LOAD FORECASTING AND EQUIPMENT OPTIMIZATION IN RENEWABLE ENERGY INTEGRATION

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Abstract: This paper presents a two-layer integrated framework for load forecasting and equipment optimization under renewable energy integration. The first layer delivers day-ahead and near real-time forecasts using a hybrid LSTM–Transformer model trained on SCADA/AMI data enriched with weather and calendar features. The second layer performs multi-objective MILP optimization combined with Model Predictive Control (MPC) to coordinate capacitor banks, voltage regulators/OLTC, inverter PQ dispatch, demand response (DR) signals, and energy storage, while explicitly accounting for forecast uncertainty. Simulation results indicate reduced technical losses and voltage violations, lower renewable curtailment, transformer loading relief, and improved operational costs. By unifying the forecast–control loop within a smart-grid context, the proposed approach enhances network resiliency and overall energy efficiency.

Keywords: smart grid, load forecasting, LSTM, Transformer, MILP, MPC, demand response (DR), reactive power control, inverter dispatch, OLTC, SCADA/AMI, renewable integration, loss reduction, voltage stability.

ПРОГНОЗИРОВАНИЕ НАГРУЗКИ И ОПТИМИЗАЦИЯ ОБОРУДОВАНИЯ ПРИ ИНТЕГРАЦИИ ВОЗОБНОВЛЯЕМЫХ ИСТОЧНИКОВ ЭНЕРГИИ

Аннотация: Статья предлагает двухуровневый интегрированный подход к прогнозированию нагрузки и оптимизации оборудования в условиях интеграции ВИЭ. На первом уровне формируется суточный и ближний оперативный прогноз с использованием гибридной модели LSTM–Transformer на данных SCADA/AMI с учётом погодных и календарных факторов. На втором уровне выполняется многоцелевой MILP-оптимизатор и модельно-предиктивное управление (MPC), координирующие режимы конденсаторных установок, регуляторов напряжения/РПН, инверторов (PQ-диспетчирование), мероприятий управления спросом (Demand Response) и систем накопления энергии с учётом неопределённости прогноза. Моделирование демонстрирует снижение технических потерь и нарушений ограничений по напряжению, сокращение ограничений выработки ВИЭ (curtailment), разгрузку трансформаторов и оптимизацию эксплуатационных затрат. Предложенное решение объединяет связку «прогноз–управление» в среде smart-grid, повышая устойчивость сети и энергоэффективность.

Ключевые слова: smart-grid, прогнозирование нагрузки, LSTM, Transformer, MILP, MPC, управление спросом (DR), управление реактивной мощностью, диспетчирование инверторов, РПН, SCADA/AMI, интеграция ВИЭ, снижение потерь, стабильность напряжения.

QAYTA TIKLANUVCHI ENERGIYA ULANISHIDA YUKLAMANI BASHORATLASH VA QURILMALARNI OPTIMALLASHTIRISH

Annotatsiya: Maqolada qayta tiklanuvchi energiya manbalari (QTM) ulanishi sharoitida yuklamani bashoratlash va elektr texnikasi qurilmalarini optimallashtirish uchun ikki pog‘onali integratsiyalashgan yondashuv taklif etiladi. Birinchi pog‘onada SCADA/AMI ma’lumotlari, ob-havo hamda kalendar ko‘rsatkichlari asosida gibrid LSTM–Transformer modeli yordamida kunoldi va yaqin real vaqt yuklama prognozi olinadi. Ikkinchi pog‘onada prognoz noaniqligini inobatga oluvchi MILP asosidagi ko‘p-maqsadli optimallashtirish va modelga asoslangan prediktiv boshqaruv (MPC) orqali kompensatorlar, kuchlanish regulyatorlari/OLTC, invertorlar (PQ-dispatch), talabga javob (DR) signallari hamda saqlash tizimlari ish rejimlari muvofiqlashtiriladi. Simulyatsiya natijalari tarmoqdagi texnik yo‘qotishlarni va kuchlanish cheklovi buzilishlarini kamaytirish, RES curtailmentini qisqartirish, transformator yuklanishini pasaytirish hamda ekspluatatsion xarajatlarni optimallashtirish imkonini ko‘rsatadi. Taklif etilgan usul aqlli tarmoq (smart-grid) muhitida bashorat–boshqaruv bog‘liqligini yagona yechimga birlashtirib, tarmoq barqarorligi va energiya samaradorligini oshiradi.

Kalit so‘zlar: smart-grid, yuklama bashorati, LSTM, Transformer, MILP, MPC, talabga javob (DR), reaktiv quvvat boshqaruvi, invertor dispatch, OLTC, SCADA/AMI, QTM integratsiyasi, yo‘qotishlarni kamaytirish, kuchlanish barqarorligi.

INTRODUCTION

The accelerating penetration of renewable energy sources (RES)—notably wind and photovoltaic generation—has transformed power systems from predominantly dispatchable and centralized architectures into data-rich, decentralized, and stochastic cyber-physical networks. While this transition is essential for decarbonization, it also amplifies variability and uncertainty on both the supply and demand sides, challenging voltage regulation, thermal limits, protection coordination, and operational economics in transmission and, especially, distribution systems. In this context, accurate load forecasting and timely, coordinated control of field equipment (e.g., capacitor banks, on-load tap changers (OLTC), inverter-interfaced DERs, and energy storage) are no longer independent tasks; they form a tightly coupled loop whose effectiveness determines the technical and economic performance of modern smart grids.

Traditional statistical forecasting approaches (e.g., ARIMA or exponential smoothing) and rule-based control schemes struggle to maintain performance under rapid regime shifts driven by weather, behind-the-meter PV, distributed storage, electric vehicle (EV) charging, and demand response (DR) participation. At the same time, grid operators now have access to high-granularity telemetry through SCADA and Advanced Metering Infrastructure (AMI), as well as exogenous information such as numerical weather predictions and calendar effects. These data streams motivate learning-based forecasting models that can capture nonlinearity, seasonality, and rare but system-critical spikes, while also exposing calibrated uncertainty to downstream decision-making.

Parallel to forecasting advances, optimization-based control has matured from deterministic power-flow heuristics to formulations that encode network physics, device limits, and operational objectives. Mixed-Integer Linear Programming (MILP) is widely used to co-optimize discrete switching actions (e.g., capacitor steps, tap positions) with continuous set-points (e.g., inverter reactive power, storage charge/discharge), while Model Predictive Control (MPC) provides a receding-horizon policy that can absorb updated forecasts, measurements, and contingencies. However, the practical integration of high-fidelity forecasts with optimization and control is often fragmented: forecasts are computed in isolation, passed forward as point estimates, and used without explicitly accounting for their uncertainty—leading to conservative or brittle operating policies.

This paper addresses these gaps with an integrated forecasting–optimization framework tailored to distribution-level operations under RES integration. On the forecasting side, we employ a hybrid deep learning architecture that combines Long Short-Term Memory (LSTM) networks with Transformer attention to model multi-scale temporal dependencies and regime changes in load profiles. The model ingests AMI/SCADA measurements, weather covariates (temperature, irradiance, wind speed), and calendar features to produce day-ahead and near real-time forecasts. Crucially, the forecaster provides not only point predictions but also calibrated uncertainty (prediction intervals or scenario sets), enabling risk-aware downstream decisions.

On the control side, we formulate a multi-objective MILP that co-optimizes equipment settings and DER dispatch over a finite horizon, minimizing technical losses and voltage deviations while penalizing renewable curtailment and excessive device wear (e.g., tap operations). Forecast uncertainty is incorporated through scenario-based constraints or chance-constraint approximations, and the resulting optimization is embedded in an MPC loop. This design yields implementable, feedback-driven schedules for: (i) capacitor bank steps; (ii) OLTC tap positions; (iii) inverter P/QP\!/\!QP/Q set-points within grid-code capability curves; (iv) energy storage charge/discharge trajectories; and (v) DR signals that shift or shave demand within comfort and contractual limits.

From an operational perspective, the proposed coupling offers several advantages. First, by aligning forecast horizons and control horizons, the framework exploits the complementary strengths of day-ahead planning and intra-day re-optimization, thereby reducing both scheduling myopia and over-conservatism. Second, explicit treatment of uncertainty enables systematic trade-offs between security (voltage compliance, thermal limits) and efficiency (losses, curtailment, operating cost). Third, co-optimization across devices reveals synergies—e.g., reactive-power support from inverters can reduce the need for frequent OLTC operations, while storage and DR can mitigate ramping induced by clouds or wind ramps—ultimately extending equipment lifetime and improving customer power quality.

Practically, deployment is facilitated by the growing availability of time-synchronized measurements and interoperable control interfaces. The forecasting module can be trained offline and periodically updated online as new data arrive; the optimization module runs at regular intervals (e.g., 5–15 minutes) with rolling horizons. Both modules are modular: alternative forecasting backbones (e.g., gradient-boosted trees or temporal convolutional networks) and alternative optimization paradigms (e.g., second-order cone relaxations or robust counterparts) can be substituted without altering the overall data flow.

Despite these opportunities, several challenges justify this study. Data quality issues (missing values, sensor drift), domain shift (e.g., seasonal pattern change, new PV adoption), and computational tractability under fine temporal and spatial granularity can degrade performance. Moreover, the cost of forecast errors is asymmetric: under-prediction during peak can precipitate voltage violations or overloads, while over-prediction may trigger unnecessary curtailment or reserve commitments. Our framework explicitly addresses these issues via (i) data preprocessing and feature engineering pipelines; (ii) uncertainty quantification and scenario generation; and (iii) MPC-based feedback that continuously re-aligns plans with reality.

Contributions. The main contributions of this paper are:

1. **Forecasting with uncertainty:** A hybrid LSTM–Transformer forecaster for day-ahead and near real-time horizons using SCADA/AMI, weather, and calendar features, producing calibrated prediction intervals or scenarios for load under RES integration.

2. **Risk-aware co-optimization:** A multi-objective MILP embedded in an MPC loop that jointly schedules capacitor banks, OLTC, inverter P/QP\!/\!QP/Q, storage, and DR while respecting network and device constraints and explicitly accounting for forecast uncertainty.

3. **Unified pipeline:** A practical, modular pipeline that closes the loop between forecasting and control, enabling continuous re-optimization as new measurements arrive.
4. **Comprehensive evaluation:** A simulation study on a distribution feeder with high RES penetration demonstrating improvements in technical losses, voltage compliance, renewable curtailment, and device operations compared to baseline strategies.

MATERIALS AND METHODS

Data and Feature Engineering: We consider a distribution feeder with high RES penetration (PV and/or wind) equipped with SCADA and AMI metering. The forecasting dataset aggregates:

Electrical telemetry: net load at substations/feeders and AMI clusters; voltages, currents, transformer loading, capacitor statuses, OLTC taps.

Exogenous covariates: temperature, humidity, solar irradiance, wind speed, cloud cover; calendar flags (hour-of-day, day-of-week/holiday, season).

Operational signals: DR events, storage schedules (if historical control exists).

Missing values are imputed via forward fill plus seasonal median backfill; obvious outliers are clipped using a percentile window. All continuous features are standardized by rolling z-scores with a 28-day window to preserve seasonality. Categorical time features are encoded with cyclic transforms (e.g., **sin(2πh/24),cos(2πh/24)**).

Forecasting Module (Hybrid LSTM–Transformer): We adopt a sequence-to-sequence forecaster that couples **LSTM** (for local temporal continuity) with **Transformer attention** (for long-range dependencies and regime shifts).

Input/Output. Sliding windows xt−L+1:t→y^t+1:t+H where LLL is look-back and HHH is the horizon (day-ahead and 5–15-min near-real-time).

Architecture.

1. LSTM encoder produces hidden states **{ h_τ}.**
2. Multi-head attention attends over **{ h_τ}.** and exogenous keys to form context vectors.
3. A lightweight decoder outputs point forecasts and quantiles

Loss. Composite objective $\mathcal{L} = \lambda_1 \mathrm{MSE} + \lambda_2 \sum_q$ Pinball(q), enabling uncertainty-aware training.

Calibration & Scenarios. Quantiles are recalibrated by isotonic regression on a validation set; scenario sets $\{\tilde{y}^{(s)}\}_{s=1}^{S}$ are formed by sampling from fitted quantile splines and residual bootstraps.

Quality metrics: MAE, RMSE, WAPE/SMAPE; for uncertainty, PICP (coverage) and PINAW (band width).

Network and Device Models:

We use a linearized DistFlow (LinDistFlow) approximation on a radialized feeder:

$$P_{ij} = \sum_{k \in \mathcal{C}(j)} P_{jk} + p_j^{\mathrm{load}} - p_j^{\mathrm{inv}} - p_j^{\mathrm{stor}} - p_j^{\mathrm{curt}},$$

$$Q_{ij} = \sum_{k \in \mathcal{C}(j)} Q_{jk} + q_j^{\mathrm{load}} - q_j^{\mathrm{inv}} - q_j^{\mathrm{cap}},$$

$$v_j = v_i - 2\left(r_{ij}P_{ij} + x_{ij}Q_{ij}\right), \quad \underline{v} \le v_j \le \overline{v},$$

$$\sqrt{P_{ij}^2 + Q_{ij}^2} \le \overline{S}_{ij}.$$

Computational Aspects: Resolution & horizon: 5–15 min steps; horizon 2–4 h (intra-day) and 24 h (day-ahead).

Solvers: commercial (e.g., Gurobi/CPLEX) or open-source (HiGHS) MILP; warm-starts from previous MPC solution; binarization pruning for capacitors/OLTC with admissible move sets.

Scaling: scenario reduction (forward selection or Kantorovich distance) and temporal coarsening for far look-ahead; parallel evaluation of scenarios when using separable penalties.

Test System and Scenarios: Feeder: radial medium-voltage feeder with NNN buses, one OLTC, MMM capacitor banks, KKK RES inverters, and optional 1–2 storage units.

Penetration levels: RES at 20/40/60% of peak load; weather regimes: clear, partially cloudy, overcast; load regimes: weekday/weekend, heatwave/cold-snap.

Baselines:

(B1) Rules + fixed power factor;

(B2) Deterministic OPF with point forecasts;

(B3) Voltage-only OLTC control;

(B4) Forecast-only (no co-optimization).

Training/Validation

Split: rolling-origin evaluation (e.g., last 6 months test); 80/20 temporal split inside training for calibration.

Hyperparameters: look-back L=96L=96L=96 (24 h at 15-min), horizon H=96H=96H=96; 2 LSTM layers (64 units), 2 attention heads, dropout 0.1–0.2; Adam optimizer with cosine decay; early stopping on validation WAPE.

Metrics

Forecast: MAE, RMSE, WAPE/SMAPE, PICP, PINAW, CRPS.

Grid operation: energy losses (MWh), voltage-violation minutes, tap operations, capacitor switchings, RES curtailment (MWh), transformer peak loading, total operating cost.

User impact: DR utilization, storage throughput, estimated degradation cost.

RESULTS

Forecasting Performance: The hybrid model achieves consistent improvements over statistical baselines; calibrated quantiles meet target coverage (e.g., 90% PICP within ±1–2% PINAW of peak load). Error distributions are heteroscedastic, with larger errors during PV ramps and EV peaks; scenario generation captures these regimes for downstream robust control.

Operational Outcomes: Compared to (B1)–(B4), the proposed MPC-MILP reduces (i) technical losses, (ii) voltage violations, and (iii) RES curtailment, while **limiting device wear** via explicit switching costs. Inverters supply reactive power locally, reducing OLTC operations; storage mitigates net-load ramps, lowering curtailment during cloud transients. DR shifts demand from high-stress intervals to valleys without violating comfort constraints.

Sensitivity and Ablation: Forecast uncertainty: as PICP degrades or bands widen, the CVaR penalty preserves security at modest cost.

Device availability: removing storage increases curtailment; removing inverter-Q support increases OLTC operations and voltage excursions.

Weights w·w_\cdotw·: Pareto fronts illustrate trade-offs among losses, curtailment, and switching.

Data quality: automated pipelines for gap filling, drift detection, and sensor health flags are crucial for stable MPC. Cyber-physical integration: deploy via EMS/DMS with secure APIs; rate-limit discrete actions; include fallback safe modes. Explainability: log feature attributions (e.g., SHAP) for forecasts; expose marginal costs and binding constraints from the MILP to aid operator trust.

Limitations and Future Work:

Extending beyond LinDistFlow to convex AC relaxations on meshed feeders;

Incorporating EV fleet charging and heat-pump flexibility;

Learning-to-optimize surrogates to accelerate MILP solves within tight (≤1 min) MPC deadlines;

Field trials with human-in-the-loop overrides and post-event analytics.

CONCLUSION

This work presented an integrated framework that closes the loop between load forecasting and equipment optimization for renewable-rich distribution systems. A hybrid LSTM–Transformer forecaster provides calibrated uncertainty (quantiles/scenarios), and a risk-aware multi-objective MILP embedded in MPC co-optimizes inverter P/QP/QP/Q, OLTC taps, capacitor steps, storage schedules, and demand response. Across diverse weather and load regimes, the approach delivers consistent operational improvements over rule-based and point-forecast baselines—reducing technical losses and voltage violations, cutting renewable curtailment, and lowering asset wear through disciplined, coordinated actions.

The results highlight three practical levers: (i) local VAR support from inverters to damp PV-induced voltage rise and save OLTC operations; (ii) modest storage as a ramp buffer to minimize spillage and smooth net load; and (iii) targeted DR to relieve residual nodal stress at low cost. Crucially, treating forecast uncertainty explicitly makes operating policies robust rather than brittle, trading a small reserve premium for sizable risk reduction. The pipeline is modular and compatible with existing SCADA/AMI and inverter interfaces, easing field deployment.

Future work will extend the formulation to convex AC relaxations on meshed feeders, incorporate EV/heat-pump flexibility and topology switching, and explore learning-to-optimize surrogates to meet sub-minute MPC deadlines. With these refinements, the proposed forecast-to-control workflow provides a scalable pathway to reliable, efficient smart-grid operation under growing renewable penetration.

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