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THE SOLAR POWER GENERATION FORECAST METHODOLOGY FOR SECURE SYSTEM OPERATION WITH HIGHLY DISTRIBUTED POWER GENERATION

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Abstract: Policies promoting a carbon-neutral economy are accelerating the energy transition towards renewable electricity generation, primarily through small-scale investments within distribution networks. As penetration of distributed generation increases, transmission system operators encounter increasing challenges in predictability. This study presents a coordination approach between transmission and distribution network operators in Türkiye, highlighting an advanced solar generation forecasting method to enhance secure network operations. In the initial phase, a centralized database was established to catalog distributed generation capacity and plant specifications. Web-based applications and services were developed to integrate distribution company assets into the transmission network model. By September 2024, over 30,000 power plants (99% photovoltaic, 17.8 GW total) had been integrated. Distribution companies are expected to supply real-time generation data to the transmission operator, though issues such as measurement errors and communication problems may limit data accuracy and continuity. Thereafter, a short-term solar forecasting system was developed to support intraday and day-ahead congestion analysis. The system provides high-resolution forecasts at the individual plant level for more than 20,000 locations. Machine learning algorithms were used for large-scale plants, while small-scale plant forecasts were based on meteorological data and physical modeling. Because accurate forecasting requires detailed plant parameters, a Particle Swarm Optimization algorithm was implemented to calibrate photovoltaic models. This approach enables accurate parameter estimation even when on-site data is limited, improving the performance and reliability of solar generation forecasts. This paper provides valuable insights into the coordination between transmission system operators and distribution system operators, emphasizing the importance of data integration and forecasting accuracy in managing distributed solar generation. Furthermore, it details the outcomes of an advanced solar generation forecasting system, demonstrating its effectiveness in improving predictability and supporting secure and efficient power system operations.

Keywords: Parameter Estimation, Particle Swarm Optimization, Solar Generation Forecast

INTRODUCTION

The expansion of renewable energy production, driven by carbon-neutral economy goals and international climate agreements, is becoming a significant issue worldwide and in Türkiye. The integration of intermittent renewable energy sources into power systems presents a significant challenge for Transmission System Operators (TSOs) in maintaining the predictability and stability of the grid.

Solar Photovoltaic (PV) and wind are expected to contribute 95% of all renewable capacity additions by 2030 due to their lower generation costs than fossil and non-fossil alternatives in most countries, along with continued policy support. Solar PV adoption accelerates thanks to declining equipment costs, relatively rapid permitting and widespread social acceptance [1].

In Türkiye, the total installed electricity generation capacity is approximately 118 GW. Of this, around 71 GW (about 60%) is derived from renewable energy sources, including hydropower (32 GW), solar (22 GW), wind (13 GW), and other sources such as geothermal and biomass (4 GW). The remaining ~47 GW (~40%) is provided by thermal power plants, primarily fueled by natural gas and coal. Total annual electricity generation stands at approximately 343 TWh, with renewables accounting for around 156 TWh, or 45% of the total.

Solar power plants tend to be connected to the distribution grid as individuals, small companies, medium-scale industries are becoming prosumers. For example, 80% of the installed solar capacity in Türkiye between 2021 – 2024, corresponding to 11 GW, was connected to the grid at the distribution level. The distribution system in

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Türkiye typically operates at voltage levels ranging from 6 kV to 36 kV, covering both low and medium voltage ranges. The transmission system, on the other hand, includes voltage levels of 36 kV, 66 kV, 154 kV, and 400 kV, which are managed by TSO. With the increasing rate of distributed generation, effective information exchange between transmission system operators and distribution system operators is becoming essential to ensure efficient and secure system operation.

This study introduces an advanced generation forecasting approach for distributed solar power plants to enhance system predictability and improve system security. Additionally, it presents a methodology for obtaining solar generation data and integrating information from plants with a high proportion of installed capacity at the distribution level, thereby strengthening coordination between TSOs and Distribution System Operators (DSOs).

1. COORDINATION OF TRANSMISSION AND DISTRIBUTION SYSTEM OPERATORS

The exchange of information and coordination between transmission system operators and distribution system operators are essential for optimizing resource utilization, ensuring secure and efficient system operation, and facilitating market development. Several projects have already proposed TSO-DSO coordination mechanisms [2]. These projects primarily focus on market models, such as centralized and local market models, and aim to integrate Distributed Energy Resources (DERs) into ancillary services.

This project primarily emphasizes the exchange of information related to physical electricity network models. The electricity network of Türkiye is structured with a single state-owned transmission company (TEİAŞ), 21 distribution companies, and over 200 distribution-licensed organized industrial zones. Data integration between these entities encompasses information on DERs, PV systems, real-time DER generation, and tie-line flows, as illustrated in Figure 1.

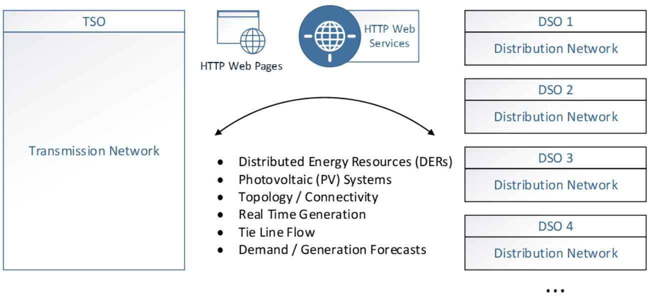

Figure 1: TSO - DSO Integration Business Model

A centralized database has been established within the TSO's information system, known as the Dispatcher Information System (YTBS, an abbreviation for Yük Tevzi Bilgi Sistemi in Turkish). YTBS serves as an infrastructure for transmission system modelling, measurement and data collection, computational tools and operational processes, power system security analyses, forecasting systems, dynamic reporting, and decision-support mechanisms.

To facilitate data collection and modelling, web-based interfaces and web services were developed within the software to record the installed capacity and technical characteristics of distributed generation plants. Operators in distribution companies can supply and monitor this information either manually via a web application or automatically through web service integration. Each DSO has undergone an IT harmonization process to comply with nationwide grid data standards.

As of March 2025, this integration has successfully collected data from more than 33,000 power plants, with a total installed capacity of 20 GW, 98% of which are PV solar plants. This process is designed as a continuous integration between the TSO and DSOs, enabling the monitoring of new generation investments. Additionally, real-time generation data from power plants is expected to be provided by the DSOs. However, practical challenges such as errors in measurement systems and communication issues highlight the complexities of ensuring accurate and reliable data access.

2. SOLAR GENERATION FORECAST METHODOLOGY

Generation adequacy and congestion forecast assessments in short-term grid operation planning require accurate renewable generation forecasting systems. In this study, detailed and up-to-date DER data was first utilized within the PV solar generation forecasting system. To ensure that the forecast results can be effectively incorporated into intraday and day-ahead network power flow analyses and congestion forecasts, the generation forecast resolution must be spatially specific at least at the transmission substation level. Therefore, this study was conducted at the individual power plant level, covering over 22,000 locations.

Initially, a categorization process was applied to determine the appropriate level of forecasting complexity for each power plant. PV power plants were classified into two categories such as grid-scale and small-scale. Grid-scale plants are defined as those either possessing a generation license or being directly connected to the transmission grid, with an installed capacity exceeding 1 MW. Small-scale plants are those connected to the distribution grid with an installed capacity of more than 50 kW.

Machine learning-based forecasting algorithms were applied to grid-scale plants with available production data. In contrast, for small-scale plants, forecasting algorithms

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were developed using a meteorological data-driven model and a physical model based on plant specifications. Given that distributed solar generation plants have a total installed capacity of 19 GW, with a substantial portion lacking accessible production data, the implementation of a meteorological data-driven physical model becomes crucial for accurate forecasting.

The physical model-based solar generation forecasting approach relies on fundamental physical principles while incorporating atmospheric conditions. This method uses a PV system's electrical production characteristics to predict environmental factors such as solar radiation, temperature, and wind speed, as well as the physical and technical specifications of the panels. The PV model of each power plant is represented through an equivalent model constructed under specific assumptions, with parameter estimation in the equivalent model playing a key role in improving production forecasts. Further details on the physical model-based solar generation forecasting approach are provided in the next chapter.

3. SOLAR GENERATION FORECASTING BASED ON PHYSICAL MODEL

Physical model-based solar power forecasting is an approach that applies fundamental physical principles while incorporating atmospheric conditions to enhance prediction accuracy. In this context, two meteorological forecast providers are integrated into the system: the numerical weather forecast from the ALARO model of the Turkish State Meteorological Service and the mix model of Meteomatics. This dual-input approach improves redundancy and enhances the accuracy of hybrid estimations.

Physical models estimate the electricity generation of a PV system by incorporating the panel's physical and technical characteristics along with meteorological forecasts, including solar radiation, total cloud cover, temperature, and wind speed [3]. The forecasting process based on the physical model consists of six key steps, as outlined below and illustrated in Figure 2:

- Converting local time to solar time
- Calculating the angle of solar incidence on the panel
- Decomposing solar radiation on the horizontal plane
- Converting horizontal solar radiation to the radiation received by the panel
- Calculating panel temperature
- Forecasting the active power generation of the power plant

The input set for physical model-based solar power forecasting includes both precisely known data such as location, date, and time and estimated values, including the equivalent power plant model and meteorological forecast data. The accuracy of the equivalent model and meteorological forecasts directly impacts the performance of solar power predictions.

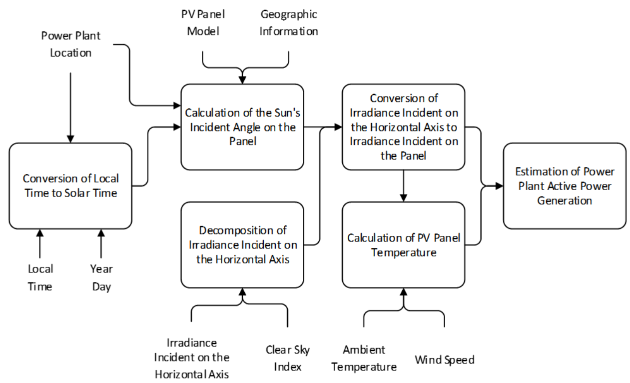

Figure 2: Physical Model Based Solar Generation Forecasting Process

When constructing the equivalent power plant model, a simplified yet functionally representative approach is adopted to reduce system complexity. However, large geographical variations within a plant site or rooftop installations can lead to differences in tilt and orientation across different sections. Additionally, variations in PV cell types within the same plant make it challenging to establish an accurate equivalent model, sometimes resulting in discrepancies between the model and actual plant characteristics.

The accuracy of the developed model was validated by on-site measurements of power generation and solar irradiation. This plant has an installed capacity of 10 MW, and its technical specifications such as panel technology, tracking type, tilt, and azimuth are well documented.

Solar power generation estimations were calculated using meteorological observations and the plant model. The results indicate that the average error remains within 1–3%, even on days with high meteorological variability, as shown in Figure 3. This study demonstrates that when a well-calibrated PV model is combined with accurate meteorological forecasts, the physical model-based generation forecast can achieve highly reliable results.

Due to these challenges, obtaining precise data for each plant is difficult. To address this issue, a model optimization approach, specifically parameter estimation algorithms, is required. This approach enables the calibration of PV models even with limited production data, thereby improving forecast accuracy and ensuring that predictions more accurately reflect actual power generation.

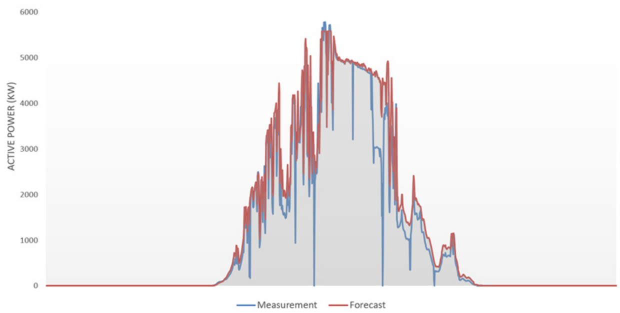

Figure 3: Forecast Performance of Physical Model based Forecast

4. PARAMETER ESTIMATION IN PV SYSTEMS

Parameter estimation is a method used to align physical or mathematical models with real-world data [4]. In renewable energy systems, it plays a critical role in power plant performance analysis and production forecasting [5]. In PV systems, accurately determining key parameters such as panel tilt, azimuth angle, and inverter efficiency is essential to ensuring the reliability of generation forecasts [6].

Various methods have been proposed in the literature for estimating PV model parameters, categorized as conventional parameter estimation techniques:

- Deterministic Methods: Optimization techniques such as Newton-Raphson and Levenberg-Marquardt offer fast convergence but risk getting trapped in local minima [7].
- Statistical Methods: Regression analyses and the Least Squares Estimation (LSE) method perform well with large datasets but are sensitive to noisy data.
- Machine Learning and AI-Based Methods: Techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) enable data-driven predictions but come with challenges like overfitting and high computational costs [8].

To address the limitations of traditional methods, metaheuristic optimization algorithms have been developed [9]. The advantages of these evolutionary algorithms in PV parameter estimation are as follows:

- Genetic Algorithms (GA): Capable of searching the solution space for the global optimum, but computationally expensive for large datasets [10].
- Differential Evolution (DE): Designed for PV model parameter estimation with lower computational costs; however, it has a higher likelihood of getting stuck in local minima [11].
- Particle Swarm Optimization (PSO): Notable for its ability to converge toward the global optimum with low computational cost [12].

Among these methods PSO has gained widespread use in PV model parameter estimation in recent years due to the following advantages:

- It has a low risk of getting trapped in local minima and can explore a broad solution space [13].
- As a stochastic optimization method, it effectively handles noisy and incomplete data [14].
- It exhibits faster convergence compared to other evolutionary algorithms, making it particularly suitable for large-scale solar power plant modelling [15].

When technical details of PV plants may be incomplete or unavailable, the PSO method proves to be an effective solution, enabling accurate PV model parameter estimation even when generation data is irregular or missing. This, in turn, enhances forecasting accuracy. Among the various conventional and metaheuristic optimization techniques proposed in the literature, PSO was selected for this study due to its computational efficiency and its ability to consistently reach the global minimum.

5. PARTICLE SWARM OPTIMIZATION FOR PARAMETER ESTIMATION OF PV MODELS

PSO, introduced by Kennedy and Eberhart in 1995, is an optimization algorithm inspired by the collective behavior of swarms in nature, such as the coordinated movement of birds or fish. It is particularly effective for solving global optimization problems.

In PSO, solution candidates are represented as particles, which navigate a multidimensional solution space in search of the optimal solution. Each particle updates its position based on:

- Personal Best (pBest): The best solution found by the particle so far.
- Global Best (gBest): The best solution found by any particle in the swarm.

Each particle adjusts its position based on these two factors, along with a random component to encourage exploration.

PV model data includes key parameters such as panel type, tracking type, tilt angle, azimuth angle, inverter efficiency, system losses, and AC/DC rated power. To enhance forecast performance, some of these parameters are optimized using PSO method and integrated into the forecasting process.

The PSO algorithm applied in this study follows these steps:

- Initialization: Particles are assigned random positions and velocities.
- Objective Function Evaluation: Each particle calculates the objective function value at its current position.

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- Updating pBest and gBest: The current position of each particle is compared to its pBest and the swarm's gBest, updating them if necessary.
- Velocity and Position Update: Each particle updates its velocity and position according to the following equations:

$$v_i(t+1) = w \times v_i(t+1) + c_1 \times r_1 \times (pBest_i - x_i) + c_2 \times r_2 \times (gBest_i - x_i)$$
$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where:

v_i = Velocity of the particle
x_i = Position of the particle
w = Inertia weight
c_1, c_2 = Cognitive and social coefficients
r_1, r_2 = Random numbers between 0 and 1
$pBest$ = Best position found by the particle
$gBest$ = Best position found by the swarm

- Stopping Criterion: The algorithm terminates when either a predefined number of iterations is reached or the solution is sufficiently close to the optimum.

By applying PSO, PV model parameters are refined to improve forecast accuracy. The optimized solar power generation forecasts are then compared with previous weather-based forecasts, and the results are discussed in the final section.

6. NUMERICAL RESULTS

It has been observed that the physical model-based forecasting approach achieves high accuracy when tested with measured meteorological data and a well-structured PV model. Therefore, a PV model constructed with simplified assumptions can be further improved by applying PSO, which calibrates the model parameters to better reflect real system behavior and enhance forecasting performance.

The PSO-based parameter estimation algorithm was applied to grid-scale solar power plants across different regions of Türkiye to enhance the accuracy of PV generation forecasts. Specifically, DC power, tilt angle, and azimuth angle critical parameters influencing solar power output were estimated using the PSO method for the generation period between January 14 and June 6, 2024.

Following the parameter estimation process, solar power generation forecasts were conducted based on the optimized models. The results demonstrated that integrating PSO-based parameter estimation significantly improved the forecasting accuracy by refining the representation of plant characteristics.

Table I summarizes representative results from selected solar power plants located in different regions, illustrating the impact of parameter optimization on forecast performance. The findings highlight the effectiveness of the PSO approach in adapting PV models to real-world conditions, ultimately leading to more precise solar power predictions.

Additionally, the results indicate that the accuracy of the forecasts varies across different geographical and climatic conditions, emphasizing the importance of regional parameter tuning. In particular, regions with higher meteorological variability benefited the most from the improved parameter estimation, as traditional static models often struggle to capture the dynamic nature of solar radiation and environmental influences.

Table I. Results of Parameter Estimation and Solar Generation Forecasting

REGION OF THE SOLAR POWER PLANT	PRE-OPTIMIZATION				POST-OPTIMIZATION				
	DC POWER (MW)	TILT ANGLE	AZIMUTH ANGLE	NMAE (%)	DC POWER (MW)	TILT ANGLE	AZI-MUTH ANGLE	NMAE (%)	IMPROVEMENT (%)
BİTLİS	24.19	28	0	8.34	25.6	25.12	-52.48	5.66	47.4
BURDUR	7	20	0	10.98	9.6	30.86	-44.46	7.23	51.97
DENİZLİ - I	10.73	30.38	0	18.34	6.3	45	-5.19	13.06	40.41
DENİZLİ - II	6.05	25	0	15.04	8	45	-77.2	7.12	111.29
ERZURUM	5.31	20	0	8.04	3.43	23.08	-90	3.79	112.44
KONYA – I	16.34	24	0	14.05	17.28	45	-79.54	7.86	78.7
KONYA – II	13.72	25	0	14.86	12.11	45	-47.2	10.94	35.93
KONYA - III	3.08	25	0	9.63	2.65	31.3	-55.96	7.68	25.39
KONYA – IV	12	20	0	9.8	12.8	25.64	-52.03	7.07	38.59
KONYA - V	6.05	25	0	7.94	8	18.72	-7.48	5.83	36.13
MERSİN	36.44	29.97	0	12.73	55.87	19.48	-13.25	7.04	80.95
ŞIRNAK	10.42	25	0	7.6	7.6	29.54	-50.03	3.84	97.58

These findings underscore the potential of metaheuristic optimization methods in enhancing renewable energy forecasting, particularly in large-scale distributed generation systems where accurate and reliable predictions are essential for grid stability and efficient energy management.

Improvements in forecast accuracy demonstrates the effectiveness of the PSO parameter estimation method. However, in certain plants, the improvements were limited, indicating that updating PV model parameters was not necessary for those specific cases. For power plants where the percentage forecast error improved by more than 10%, the optimized parameters obtained from the PSO algorithm can be effectively used to enhance future forecasts. To illustrate these improvements, generation forecast result graphs for selected plants where significant accuracy enhancements were observed are presented below.

In the case of a Solar Power Plant in Şırnak, a time shift between the forecasted and actual production values was observed before optimization. Additionally, the forecast consistently underestimated the actual power generation.

- The time shift was attributed to an incorrect azimuth angle in the PV model. After applying the optimization, the azimuth angle was updated to -50 degrees, indicating that the plant was oriented closer to the east than previously assumed. This correction successfully eliminated the time shift in the forecast.
- The discrepancy between forecasted and actual production values was primarily due to inaccurate model parameters, particularly DC power. After optimization, the DC power value was adjusted from 10.4 MW to 7.6 MW, resulting in a significant improvement in forecast accuracy, with a much closer alignment between predicted and actual production values.

The impact of these optimizations is shown in Figure 4, which compares the pre-optimization and post-optimization generation forecasts for Şırnak SPP.

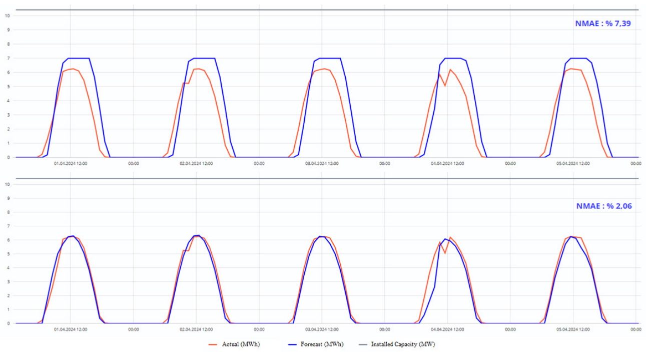

Figure 4: Şırnak SPP (a) Pre-Optimization and (b) Post-Optimization Forecast Result

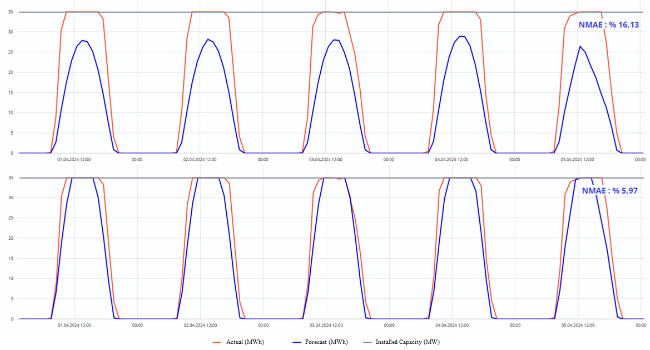

Figure 5: Mersin SPP (a) Pre-Optimization and (b) Post-Optimization Forecast Result

7. CONCLUSION

The collaboration between TSOs and DSOs plays a pivotal role in enhancing the predictability and stability of energy systems, particularly as the integration of renewable energy sources continues to expand. Solar energy generation has become essential for green transition, and with the increasing share of distributed energy generation, the accurate and continuous monitoring of solar plants within distribution networks is critical for ensuring system security.

This study presents an approach to forecasting solar energy production that enhances grid operation security. By leveraging machine learning algorithms for large-scale plants with available production data and employing physical models for smaller-scale plants, this work provides a comprehensive solution to forecasting challenges. The application of parameter estimation techniques, such as Particle Swarm Optimization, has significantly improved the accuracy of physical model-based forecasting by optimizing key PV model parameters.

The findings underscore the importance of accurate solar energy production data acquisition and the advancement of forecasting methodologies. In particular, the ability to utilize limited and intermittent production data for parameter estimation enhances forecasting precision, offering a viable solution even for plants with incomplete datasets.

In summary, the coordination between DSOs and TSOs, combined with advanced forecasting techniques and improved solar energy data acquisition, is crucial for the effective and secure management of future energy systems. This study contributes to the development of a novel forecasting model that not only enhances the accuracy of solar energy predictions but also provides valuable insights for the future integration of renewable energy sources into power grids.

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BIOGRAPHY

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