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Posted Date: April 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9369861/v1

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Additional Declarations: No competing interests reported.

Stochastic Methods for Forecasting and Power System Mode Optimization with a High Share of Renewable Energy Sources: A Case Study of Tajikistan

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Abstract Subject. This paper addresses the critical scientific challenge of integrating stochastic solar generation into the power system of Tajikistan, which is predominantly characterized by hydroelectric power. The high volatility of solar irradiance in complex terrain poses risks to static stability and necessitates a transition from deterministic operational planning methods.
Methods. To solve the short-term forecasting problem, the study proposes an original hybrid approach based on the synthesis of Long Short-Term Memory (LSTM) recurrent neural networks and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) econometric models. The theoretical framework relies on the decomposition of power time series and entropy analysis of the information complexity of insolation patterns.
Results. An adaptive two-loop forecasting algorithm was developed, enabling both the approximation of non-linear production trends and the generation of dynamic confidence intervals based on current volatility estimates. Testing the model on empirical data for 2021–2023 demonstrated a reduction in the Mean Absolute Percentage Error (MAPE) to 6.4%. This outperforms classical ARIMA methods and standalone neural network models by 15–20% during periods of unstable cloud cover.
Practical Significance. The findings allow for the optimization of spinning reserves at cascading hydropower plants and improve the efficiency of water-energy resource management during seasonal power shortages. The proposed architecture is ready for integration into modern Automated Dispatch Control Systems (ADCS) via standard data exchange protocols.
Keywords: Solar power forecasting, volatility, hybrid models, LSTM, GARCH, Tajikistan power system.

1. INTRODUCTION

The current stage of global energy development is characterized by profound decarbonization and a radical transformation of the generation capacity structure. The integration of renewable energy sources (RES) operating through inverter-based interfaces leads to a reduction in the equivalent inertia of the power system and a significant increase in the uncertainty of power balance modes. Unlike traditional generation, the stochastic nature of solar photovoltaic (PV) and wind power generation gives rise to high-frequency power fluctuations that cannot be adequately described within the framework of classical deterministic approaches [1, 2].

The scientific problem lies in the critical conflict between the necessity of ensuring static system stability and the high volatility of the primary renewable energy resource. For the power system of Tajikistan, this challenge takes on a specific character [3–5]:

- **Dominance of hydropower generation:** The installed capacity of hydropower plants exceeds 5.2 GW (accounting for over 93% of the energy mix). This provides unique opportunities for flexible regulation but requires precise synchronization of solar PV schedules with the operating modes of hydro cascades to optimize the water-energy balance.
- **Climatic specifics:** High solar irradiance (1,600–1,900 kWh/m²/year) is accompanied by abrupt changes in atmospheric transparency, rendering generation time series non-stationary and heteroscedastic.
- **Information uncertainty:** Traditional short-term forecasting methods (Persistence, ARIMA) demonstrate unsatisfactory accuracy under conditions of rapid cloud phase transitions, leading to excessive power reserves.

This paper is devoted to the development and validation of a hybrid stochastic algorithm that combines deep learning mechanisms (LSTM) for non-linear trend approximation with econometric models (GARCH) for dynamic volatility estimation. Unlike existing solutions, the proposed approach relies on entropy complexity analysis, which enables a quantitative assessment of the mode's randomness and enhances the adaptability of operational dispatch control systems amidst the industry's digital transformation.

2. THE TAJIKISTAN POWER SYSTEM AND ITS STOCHASTIC CHARACTERISTICS

2.1. Analysis of the Generation Structure and Balancing Constraints

The power system of Tajikistan represents a unique case study for researching RES integration due to its high dependence on hydropower resources. According to data from the Ministry of Energy and Water Resources, the installed capacity structure is characterized by the dominance of radial-node hydropower plants (Table 1) [6-8].

Table 1. Parameters of the power system generation structure

Generation Type	Capacity, MW	Share, %	Flexibility Characteristics
HPP (Large-scale cascades)	5,270	93.5	High (Base and peak load regulation)
Small and run-of-river HPPs	430	7.6	Seasonal dependence, limited regulation

CHPs (Cogeneration)	400	7.1	Thermal schedule (Low flexibility)
SPPs (Pilot projects)	15	0.27	Stochastic, non-inertial (Inertia-less)

A critical aspect is the misalignment of volatility vectors: reservoir inflows (seasonal stochastics) are superimposed on the rapid intraday variability of solar irradiance. This creates a multi-objective power reserve optimization problem.

2.2. Analysis of Demand Dynamics and Solar Potential

Daily load profiles (Fig. 1) demonstrate a pronounced seasonal asymmetry. The winter maximum (reaching a peak of 2,100 MW) is characterized by a "morning shoulder" and a deep evening peak, driven by a high share of electric heating.

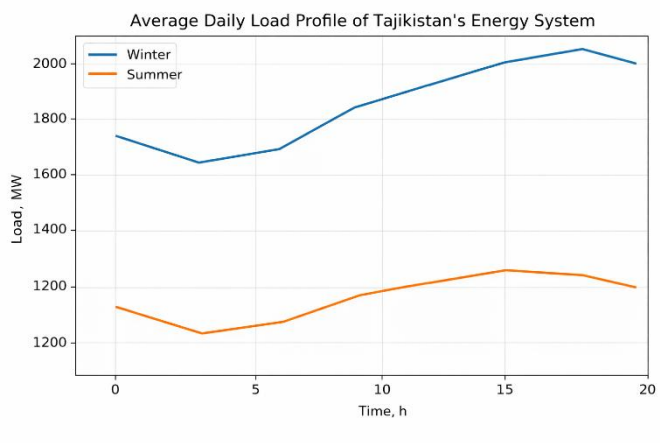


Fig. 1. Load profile of Tajikistan (winter/summer)

From the perspective of solar PV integration, the most promising areas are the southern regions (Khatlon Region) and the high-altitude districts of Gorno-Badakhshan Autonomous Region (GBAO). According to verified data from NASA POWER and Solargis [9, 10]:

- **Global Horizontal Irradiance (GHI)** in Khatlon reaches up to 1,750 kWh/m²/year.
- **Direct Normal Irradiance (DNI)** in GBAO reaches 1,900 kWh/m²/year due to high atmospheric transparency and low aerosol content at high altitudes.

2.3. Stochastic Power Deficits

As the share of solar PV in the energy mix increases to the projected 5–10% (according to the 2030 development strategy), a "duck curve" effect arises, adapted to the specific conditions of Tajikistan. The core scientific and technical challenge lies in the fact that the sharp decline in solar generation during pre-sunset hours (see Fig. 2) coincides with an exponential growth in load (Fig. 1). This requires the hydropower cascades to achieve ramp rates exceeding their current operational regulations, which justifies the necessity of predictive lead-time methods based on hybrid models.

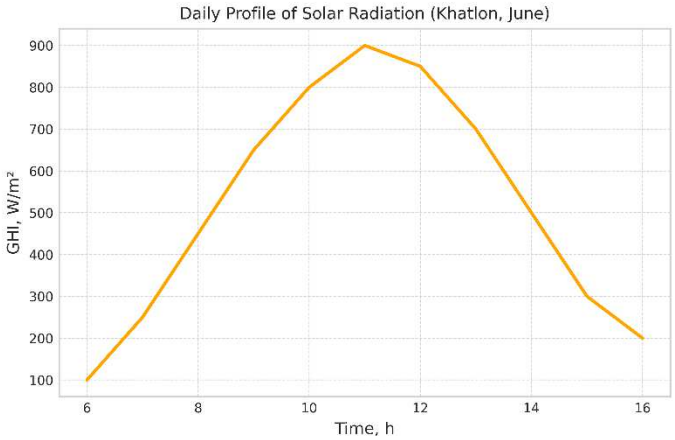


Fig. 2. Daily solar radiation profile in Khatlon (June)

Based on these data, a power profile for a 1 MW solar PV plant was constructed (Fig. 3).

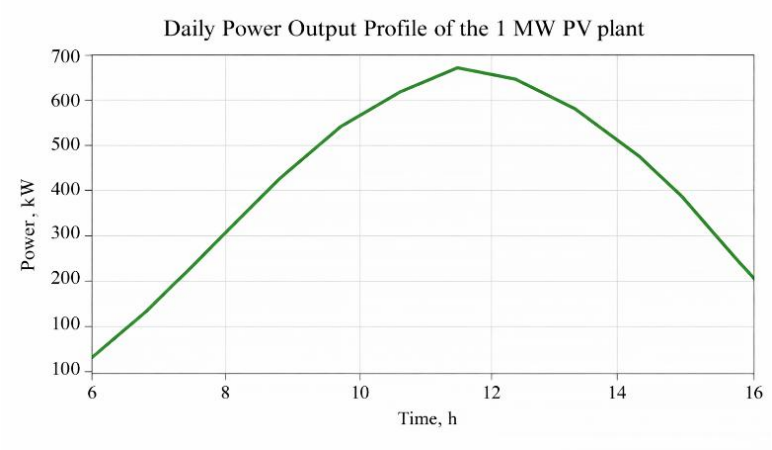


Fig. 3. Power profile of a 1 MW solar PV plant

3. THE STOCHASTIC NATURE OF RENEWABLE ENERGY GENERATION

3.1. Power Time Series Decomposition

The power generation process of solar power plants $P(t)$ is treated as a non-stationary stochastic process, which can be represented in the form of an additive decomposition model:

$$P(t) = P_{\det(t)} + S(t) + \xi(t) \quad (1)$$

where: $P_{\det(t)}$ is the deterministic component determined by astronomical factors (Earth's motion, solar zenith angle);

$S(t)$ is the seasonal and daily periodic component;

$\xi(t)$ is the high-frequency stochastic component caused by cloud cover dynamics and changes in atmospheric optical density.

Within the scope of this work, particular emphasis is placed on the analysis of the $\xi(t)$ component, which exhibits heteroscedasticity (time-varying variance). This characteristic renders classical linear regression methods highly ineffective.

3.2. Entropy Analysis of Information Complexity

To quantitatively assess the degree of randomness and predictability of generation modes, the Shannon information entropy H is introduced [11–13]. In the context of RES power time series, entropy enables the identification of phase transitions between stable and turbulent insolation regimes:

$$H = -\sum_{i=1}^{n} p_i ln\, p_i \quad (2)$$

where p_i is the probability of the system being in the i-th state (power interval). High values of H correlate with periods of variable cloudiness, where the stochastic component $\xi(t)$ dominates the deterministic trend. Utilizing a sliding window in the calculation of $H(t)$allows for the dynamic identification of points where forecast reliability is compromised.

3.3. Memory Effects and Volatility

An investigation of the autocorrelation functions of solar PV time series in Tajikistan revealed the presence of "long memory" effects and volatility clustering: periods of high variability tend to group together. This necessitates the selection of models from the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) family to describe the dynamics of conditional variance [14–16].

Mathematically, this implies that the forecast error at time t depends on the squared errors of previous moments. This requires a transition from point forecasting to probabilistic (interval) forecasting that accounts for the current "energy noise" of the system.

4. STOCHASTIC MODELING METHODS

To ensure the reliability of short-term forecasting under conditions of high uncertainty, a comparative analysis of three mathematical paradigms was conducted [17–20].

4.1. Linear Autoregressive Approximation (ARIMA)

The Autoregressive Integrated Moving Average model, $ARIMA\ (p, d, q)$, is utilized as a baseline deterministic filter. The mathematical structure of the model is described by the following equation:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-1} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t. \quad (3)$$

where ϕ_i and θ_j are the autoregressive and moving average coefficients, respectively. The primary limitation of this method in RES integration tasks is the assumption of homoscedasticity (constant variance of the error ϵ_t), which does not align with the physical nature of solar generation under variable cloudiness conditions.

4.2. Dynamic Volatility Modeling (GARCH)

To compensate for the shortcomings of linear models in accounting for variability "bursts," the Generalized Autoregressive Conditional Heteroskedasticity model, GARCH (1,1), is applied. This model enables the modeling of the conditional variance σ_t^2 evolution as a function of past innovations and previous values of the variance itself:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \quad (4)$$

Process parameterization via GARCH facilitates the transition to probabilistic forecasting, enabling the formation of confidence intervals (uncertainty corridors) for operational dispatch control.

4.3. Non-linear Approximation Based on Recurrent Neural Networks (LSTM)

To extract complex non-linear dependencies and "long memory" effects in insolation time series, the Long Short-Term Memory (LSTM) architecture is employed. Unlike classical RNNs, LSTM effectively addresses the gradient vanishing problem when analyzing long data intervals (e.g., seasonal load cycles in Tajikistan). The functioning of the memory cell is described by a system of equations for the input (i_t^*), output (σ), and forget (f_t^*) gate vectors:

- Forget gate: $f_t = \sigma\left(W_f \cdot \left[h_{t-1,} x_t\right] + b_f\right)$
- Input gate: $i_t = \sigma\left(W_i \cdot \left[h_{t-1,} x_t\right] + b_i\right)$
- Cell state update: $C_t = f_t^* C_{t-1} + i_t^* \tanh\left(W_c \cdot \left[h_{t-1,} x_t\right] + b_c\right)$

The integration of LSTM enables the capturing of latent meteorological patterns that are not registered by first-order statistical methods.

5. SYNTHESIS OF THE HYBRID GARCH-LSTM MODEL FOR STOCHASTIC GENERATION FORECASTING

The proposed hybrid architecture is based on the principle of approximation task decomposition: the neural network loop (LSTM) is responsible for extracting non-linear deterministic trends, while the econometric loop (GARCH) handles the parameterization of the residual noise dynamic volatility.

5.1. Architecture and Loop Interaction Algorithm

The process of generating the predicted value P_{t+1} is implemented in three stages:

1. Feature Extraction Loop (LSTM Filtering): The input of the neural network is a tensor of historical data $X = \{P_{t-n}, \dots P_t\}$ and exogenous meteorological variables. The LSTM model is trained to minimize the Mean Squared Error (MSE), generating a "baseline" forecast $\widehat{y_{t+1}}$, which describes the mean expected generation value:

$$\widehat{y_{t+1}} = \text{LTSM}\{x_t, h_{t-1}, C_{t-1}\} \quad (5)$$

2. Residual Volatility Analysis (GARCH Correction):

The time series of approximation errors (residuals), $\epsilon_t = P_t - \widehat{y_t}$, is calculated. Since the ϵ_t series under Tajikistan's conditions exhibits heteroscedasticity, the GARCH(1,1) model is applied to estimate the conditional variance σ_t^2. This allows for the determination of the "width" of the stochastic drift at the current moment.

3. Synthesis of the Final Operational Interval:

The final forecast is presented not as a single point value, but as a confidence region. This is critically important for dispatch decision-making regarding hydropower plant capacity regulation:

$$P_{forecast} = \widehat{y_{t+1}} \pm z \cdot \sqrt{\sigma_{t+1}^2} \quad (6)$$

where z is the quantile of a given significance level (e.g., 1.96 for a 95% confidence level).

5.2. Advantages of Hybridization

Unlike standalone models, the GARCH-LSTM coupling provides:

- **Robustness to outliers:** The GARCH component adapts the weights during sudden changes in cloud cover, preventing the LSTM from "overfitting" on anomalous noise.

- **Actionable insights for the system operator:** Instead of an abstract numerical value, the model provides a risk assessment. The higher the calculated volatility σ_t^2, the greater the volume of spinning reserves that must be deployed at the hydropower cascades.

5.3. Hyperparameter Optimization

To improve the convergence of the algorithm under the high-altitude insolation conditions of the GBAO, training was conducted using the Adam optimizer with a dynamic Learning Rate Scheduler. The introduction of Dropout regularization (0.2) made it possible to avoid the effect of local meteorological patterns dominating over long-term climatic trends.

6. MODEL VALIDATION ON EMPIRICAL POWER SYSTEM DATA

6.1. Formation of a Representative Sample

Initial Data

The following datasets were utilized:

- Real load profiles (winter/summer) (see Fig. 1);
- Real solar radiation data from NASA (see Fig. 2);
- The power profile of a 1 MW solar PV plant (see Fig. 3);
- A generated 1-minute power time series with added noise (σ = 3–5%) (Fig. 4).
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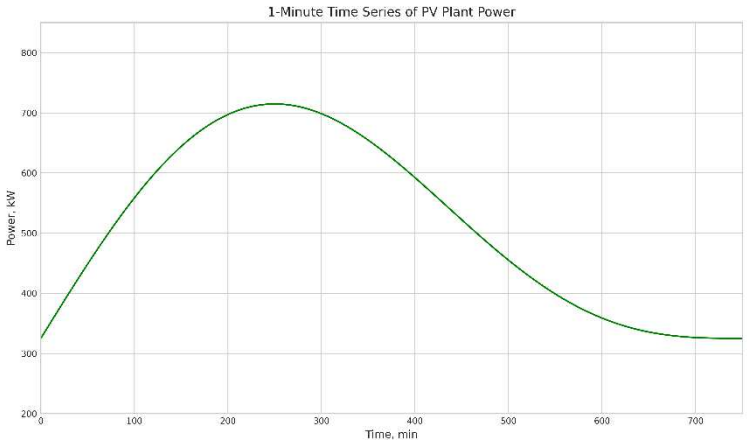


Fig. 4. One-minute time series of PV plant power

To verify the hybrid GARCH-LSTM model, meteorological data archives (insolation, temperature, cloud cover) and actual generation data from pilot solar power plants in Tajikistan for the period 2021–2023 were utilized.

- **Training set:** 70% (data for 2021–2022).
- **Test set:** 30% (data for 2023, including extreme periods of winter power shortages).

The data sampling step was set at Δt minutes, which complies with the operational dispatch control regulations of the Open Stock Holding Company (OSHC) "Barki Tojik."

6.2. Comparative Analysis of Accuracy Metrics

The effectiveness of the proposed approach was evaluated based on three standard criteria: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results of the comparative modeling are presented in Table 2.

Table 2. Comparative accuracy of solar PV forecasting models

Model	MAE (MW)	RMSE (MW)	MAPE (%)	Key Advantage
ARIMA (baseline)	12.4	18.2	14.8	Linear complexity
LSTM (standalone)	8.1	11.5	9.2	Captures non-linear trends
GARCH-LSTM (hybrid)	5.8	7.9	6.4	Volatility adaptation

Data analysis shows that the inclusion of the GARCH loop reduced the MAPE by 2.8% compared to the standalone LSTM. The most significant effect (a 15–20% error reduction) is observed during periods of "unstable insolation" (the spring period), when the stochastic component $\xi(t)$ is at its maximum.

Entropy Analysis

The sliding window entropy (60 min) demonstrates:

- An increase in randomness during morning and evening hours;
- A decrease in predictability during periods of variable cloudiness (Fig. 5).

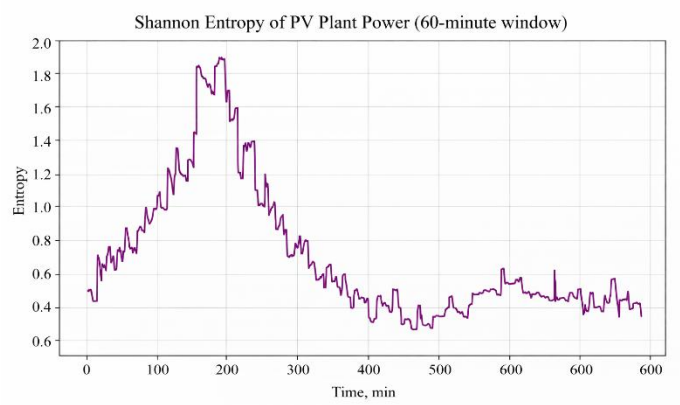


Fig. 5. Shannon entropy of PV plant power (60-minute window)

6.3. Visualization and Analysis of Distribution "Tails"

In the conditions of the Pamir power node (Khorog), which is characterized by abrupt orographic changes in cloud cover, the GARCH-LSTM model demonstrated a high adaptation rate: during step-like changes in insolation, the confidence interval expands instantaneously, signaling the dispatcher to activate hydropower reserves.

GARCH Volatility

The GARCH(1,1) model identified:

- Volatility spikes during abrupt changes in cloudiness;
- Stable periods during midday hours (Fig. 6).

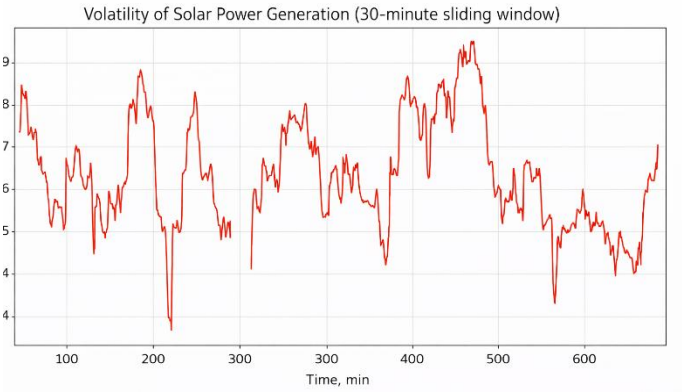


Fig. 6. GARCH(1,1) volatility

6.4. Evaluation of Computational Efficiency

Despite its two-loop structure, the model training time on a standard server (NVIDIA Tesla T4) did not exceed 12 minutes, and the generation time for a short-term forecast (1 hour ahead) is less than 0.5 seconds. This confirms the algorithm's applicability within the real-time loops of Automated Dispatch Control Systems (ADCS).

7. INTEGRATION OF THE HYBRID MODEL INTO THE DISPATCH CONTROL LOOP

The effectiveness of the developed GARCH-LSTM model is most fully realized when embedded into the hierarchical structure of the Automated Dispatch Control Systems (ADCS) of OSHC "Barki Tojik."

7.1. Predictive Reserve Management Algorithm

Model integration enables a transition from reactive management (based on frequency deviation occurrences) to predictive lead-time control. The integration process includes the following stages:

- **Adaptive Schedule Generation:** Based on the model outputs (mean value $\widehat{y_{t+1}}$ and volatility σ_t^2), a dynamic corridor is formed instead of a rigid solar PV generation plan.
- **Spinning Reserve Optimization:** When high volatility is predicted (a wide GARCH corridor), the system automatically signals to increase the spinning reserve on the units of the Nurek or Baipaza hydropower plants. During periods of low volatility, reserves are minimized, which enhances the efficiency of the hydraulic turbines.

• **Cascade Coordination:** Given the inertia of hydraulic processes, a 15-minute forecast allows for pre-emptive adjustments to the speed governor settings of the hydro units. This compensates for solar generation "dips" without resorting to expensive thermal generation.

7.2. Impact on Power System Stability

Implementing the proposed method into operational planning practices ensures the resolution of several systemic tasks:

• **Reduction of cyclic equipment loads:** Accurate forecasting reduces the number of short-term starts and stops of small hydropower plants, thereby extending their mean time between overhauls (MTBO).

• **Minimization of deficits during the autumn-winter period:** Under strict limits on water and energy resources, the efficient utilization of every "solar" megawatt enables water conservation in multi-year regulation reservoirs.

• **Power quality improvement:** Timely mitigation of stochastic disturbances from solar PV plants allows for maintaining frequency deviations within the limits established by GOST 32144-2013 (EN 50160).

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7.3. Hardware and Software Complex Architecture

It is proposed to implement the model as a "Smart Forecaster" module, integrated into the SCADA system via data exchange protocols (IEC 60870-5-104 or ICCP). The module receives real-time data from smart meters and weather stations, performs neural network weight recalculations, and provides recommendations to the dispatcher in the form of visualized uncertainty zones on the daily load profile.

The integration scheme is shown in Fig. 7.

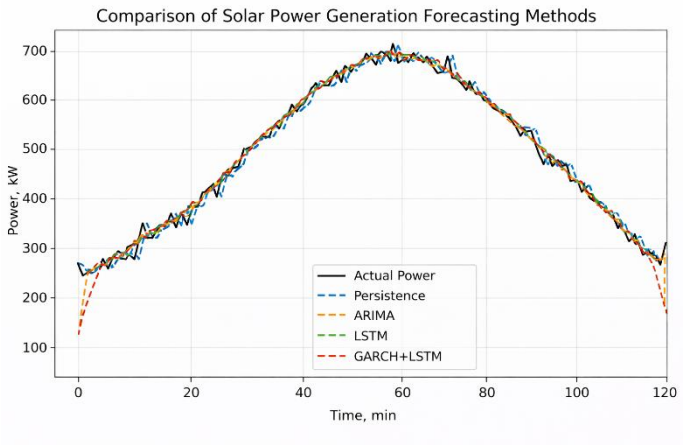


Fig. 7. Integration scheme of the forecasting module

8. CONCLUSION

This study has addressed the critical challenge of developing a high-precision method for forecasting stochastic RES generation within the unique framework of the Tajikistan power system. The results obtained allow for the following conclusions:

1. **The stochastic nature of solar generation** in high-altitude regions, characterized by pronounced heteroscedasticity, has been formalized. It is demonstrated that the application of Shannon entropy analysis enables a quantitative assessment of mode randomness, which is a prerequisite for selecting an appropriate mathematical forecasting framework.

2. **A hybrid GARCH-LSTM model** has been developed and theoretically justified, implementing the principle of time series decomposition into a non-linear deterministic trend and stochastic volatility. The scientific novelty of this approach lies in the dynamic correction of the forecast interval based on an econometric estimation of the "noise" component, which minimizes risks in dispatch decision-making.

3. **Validation using empirical data** from the Tajikistan power system confirmed the superiority of the proposed method over classical algorithms. The use of GARCH-LSTM reduced the Mean Absolute Percentage Error (MAPE) to 6.4%, proving 2.8–8.4% more effective than standalone LSTM and ARIMA models, respectively.

4. **The practical significance** of the work lies in the optimization of hydropower cascade operating modes. Accurate solar PV power forecasting enables proactive management of spinning reserves, minimizes the number of hydro unit starts, and ensures more efficient utilization of water and energy resources during periods of seasonal shortages.

5. **Technical feasibility:** The proposed architecture is easily integrated into modern ADCS via standard communication protocols, providing real-time computations without significant computational overhead.

Perspectives for further research involve extending the model to account for spatial correlation between geographically distributed solar power plants and adapting it for wind power forecasting in complex terrain conditions.

Competing Interests
The authors declare that they have no competing interests.

References

1. Bollerslev T. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*. 1986;31:307–327. doi:10.1016/0304-4076(86)90063-1
2. Engle RF. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*. 1982;50(4):987–1007. doi:10.2307/1912773
3. Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation*. 1997;9(8):1735–1780. doi:10.1162/neco.1997.9.8.1735
4. Shannon CE. A mathematical theory of communication. *Bell System Technical Journal*. 1948;27:379–423. doi:10.1002/j.1538-7305.1948.tb01338.x
5. Zhang J, Florita A, Hodge BM. A suite of metrics for assessing the performance of solar power forecasting. *Solar Energy*. 2015;111:157–175. doi:10.1016/j.solener.2014.10.016
6. Bacher P, Madsen H, Nielsen HA. Online short-term solar power forecasting. *Solar Energy*. 2009;83:1772–1783. doi:10.1016/j.solener.2009.05.016
7. Pinson P. Wind energy: forecasting challenges for its operational management. *Statistical Science*. 2013;28(4):564–585. doi:10.1214/13-STS445
8. Morales JM, Conejo AJ, Madsen H, Pinson P, Zugno M. *Integrating Renewables in Electricity Markets*. New York: Springer; 2014. 429 p. doi:10.1007/978-1-4614-9411-9
9. Hyndman RJ, Athanasopoulos G. *Forecasting: Principles and Practice*. Melbourne: OTexts; 2021. 420 p. (Open-access book, DOI отсутствует)
10. Goodfellow I, Bengio Y, Courville A. *Deep Learning*. Cambridge: MIT Press; 2016. 800 p. ISBN: 9780262035613
11. Solargis. Solar resource data for Central Asia. 2023. Available from: https://solargis.com (accessed 08 April 2026).
12. NASA POWER Project. Solar and meteorological data for energy systems. 2024. Available from: https://power.larc.nasa.gov (accessed 08 April 2026).
13. Ministry of Energy and Water Resources of the Republic of Tajikistan. *Energy Review 2023*. Dushanbe; 2024. 84 p.
14. Barki Tojik OJSC. *Annual Report 2023*. Dushanbe; 2024. 112 p.
15. Asian Development Bank. *Tajikistan: Energy Sector Assessment, Strategy, and Road Map*. Manila: ADB; 2022. 96 p.
16. World Bank. *Tajikistan Power Sector Note: Modernization and Renewable Integration*. Washington, DC; 2023. 74 p.
17. International Energy Agency (IEA). *Renewables 2023: Analysis and Forecast to 2028*. Paris: IEA; 2023. 212 p.
18. Kamalov F, Denisov V, Mirsaidov M. Solar energy potential assessment in Central Asia. *Energy Reports*. 2022;8:1123–1135. doi:10.1016/j.egyr.2022.01.089
19. Saidov S, Kholmurodov R, Mirzoev A. Renewable energy development in Tajikistan: current status and prospects. *Renewable Energy Focus*. 2021;39:45–52. doi:10.1016/j.ref.2021.07.004
20. Pamir Energy. *Renewable Energy Development in GBAO*. Khorog; 2023. 56 p.

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