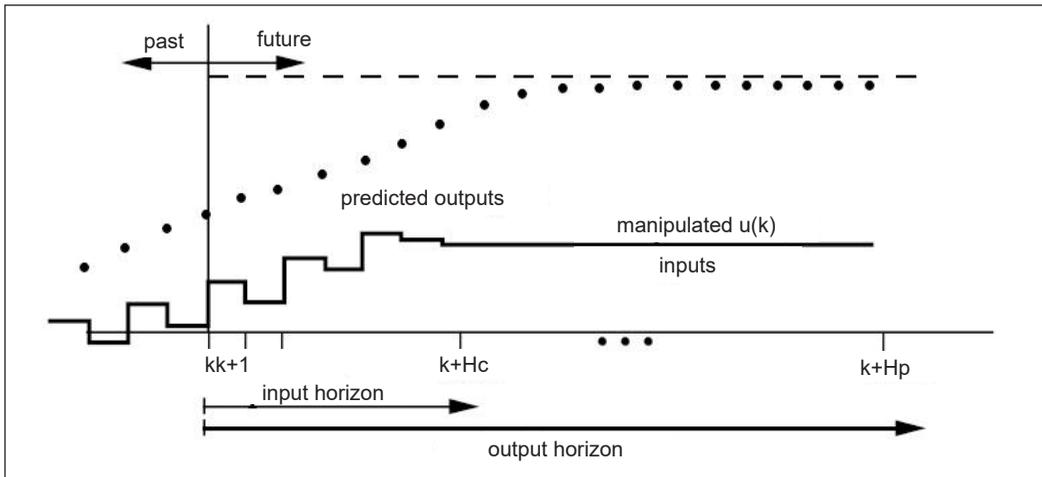


Figure 5. The receding horizon concept shows an optimization problem (Shahriar et al., 2013)

The sampling-based MPC systems keep the control signal constant over the interval $[t, t+h]$. The value of h can then be considered as the sampling interval, and the prediction horizon can be a small number of sampling intervals. It can reduce the computational power required to employ a model predictive controller (Halvgaard et al., 2012).

Only the initial measure of the process control system strategy is executed. The state of the plant is tested again, and the calculations are repeated starting from the new current state, which in turn yields a new control and a new predicted state path (Gonela et al., 2019). The prediction horizon that remains being shifted forward and meant for this re-computation technique, the Model Predictive Controller (MPC), is also known as Receding Horizon Control (RHC) (Alqahtani et al., 2016).

RESULTS AND DISCUSSION

System Identification Fitness

The real-time sample data have been collected from the solar power plant system under various conditions through Zever Solar Data logging systems for linear system fitness, and the data have been taken for estimation and validation. Figure 6 shows the simulated result of the selected model with the measured output obtained from the MATLAB platform. The system identification tool preferred showing the residual analysis results for every chosen model. The validation data set computed the prediction errors or the residuals (Arnold & Andersson, 2011). The correlation functions are shown in Figure 7. Graphical User Interface in the system identification tool allows us to view and analyze the linear/non-linear system responses. The transient response of the system obtained from the MATLAB software is represented in Figure 8. Correlation analysis identifies the fascinating relationships in data and helps us realize the relevance of attributes concerning

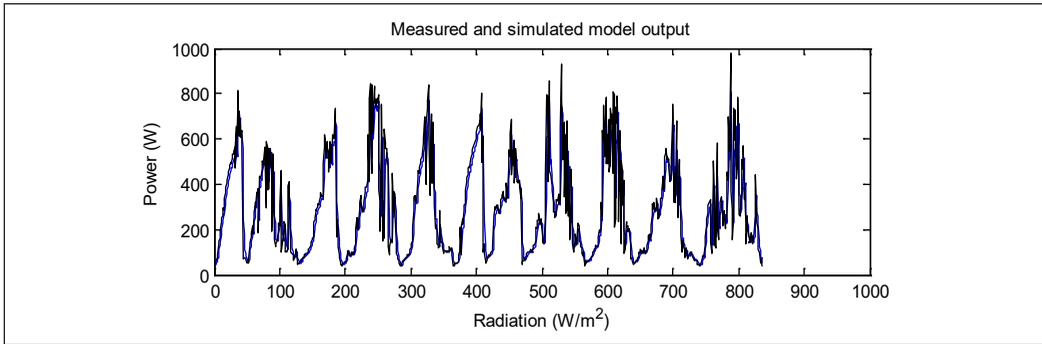


Figure 6. Model validation output

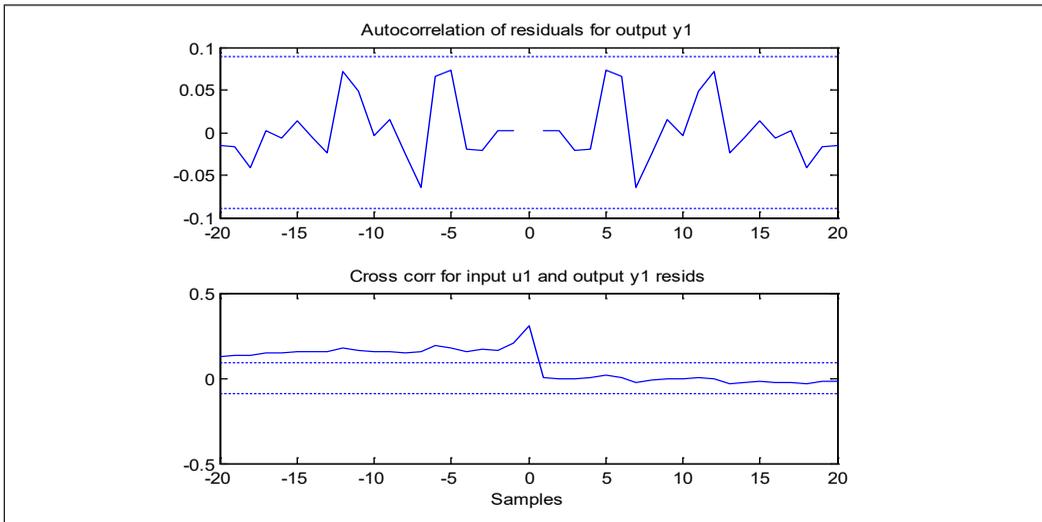


Figure 7. Residual analysis of the system

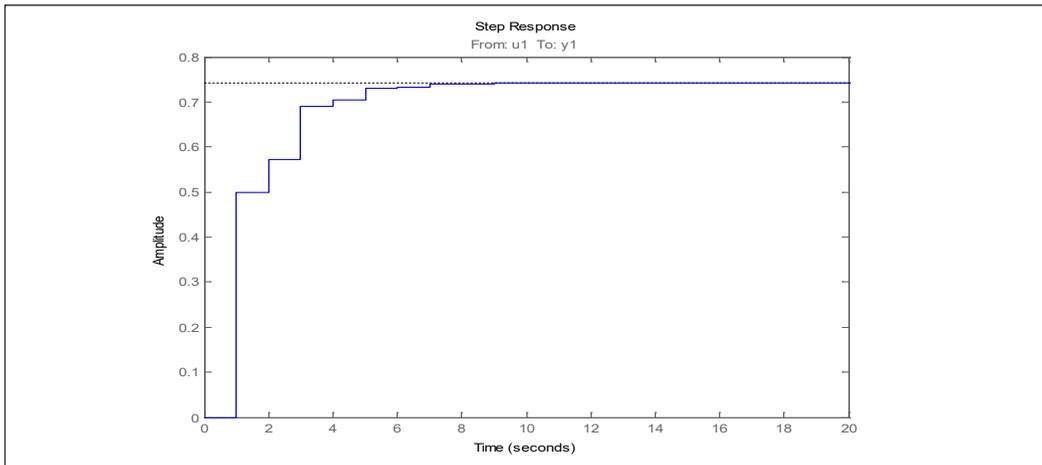


Figure 8. Power response of a system with a system identification tool

the objectives. It helps optimize the input variables and the data size, which will help in memory reduction. Autocorrelation and cross-correlation values between input and predicted output are 0.02 and 0.15 (Enríquez et al., 2016).

Model Predictive Control (MPC)

The transfer function obtained from the system identification tool is imported into the MPC tool. MPC offers a better understanding of the experimental phenomena (machine learning process), is excellent in predicting events in the future (time series analysis), and makes it easy to obtain a system model of signal in filter design (signal processing techniques) (Basallo et al., 2017).

The control actions of providing values for horizon, constraints, and adjusting the weights were done accordingly in the MPC tool based on our required control action. Figure 9 shows the MPC structure for a solar power plant system. By importing a plant model (or controller) in the MATLAB MPC tool, the graphic shows the count for the five possible signal types (Godina et al., 2018). The overall result for the solar power plant System design by MPC in MATLAB/Simulink is shown in Figure 10.

As the simulation runs, the plant output and the reference signal are displayed, and the MPC response is shown in Figure 11 and Figure 12, representing the step response of a dynamic system model to a step input of unit amplitude.

The performance index is a steady-state error, defined as the error between the power response and the predicted power response, with a value of 0.8. Hence, Figure 12 gives a solution for an optimization problem to find the optimal control action that drives the response of predicted plant output to the desired set-point as close as possible. The system identification process contributes to the proper functioning of the MPC controller, which performs the prediction. The System Identification Process (SIP) and MPC complement each other for better efficiency.

The performance of the proposed predictor model can be well understood from the results. The error variation of the predicted values from the actual values for the proposed system is 0.8. Achieving the error of such a low value with very few datasets describes the efficiency of the model design. The results of the proposed model are compared with the other models discussed in the literature review. Table 3 compares the methods employed, indices used for performance evaluation, and the actual error value obtained through simulation. This comparison is not exhaustive since the compared models are designed for different specifications, sizes, and locations. Also, the metrics used for comparison vary widely; no standard error metrics are used in all literature. From Table 3, the numerical methods show good performance only in some instances, and the intelligent techniques-based models like artificial neural networks, fuzzy logic, and ANFIS demonstrate better performance in almost all cases. However, the hybrids remain competitive with intelligent

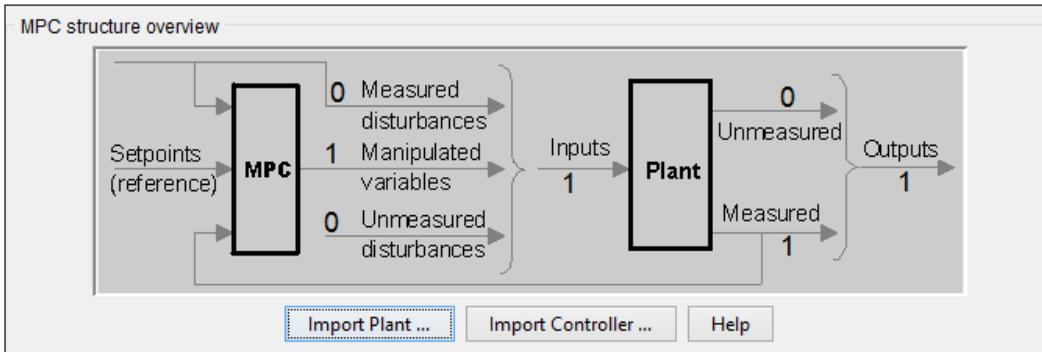


Figure 9. MPC structure

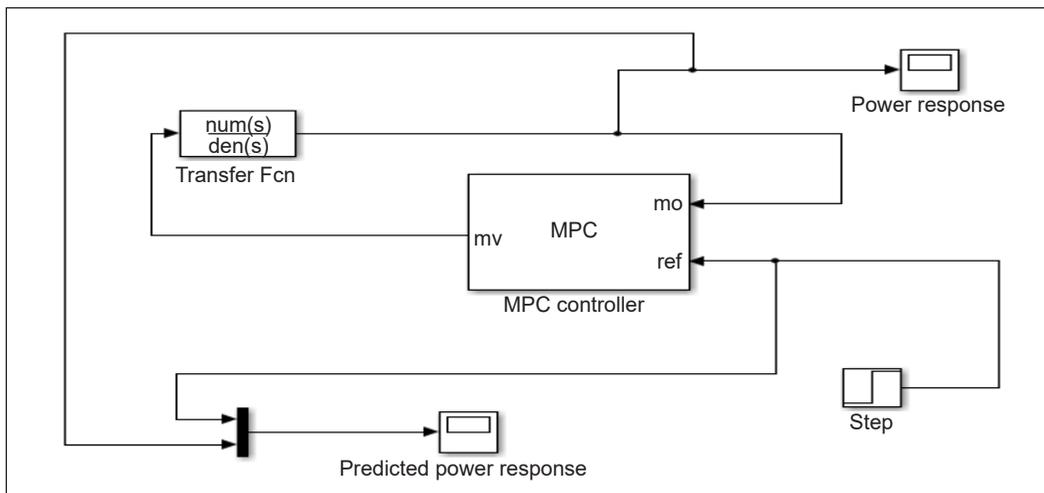


Figure 10. Simulation block diagram

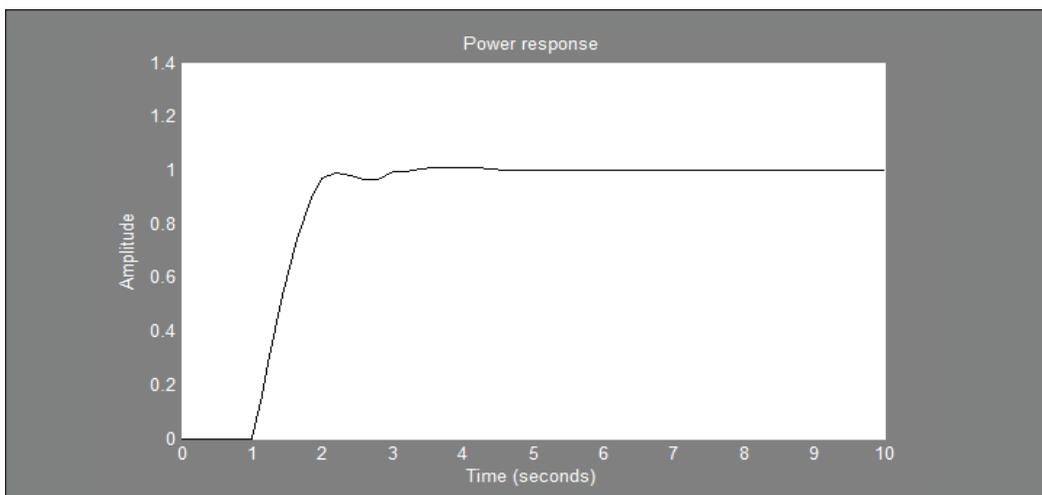


Figure 11. Power response in Model Predictive Controller

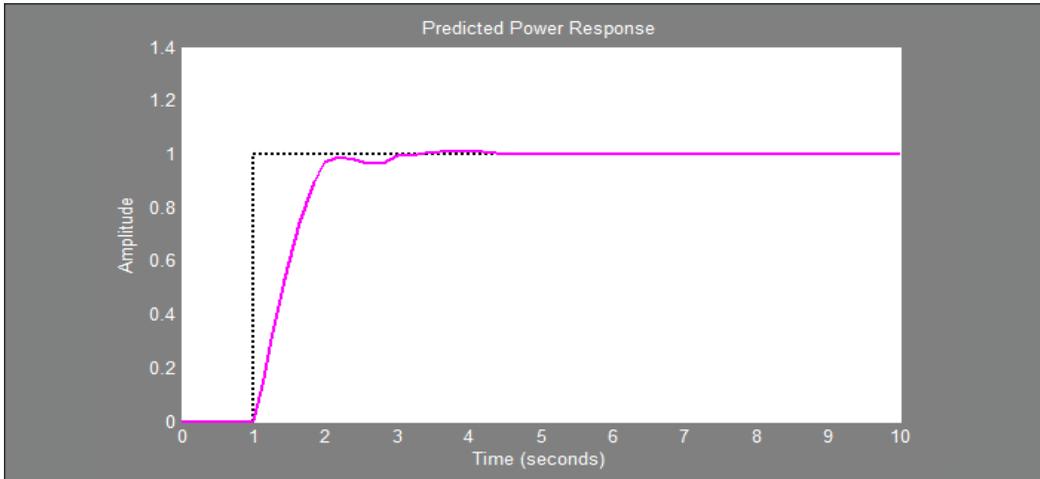


Figure 12. Predicted power response in Model Predictive Controller

Table 3

Comparison of methods employed, indices used for performance evaluation, and the actual error value obtained through simulation

Reference	Method	Performance Index	Error Value
Yadav et al., 2019b	PSO ANFIS	MAPE	BPNN – 11.5852 ANFIS – 10.7300 PSO-ANFIS – 3.5196
Ehsan et al., 2014	ANN	MSE	0.0198 to 0.025.
Semero et al., 2018	GA- PSO-ANFIS	NMAE	5.31
Viswawandya and Mohanty, 2018	Fuzzy logic & ANFIS	MAE	ANFIS – 0.067 Fuzzy – 0.187
Abdullah et al., 2019	HFPSO – WT ANFIS	MAE	25.6249 to 44.8471
Chugh et al., 2015	Fuzzy Logic	MAPE	1.052
Abuella and Chowdhury, 2015	MLRA	RMSE	0.0736
Mandal et al., 2012	WT-BPNN & WT-RBFNN	RMSE	WT+BPNN 0.55 to 2.05 WT+RBFNN 0.32 to 1.57
Ncane and Saha, 2019	Fuzzy & ANN	MAE	Fuzzy – 1.924 ANN – 2.626
Yadav et al., 2019a	GA-ANFIS	RMSE	0.023 TO 0.316
Lin and Pai, 2016	ESDLS-SVR	RMSE	0.1618 to 0.5502
Our proposed Model	MPC	SSE	0.8

performance, speed, and accuracy techniques. However, the design complexity makes it a challenge to be implemented widely (Clastres, 2011). Another factor to be discussed is how good the predictor is in solar power plant capacity scaling. Since the proposed controller is a closed-loop system, carrying the scaling even resolves for unstable controllers if the closed-loop system is stable.

The Novelty of the Model

The unique features include a built-in error feedback system for the predictive controller and the correlation analysis between the output and input variables performed in the system identification block of MATLAB. Correlation analysis identifies the fascinating relationships in data and helps us realize the relevance of attributes concerning the objectives. It helps optimize the input variables and the data size, which will help in memory reduction. Moreover, the proposed model suits building-integrated photovoltaic (BIPV) and building-attached photovoltaic (BAPV). If the energy produced and consumed by the building are equal, it is called a net-zero energy building. Data availability on power generation helps schedule power usage and storage; hence, energy prediction has become integral to such buildings. The prediction results can also help in handling overload conditions. Furthermore, an additional unit called an automatic overload alert system can be integrated with the proposed model. This feature will send a text to the residence owner once overload conditions are reached prior to the event. It will allow the residence owners to think of future overload prevention strategies. Specifically, this feature could be a significant component of smart homes, which are increasing at 15%–18% in metropolitan cities and 5%–10 % in other cities of India (Jain, 2016).

The other advantage includes the ease of tuning and replicating the proposed method, making it appropriate for industrial and residential units. Tuning is an easy chore in MPC, unlike other machine learning methods, which require an entirely new set of data for the changed condition of the SPVS. The numerical methods will require the designers to recalculate from the initial stage. The intelligent methods will require tuning, which retrains the model with new data sets. However, in the case of hybrids, most models need a complete redesign, while the self-evolving models will adapt to the new capacity. In the proposed case, tuning is unnecessary since the feedback system in the controller automatically upgrades itself for the new capacity even though many control parameters are involved in this model predictive controller.

CONCLUSION

In this study, the primary focus was on the critical importance of accurate solar power prediction, a key factor for solar energy suppliers and grid operators aiming to maintain a balanced supply-demand equilibrium within an electrical grid, ultimately impacting their profitability. The study harnessed the synergy of enhanced data availability and the computational prowess of machine learning algorithms to bolster the optimization and overall performance of prediction systems.

The System Identification process and the application of a Model Predictive Controller (MPC) were leveraged as potent tools for forecasting renewable energy, specifically in the context of solar energy. Real-time sample data from a solar power plant was gathered,

forming the basis for accurate predictions. Meteorological data played a pivotal role in predicting fluctuations in solar power generation. Data was utilized for system estimation and validation using a system identification toolbox, culminating in deriving a transfer function that exhibited optimal fitness. The obtained transfer function was incorporated into MATLAB's Model Predictive Controller (MPC) toolbox, where a controller was meticulously designed. The designed controller demonstrated exceptional accuracy in predicting the output power response for a solar power plant system with the R square value of 0.8 and MSE of 0.12.

This research underscores the significance of advanced techniques, such as System Identification and Model Predictive Control, in achieving highly precise solar power predictions. These findings directly affect the efficient management of solar energy resources and their integration into the electrical grid, with potential benefits for suppliers and grid operators.

The future scope of this research includes conducting comparative analyses with benchmark models, assessing seasonal variations in solar energy prediction, and broadening the range of case studies across diverse geographic locations and climates, emphasizing in-depth Analysis and sensitivity testing to enhance the manuscript's quality and applicability.

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