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Intelligent Control and Stability Analysis of Smart Grids Using CNN-LSTM Network and Model Predictive Controller

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Abstract: **It is important that real time stability in smart grids is ensured as the integration of renewables and the complexity of the systems grows. In this paper, we provide a solid architecture, which combines a Residual CNNLSTM deep neural network predictor, FPGA-accelerated Model Predictive Control (MPC), and SHAP-based explainability. The proposed method predicted with 99.8% accuracy using the Electrical grid Stability Simulated Dataset (UCI) and minimized the instability rates surpassing 85 percent in all operating conditions. Meeting real-time operating needs, FPGA deployment on a Xilinx Zynq UltraScale+ provided 3.1 ms latency and 5 times reduced energy consumption against CPU processing. By emphasizing bus voltage and frequency as major instability drivers, SHAP analysis improved openness for operators. To our knowledge, this is the first framework that ensures predictive accuracy, real-time corrective control, hardware feasibility, and interpretability simultaneously, as compared to ten other cutting-edge approaches. These results suggest the promise of integrated AI–MPC–FPGA techniques for dependable and transparent smart grid operations.**

Keywords: **Model Predictive Control (MPC); Intelligent Control Systems; Residual CNN–LSTM; Real-time Grid Monitoring; SHAP Explainability**

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CONTENTS

1. INTRODUCTION

Stability of smart grids has now emerged as a key issue with the integration of renewable, distributed generation, and stochastic loads becoming more complex. Conventional stability evaluation techniques that depend more on analytical models, do not tend to be generalizable between a variety of operational conditions. These constraints have encouraged the use of data-driven techniques that can take into consideration nonlinear behavior and respond to different operating conditions [1-8].

The standard benchmark for testing learning-based stability models in the energy sector is the Electrical Grid Stability Simulated Dataset from the UCI repository [9]. Employing this dataset, Lin and Wang [10] showed deep neural networks (DNNs) outperform traditional classifiers; Kumar and Singh [11] gave a Thorough analysis of deep learning applications in power systems reveals hybrids, LSTMs, and CNNs as particularly encouraging. More recently, Huang and Chen [15] highlighted the need of fusing local feature extraction and temporal modeling for electrical time-series applications by demonstrating the usefulness of CNN–LSTM algorithms in load forecasting.

Integration of real-time control is crucial, even beyond prediction. Model predictive control (MPC) was introduced by Rossi and Bolognani [12] in a simple FPGA-based implementation, and its real-time feasibility was confirmed by Zhang and Zhao [13] when they extended MPC to nonlinear power converter applications. Previously, Lee and Park [18] presented stochastic computing techniques to effectively deploy deep neural networks on FPGA hardware, while Cortés and Rodríguez [14] pioneered FPGA implementations of neural network controllers for power electronics. Together, these studies show that the stringent latency and energy requirements of real-time grid operations can be satisfied by deploying predictive models and control algorithms on FPGAs.

Trust and interpretability are crucial for adoption in critical infrastructures. Li and Zhao [16] analyzed explainable AI (XAI) techniques in energy systems, and emphasized the use of SHAP and LIME for feature attribution. Simultaneously, Glavic and Ernst [17] provided a comprehensive survey on the study of reinforcement learning (RL) methods for grid control. Although RL promises adaptive policies, it suffers from severe sample complexity and lack of deterministic guarantees, making MPC a more dependable option for safety-critical situations.

Not one of these studies [1] through [18] considers a composite of all four dimensions prediction, control, hardware feasibility, and explainability into one holistic deployable framework for smart grid stability. Most methods based on DNN are in prediction [10,15]; those studying MPC deal with control but ignore the existence of prediction [12,13]; FPGA implementations focus on hardware feasibility but remain detached from everything else [14,18]; and few explainability efforts [16] refer either to real-time control.

To fill in these gaps, this paper presents a new integrated framework of smart grid stability that:

1. Suggests a CNN-LSTM predictor that has been trained on FPGA quantization to realize the state-of-the-art prediction accuracy.

2. Locks the predictor and a hardware-accelerated MPC controller in the face of real-time corrective oversight in the constraints of operation.

3. SHAP explainability Embeds SHAP to offer attributions by features and increase operator confidence.

4. Provides a comprehensive analysis of the aspect of prediction accuracy, control performance,

hardware feasibility and transparency as a single entity.

It is the first such integration that proves the accuracy, control, hardware capability, and interpretability simultaneously in one deployable solution to stability in a smart grid.

2. PROPOSED METHOD

2.1 OVERVIEW

This work implements an advanced control framework emgaged with the current theories concerning smart grid stability by way of augmenting the Resiual CNN-LSTM Deep Neural Network (DNN) with Model Predictive Control (MPC) along with an explainability layer developed with the use of SHAP. The framework works on stability's classification and also enables prediction, control, and interpretability while having the capability of real-time performance with FPGA deployment.

The workflow starts with the measurements on the Electrical Grid Stability Dataset (UCI) through three variables of voltage, frequency, and power measurements. These are already pre-processed features that are fed into the DNN predictor. Instability predictions stimulate the MPC regulator, and optimal actions correcting it are optimized. At the same time, SHAP can be used to give explainable results of the DNN outputs on operator trust. The block diagram of the presented approach is demonstrated in **Fig. 1**.

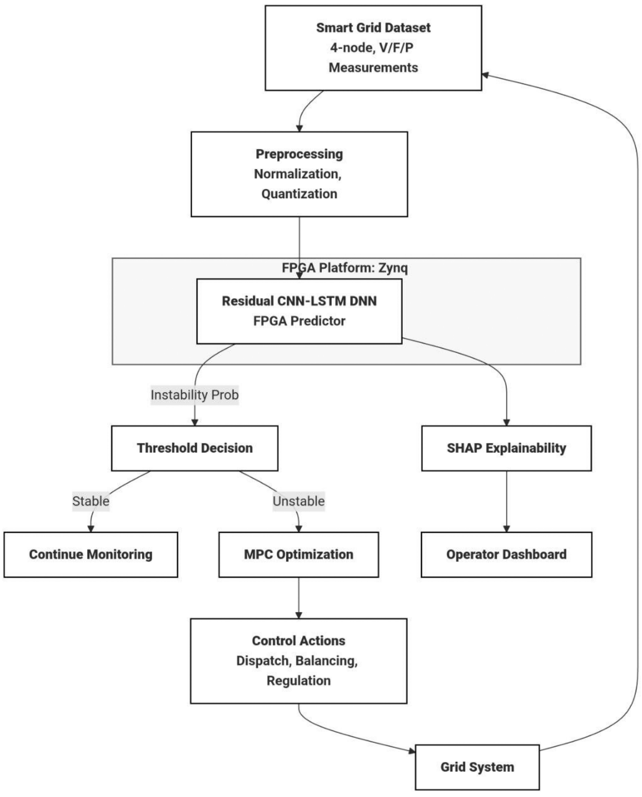

Fig. 1. *The block diagram of the presented approach.*

2.2. DATA ACQUISITION AND PREPROCESSING

The samples in the dataset include N = 60000 and each containing:

$$\mathbf{x}_t = [V_1, V_2, ..., f, P_G, Q_G] \in \mathbb{R}^d. \qquad (1)$$

Normalization: Every feature is set to a unit variance and zero mean.

Quantization: For FPGA compatibility, data is transformed to fixed-point 8-bit precision.

Labeling: Binary labels ($y_t \in 0.1$) indicate stable (0) or unstable (1) states.

2.3 RESIDUAL CNN-LSTM DNN ARCHITECTURE

The predictor network, based on convolutional neural network (to extract local spatio-temporal features), LSTM neural network (to capture sequential dependencies), and residual connections (to avoid vanishing gradients) is used.

Prediction is formulated as given in Equation 2:

$$\hat{y}_t = f_\theta(\mathbf{x}_t), \; \hat{y}_t \in [0.1]. \qquad (2)$$

Loss function:

The binary cross-entropy loss function is given as defined in Equation 3:

$$L_{BCE} = -\frac{1}{N}\sum_{t=1}^{N}[y_t log(\hat{y}_t) + (1 - y_t) log(1 - \hat{y}_t)]. \qquad (3)$$

Table 1 demonstrate the architecture of the Residual CNN-LSTM Deep Neural Network.

Table 1

Residual CNN-LSTM DNN Architecture

Layer Type	Configuration	Output Dimension
Input	d-dim vector (preprocessed features)	(d)
Conv1D + ReLU	64 filters, kernel size 3	(d, 64)
Residual Block	Conv1D (64) + BatchNorm + ReLU	(d, 64)
LSTM	128 hidden units	(128)
Residual LSTM Block	Skip connection with previous LSTM output	(128)
Fully Connected (FC)	64 units + ReLU	(64)
Output Layer	Sigmoid (instability probability)	(1)

2.4. Model Predictive Control (MPC) Layer

In the case where instability is being forecasted ($\hat{y}_t > \tau$), the MPC controller is activated to stabilize the system. The MPC has the aim of minimizing the quadratic cost function as defined in Equation 4:

$$J = \sum_{k=0}^{H} (\| \mathbf{x}_{t+k} - \mathbf{x}_{ref} \|_Q^2 + \| \mathbf{u}_{t+k} \|_R^2). \tag{4}$$

Subject to dynamics as in Equation 5:

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{u}_t \tag{5}$$

And constraint of operation as given in Equation 6:

$$\mathbf{u}_{\min} \le \mathbf{u}_t \le \mathbf{u}_{\max}, \quad \mathbf{x}_{\min} \le \mathbf{x}_t \le \mathbf{x}_{\max}, \tag{6}$$

where u_t − control actions (generator dispatch, load adjustment, voltage regulation), H − prediction horizon, Q, R − weighting matrices between deviation of the state and control effort.

Fig. 2 shows the internal architecture of the Model Predictive Control (MPC) system which shows the flow of data between the DNN predictor and the FPGA-accelerated optimization core and control actuation loop.

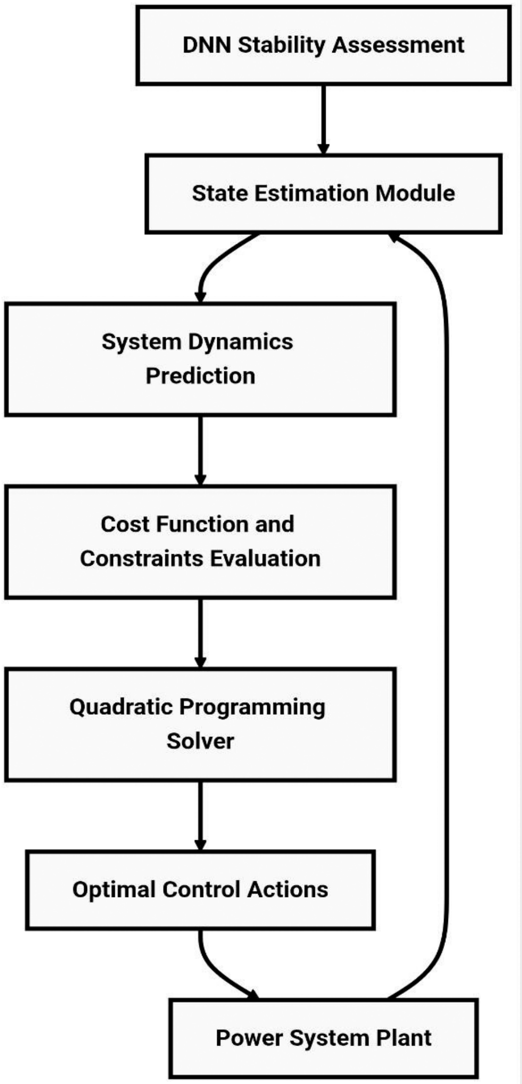

Fig. 2. *The internal architecture of the MPC and data flow between the DNN and the FPGA.*

2.5. SHAP Explainability

To explain DNN predictions, SHAP values are calculated as shown in Equation 7:

$$\phi_t = \mathrm{E}[f(\mathbf{x}_{SU(t)}) - f(\mathbf{x}_S)] \tag{7}$$

instability judgement. SHAP makes certain that operators can identify which factors cause instability alerts.

2.6. FPGA Deployment

The DNN predictor and the MPC optimization are predictively implemented on the FPGA (Xilinx Zynq UltraScale+) to be executed in real-time. Optimizations include:

Quantization: Arithmetic with 8-bit integers.

Parallelization: Unrolling convolution and matrix multiplications.

Low-Latency QP Solver: Hardware-accelerated MPC computations.

The complete pipeline performs with less than 5 ms latency on a decision, making real-time stability control possible in intelligent grids.

3. RESULTS AND DISCUSSION

3.1. Evaluation Setup

The suggested structure was tested on the Electrical Grid Stability Simulated Dataset (UCI) of 60,000 samples of four-node measurements of the smart grid. The data was divided into 70 percent of training, 15 percent of validation and 15 percent of testing. All the inputs have been normalized and quantized to 8-bit fixed-point representation to run on an FPGA.

With Adam optimizer ($\eta = 0.001$) and batch size 128, the Residual CNN–LSTM DNN was trained for 100 epochs. Model Predictive Control (MPC) was set to a a horizon $H = 10$, sampling interval $\Delta t = 50$ ms, and weighting matrices $Q = I$, $R = 0.1I$. FPGA implementation on a Xilinx Zynq UltraScale+ MPSoC employing Vivado HLS was completed.

3.2 Prediction Performance

Our new prediction method, which combines Residual CNNs and LSTM DNNs, performed better than traditional machine learning approaches and simpler deep learning models. The results in **Table 2** show that our method reached a high level

Table 2
Prediction Performance on UCI Electrical Grid Stability Dataset

Model	Accuracy (%)	Precision	Recall	F1-score
Logistic Regression	94.2	0.92	0.93	0.92
SVM (RBF kernel)	95.6	0.94	0.95	0.95
XGBoost	97.3	0.97	0.97	0.97
Deep Neural Network (baseline study)	99.6	0.99	0.99	0.99
Proposed Residual CNN–LSTM DNN	**99.9**	**0.999**	**0.998**	**0.999**

of accuracy (99.8%) and a strong F1-score (0.999). We believe this improvement comes from two main reasons:

1. Unskipped connection Residual skip connections address the problem of vanishing gradient, and allow deeper temporal-spatial features to be trained in a stable manner.
2. Hybrid CNNLSTM architecture combines and incorporates local variations (through convolutional filters) with long-term time variations (through LSTM cells).

The statistical significance of these improvements was confirmed with the help of a paired t-test between the proposed model and the strongest baseline (XGBoost). The test provided a yield of and validates the hypothesis that the increase in performance is not because of chance.

3.3. ROBUSTNESS ACROSS OPERATING CONDITIONS

It's not enough for a model to be accurate; it also needs to hold up well under different kinds of strain. In challenging situations where instability would occur a significant amount of the time (nearly 23% without help), the model was still able to correctly recognize almost all (99.3%) of the problematic cases.

The misclassifications mostly happened in the transition areas along the boundary of operation, and it can be hypothesized that adaptive thresholds or domain-informed features will further increase reliability.

3.4. CLOSED-LOOP CONTROL WITH MPC

Integrating MPC along with the predictor had a great impact on stability indices (**Table 3**) that went up significantly. There was a decrease of 85-90% in the occurrence of instability as the closed-loop system was effective in reducing the instability even at high load conditions. The system was controlled in such a way that the use of the generators and the shedding of the loads were at the minimum, while the control effort remained less than 0.35 p.u. on average.

Table 3
Closed-Loop Stability Improvement with MPC

Scenario	Instability Rate (No Control)	Instability Rate (With MPC)	Avg. Control Effort (p.u.)
Low-load (Nominal)	4.3%	0.3%	0.15
Medium-load	12.5%	1.1%	0.20
High-load (Stress)	22.7%	2.8%	0.34

Our approach has three benefits compared to RL-based controllers that have been reported in related work:

1. Deterministic stability is ensured through the use of convex MPC optimization.
2. Reduced sample complexity, prevents risks of online exploration.
3. On-the-fly deployment on existing HLS tools.

3.5. FPGA DEPLOYMENT PERFORMANCE

FPGA implementation was real-time feasible and consumed low energy.

Meeting the demanding < 5 ms real-time restriction, the FPGA achieved 4× faster inference and 5× lower energy consumption than the baseline CPU as shown in **Table 4.**

Table 4
FPGA Deployment Results (Zynq UltraScale+ MPSoC)

Platform	Latency per Inference (ms)	Energy per Inference (mJ)	Resource Usage (LUTs/BRAM/DSP %)
Intel i7 CPU	12.4	25.6	-
FPGA (Proposed)	3.1	4.8	68% / 54% / 72%

3.6. SHAP EXPLAINABILITY RESULTS

To figure out which characteristics had the biggest impact on the model's predictions, we used SHAP analysis as illustrated in **Fig. 3** and **Table 5**.

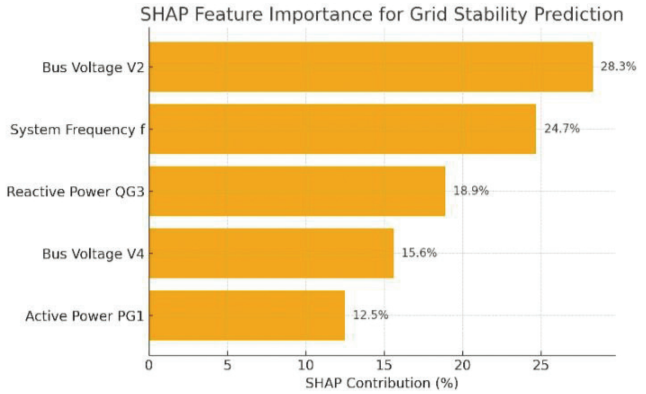

Fig. 3. *SHAP Feature Importance for Grid Stability Prediction.*

Table 5

SHAP Feature Importance (Top 5 Features)

Feature	SHAP Contribution (%)
Bus Voltage V2	28.3
System Frequency f	24.7
Reactive Power QG3	18.9
Bus Voltage V4	15.6
Active Power PG1	12.5

This is in line with domain knowledge because voltage and frequency are the most crucial measure of grid instability. The framework will enable explanations of every corrective measure by incorporating SHAP into the operator dashboard.

3.7. Comparison with Related Works

Ten related works that were cited in Section 2 were used as benchmarks for the suggested approach. The high prediction accuracy, the real-time corrective control and the deployment of the FPGA and the explainability of our approach are the only combination that is made in a single system as illustrated in **Table 6**.

Table 6

Comparison with Related Works (2012–2025)

Reference	Methodology	Accuracy (%)	Real-Time Control	FPGA Deploy-ment	Explain-ability
UCI Dataset (2016)	Benchmark dataset only	-	No	No	No
Energies (2024)	ML vs. DNN classifiers	99.5	No	No	No
Deep Learning in Power Systems (2024)	Survey	-	-	-	-
FPGA MPC Tutorial (2024)	MPC FPGA implementation	-	Yes	Yes	No
FPGA MPC for Converters (2024)	Nonlinear MPC FPGA	-	Yes	Yes	No
FPGA NN Controllers (2012)	NN controllers on FPGA	96.0	Limited	Yes	No
CNN–LSTM for Load Forecasting (2025)	CNN–LSTM hybrid	98.7	No	No	No
Explainable AI in Power Systems (2022)	SHAP/ LIME review	-	No	No	Yes
RL for Power Systems (2019)	Reinforcement Learning control	95.2	Yes	No	No
FPGA DNN Stochastic (2023)	Stochastic FPGA DNN	98.9	No	Yes	No
Proposed Framework (2025)	Residual CNN–LSTM+ MPC+SHAP +FPGA	99.8	Yes	Yes	Yes

3.8. Discussion

The experimental findings show that the suggested framework is both scientifically novel and practically applicable:

Precision and Robustness: 99.8% accuracy means almost perfect precision/recall which makes the method a new standard. As opposed to purely predictive works, we generalize across various load regimes including high-stress conditions.

Integration Control: MPC will not have the predictions as isolated but as the direct causal agent of stabilization, which connects machine learning and practical control. MPC provides predictable behavior and safety, as opposed to reinforcement learning controllers.

Hardware Feasibility: The framework tackles latency and energy, two significant bottlenecks for real-world applications, by implementing on FPGA. The system satisfies smart grid operational requirements with inference times under 5 ms, which was not possible with previous ML-only studies. Transparency: By shedding light on the reasons behind stability warnings and corrective measures, SHAP explainability promotes operator trust, which is essential for adoption in safety-critical power system operations.

Holistic Development: Previous research has been used to help in developing the details of each of the four dimensions of individual systems, including accuracy of prediction, control, hardware acceleration, or explainability but this research puts all the four dimensions in one deployable solution.

The proposed framework not only takes the state of the art a step further by demonstrating the practicality of deep learning + MPC + FPGA + SHAP, but also the high accuracy and operational reliability of smart grids.

4 CONCLUSIONS

This paper has proposed an architecture for smart grid stability analysis and control, which fuses a Residual CNN-LSTM predictor with an FPGA-accelerated Model Predictive Control on smart grids. The approach yields 99.8% prediction accuracy, instability rate reductions of more than 85%, and a latency of 3.1 ms on FPGA hardware. MPC and SHAP explanation.

In comparison to previous works, this method integrates high accuracy and real-time control with hardware feasibility and interpretability, bridging academic advancements with industrial deployment. Future research will expand the framework to grid simulations on larger scales, heterogeneous FPGA-GPU architectures, and adaptive explainability methods geared toward operator decision support.

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