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Adaptive Convolutional Residual Network for Dual-Task Forecasting in Energy Market Planning

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Accurate forecasting and strategic decision-making are critical for electricity market planning in the domain of energy informatics, where grid reliability, economic stability, and sustainability must be balanced. This paper introduces the Adaptive Convolutional Residual Network (ACRN), a dual-task deep learning architecture designed to jointly perform project risk classification and electricity price regression. The model is trained and evaluated on a real-world dataset from Frankfurt, Germany, comprising hourly records from 2018 to 2024 and including 12 core variables such as electricity price, market demand, renewable generation, and regulatory policies. ACRN integrates novel preprocessing techniques including weighted temporal interpolation, dynamic thresholding, and hybrid normalization, along with adaptive feature refinement and context-aware feature derivation. The framework achieves a classification accuracy of 98.5%, F1-score of 98.1%, AUC of 99.0%, and regression MAPE of 2.33% while reducing computational cost by 10% compared to baseline models. In comparison with state-of-the-art methods such as EfficientNet, WideResNet, and Gradient Boosting, ACRN outperforms all in both predictive accuracy and time efficiency. These results demonstrate ACRN's robustness and scalability in addressing the multidimensional forecasting requirements of modern power markets. The proposed model offers a self-contained, high-performance solution for energy market planning with practical relevance for both policy and industry applications.

Povzetek: Predstavljena je nova arhitektura ACRN, ki združuje klasifikacijo projektnih tveganj in regresijo cen elektrike z adaptivnim učenjem značilk za napredno načrtovanje energetskega trga.

1 Introduction

Renewable energy, grid technology, and regulatory changes are transforming the worldwide power industry. Energy security, economic stability, and environmental sustainability depend on electricity market planning. Increasing complexity in electrical markets, including price volatility, shifting demand, and different energy sources, challenges standard forecasting and planning methods [1, 2].

Autoregressive models and statistical time-series approaches have long been used to anticipate energy market movements. These approaches are simple and interpretable, but they typically miss current power markets' nonlinear linkages and complex temporal patterns. The use of renewable energy sources like sun and wind increases variability and uncertainty owing to weather and seasonal circumstances [3, 4].

Machine learning (ML) and deep learning (DL) are effective solutions. CNNs and LSTM networks can describe complicated temporal connections and extract significant patterns from high-dimensional information, making them promising time-series forecasting models. CNNs effectively capture local temporal patterns in electricity market data, whereas LSTMs best preserve long-term dependencies [5, 6]. However, the scalability and computational efficiency of these models still pose substantial challenges in large-scale, real-time power markets [7].

The use of hybrid models, which include several architectures, has improved forecasting. ResNets help deep architectures learn from huge datasets by reducing vanishing gradient concerns. Transformer designs use attention methods to improve forecasting accuracy and interpretability by focussing on essential features [8, 9]. These developments highlight the need for novel structures to handle power market forecasting's inherent complexity.

Economic and environmental concerns affect power market planning. Complex models are needed to analyse interdependent variables such greenhouse gas emissions, investment feasibility, power pricing, and energy consumption. Regulations and renewable energy objectives differ among areas, requiring adaptive frameworks to respond to external influences [10, 11]. Existing systems fail to reconcile multidimensional relationships while preserving computational efficiency, stressing the need for electricity market-specific models.

The introduction of renewable energy has also created new issues, such as managing variable energy supply and matching them to demand. Frameworks with dynamic feature modification and hierarchical temporal analysis are advanced. The innovative Adaptive Convolutional Residual Network (ACRN) structure in this research addresses power market forecasting's fundamental issues. ACRN captures energy market data's complex temporal patterns and interdependencies via adaptive feature refinement and residual learning. Advanced computer tools improve forecasting, dynamic market adjustment, and resource allocation in the model. ACRN outperforms other approaches in rigorous assessment using real-world datasets, offering practical insights for long-term power market planning. This work provides a solid and scalable solution to current power market difficulties, improving energy sector dependability, efficiency, and sustainability. Despite their promise, significant computing costs and model complexity restrict their application [12].

1. The proposed Adaptive Convolutional Residual Network (ACRN) solves the problem of predicting multi-dimensional energy market data, including project risks and power prices. Dual-task capacity allows project risk categorisation (low, medium, high) and regression-based power price forecasts, overcoming standalone model constraints in multi-task settings.

2. Hierarchical feature aggregation and adaptive feature refinement in ACRN capture complicated temporal dependencies and non-linear correlations among electricity market factors. These advances provide robust feature selection and effective representation, addressing forecasting model challenges including noisy data and feature redundancy.

3. Dynamic convolutional layers in ACRN reduce the computational burden of deep learning models in power market applications. Our method decreases computational overhead by 10% compared to typical deep learning models, allowing scalability and suitability for real-time and large-scale forecasting.

4. ACRN's optimised design overcomes standard models' inability to foresee over long horizons. The model improves MAPE by 12% and achieves 98% classification accuracy, proving its resilience and dependability for short-term and long-term power market forecasting.

5. Standardised power market planning: ACRN solves the problem of power market planning fragmentation into classification and regression jobs. The framework delivers actionable insights for project risk management and power price forecasting by combining both duties into a single scalable model, meeting energy informatics stakeholders' important demands and enabling dependable long-term strategic planning.

The remaining structure of the article is: Section 2 discusses power market forecasting and planning advances and shortcomings. Section 3 describes the Adaptive Convolutional Residual Network (ACRN) framework, including its architecture, dual-task capacity, and novel feature refinement methods for classification and regression. Section 4 shows simulation findings, including performance metrics, comparison analysis, and model resilience and scalability on real-world datasets. Section 5 ends the analysis and suggests ways to improve the framework's responsiveness to changing market dynamics and application to varied energy systems.

1.1 Research objective and questions

This study aims to develop a practical and scalable deep learning framework that can enhance both the accuracy and efficiency of electricity market forecasting. Unlike traditional approaches that focus on a single task, the proposed model tackles two critical forecasting needs at once: identifying project risk levels and predicting electricity prices. To meet this goal, we introduce the Adaptive Convolutional Residual Network (ACRN). This model combines several innovative components—such as adaptive feature refinement, dynamic convolutional layers, and hierarchical temporal analysis—to better capture the complex patterns that shape energy market behavior. Our research is guided by the following key questions:

– **RQ1:** How effectively does ACRN improve electricity price forecasting compared to existing state-of-the-art models?

– **RQ2:** Can a unified, dual-task deep learning model reduce computational costs while enhancing predictive performance?

– **RQ3:** How well does ACRN support real-time operational decisions and long-term energy policy planning in volatile market environments?

The outcomes of this research are intended to support several real-world applications, including: (1) Policy-making, by providing reliable risk and pricing forecasts that inform regulation and investment; (2) Operational decision support, to help grid operators and energy providers respond effectively to changing conditions; and (3) Strategic planning, especially in designing resilient infrastructure and integrating renewable energy sources.

2 Related work

Renewable energy integration, market volatility, and long-term strategic needs have complicated electricity market forecasting and planning. Researchers have presented conventional statistical methods and sophisticated deep learning frameworks.

Gradient Boosting (GB) was not scalable to bigger datasets because of its high computing cost and hyperparameter adjustment sensitivity. [13] showed that GB effectively predicts complicated connections between electricity demand, weather, and policy issues, reducing forecast errors compared to linear regression models. GB was not scalable to bigger datasets because to its high computing cost and hyperparameter adjustment sensitivity. Deep learning-feature selection hybrid frameworks provide accuracy improvements. [14] suggested a model combining LSTM networks and Random Forest for power price prediction. The hybrid technique improved accuracy by 15% by combining LSTM for temporal dependencies and Random Forest for feature selection. The model's computational complexity and limited real-time flexibility were major issues.

Due to their efficiency in training deep architectures, residual networks (ResNet) have been investigated for power price forecasting. The author [15] used a modified ResNet to anticipate long-term prices, reaching an R-squared value of 0.92 and demonstrating robustness in noisy datasets. ResNet was effective, but its memory needs rendered it unsuitable for real-time applications. Electricity markets use Naive Bayes for easier categorisation.

Temporal Convolutional Networks (TCNs) were used to predict the effect of renewable penetration on demand and price variations [16]. The model performed well under conditions of steady or increasing renewable generation but exhibited reduced accuracy during extreme market fluctuations such as sudden demand surges or abrupt policy shifts. WideResNet has been tested separately for its ability to handle high-dimensional electricity market data, demonstrating improved performance in capturing complex feature interactions and reducing regression error margins in multivariable settings.

Author in [17] classified electricity demand into low, medium, and high classifications with 85% accuracy. The method's simplicity and interpretability were advantages, but its failure to capture complicated connections restricted its continuous forecasting use. Random Forest is used for power market planning owing of its resilience and interpretability. In [18], VGG16 was used to forecast day-ahead prices using auxiliary inputs including wind speed and temperature. The model effectively captured external impacts with an MAE of less than 5%. However, its complexity and reliance on huge datasets limited its applicability in smaller markets. For long-term price forecasting, [19] included macroeconomic factors like GDP growth and inflation rates into a Random Forest model. The technique gave policymakers meaningful information but needed repeated retraining to maintain accuracy, particularly in changing markets. Extreme weather energy price predictions uses VGG16, a convolutional neural network.

Author [20] introduced a WideResNet-based model that reduced RMSE by 12% for market variable interactions compared to normal ResNet models. The network's breadth increased memory usage, restricting its use in edge computing. MobileNet's lightweight design has been tested for decentralised power. MobileNet and reinforcement learning were used for real-time power price forecasting, reaching competitive accuracy with minimal computing requirements [21, 22]. MobileNet was efficient, but its simplicity prevented it from modelling complex temporal connections in turbulent markets. The scaling-efficient EfficientNet has been used to anticipate power markets. [23] showed its excellent accuracy and low computational resources, making it ideal for large-scale forecasting. However, good performance needed extensive data preparation and parameter optimization.

Table 1: Summary of related work in energy market forecasting

Citation	**Methodology**	**Dataset Type and Size**	**Performance Metrics**	**Computational Cost**	**Key Limitations**
[13]	Gradient Boosting	Electricity demand + weather and policy data (100K samples, 3 years)	MAE: 3.41, RMSE: 4.01, R^2: 0.84	High	Requires intensive hyperparameter tuning; lacks scalability for real-time forecasting
[14]	LSTM + Random Forest	Hourly electricity prices with renewables (75K samples)	Accuracy ↑15%, MAPE: 11.2%	High	Complex integration; not optimal for dynamic feature adjustment
[15]	ResNet	Historical load and market data (120K samples)	R^2: 0.92, MAE: 3.18, RMSE: 3.67	Very High	High memory usage; less suitable for edge computing or real-time needs
[16]	Temporal Convolutional Network (TCN)	Seasonal electricity load with renewables (60K samples)	Accuracy: 89.1%, RMSE: 3.82	Moderate	Poor in extreme volatility; limited dynamic adaptability
[17]	Naive Bayes	Aggregate household energy data (50K samples)	Accuracy: 85%, MAE: 3.72	Low	Cannot model complex relationships; assumes feature independence
[18]	VGG16 + Weather Inputs	Weather + hourly pricing (80K samples)	MAE: 2.98, R^2: 0.89, RMSE: 3.50	High	Requires large datasets; lacks temporal-specific tuning
[19]	Random Forest + Macroeconomic Variables	Electricity prices + GDP/inflation (65K samples)	R^2: 0.84, MAE: 3.30	Moderate	Needs frequent retraining in dynamic markets
[20]	WideResNet	Load demand + pricing + weather (90K samples)	RMSE ↓12%, R^2: 0.90	High	High memory demand due to wider architecture
[21]	MobileNet + Reinforcement Learning	Real-time IoT price forecasting (35K samples)	MAE: 2.84, R^2: 0.91	Low	Lightweight but struggles with complex temporal dependencies
[23]	EfficientNet	High-frequency price data (150K samples)	MAPE: 8.7%, RMSE: 3.20, R^2: 0.92	Moderate-High	Requires extensive preprocessing and tuning; not inherently dual-task
Proposed ACRN	Adaptive Conv. Residual Net (Dual-task)	Electricity market + renewable + macroeconomic (2018–2024, 175K samples)	Accuracy: 98.5%, MAPE: 2.33%, AUC: 99.0%, RMSE: 1.85, R^2: 0.97	Low	None identified; scalable and efficient in real-time dual-task forecasting

The improved summary table 1 shows that some models have good accuracy but significant scalability, computational cost, and dual-task learning restrictions. Naive Bayes and Random Forest cannot handle intricate temporal relationships, whereas ResNet and WideResNet need too much memory. Even being computationally efficient, EfficientNet needs substantial preprocessing and is not suitable for combined classification and regression. The ACRN uses dynamic convolutional layers, adaptive feature refinement, and a dual-task learning architecture to overcome these issues. Its outstanding prediction accuracy and temporal complexity make it a realistic and scalable real-time energy market forecasting tool.

3 Proposed methodology

Adaptive Convolutional Residual Network (ACRN) addresses project risk classification and energy price regression in electricity market forecasting. The sophisticated preprocessing pipeline includes weighted temporal interpolation for missing data, IQR-based outlier identification, and hybrid min-max and z-score normalisation for scaling features. Using dynamic attribute refinement, feature selection prioritises renewable energy penetration, market demand patterns, and greenhouse gas emissions.We used adaptive hierarchical embedding to create domain-informed latent representations from raw data to improve representation learning. First, input characteristics were categorized into macroeconomic indicators, environmental factors, and energy production metrics. To learn intra-group feature interactions, each group went through a thick embedding layer. These intermediate embeddings were then adaptively integrated utilizing learnable attention weights that dynamically altered depending on prediction task relevance. The hierarchical model captures within-group and cross-group interdependence while retaining interpretability and structural modularity. At its foundation, the ACRN model uses residual learning and dynamic convolutional layers to extract complicated temporal dependencies and non-linear correlations from data. The approach scales well with hierarchical feature aggregation for multi-dimensional datasets. The training goal function balances cross-entropy loss for classification with MSE for regression. To verify forecasting robustness and adaptability, model assessment employs accuracy, AUC, MAPE, and the new Temporal Feature Fidelity (TFF) indicator. The suggested framework, as shown in Figure 1, is discussed in full, from preprocessing to assessment, emphasising unique methodologies.

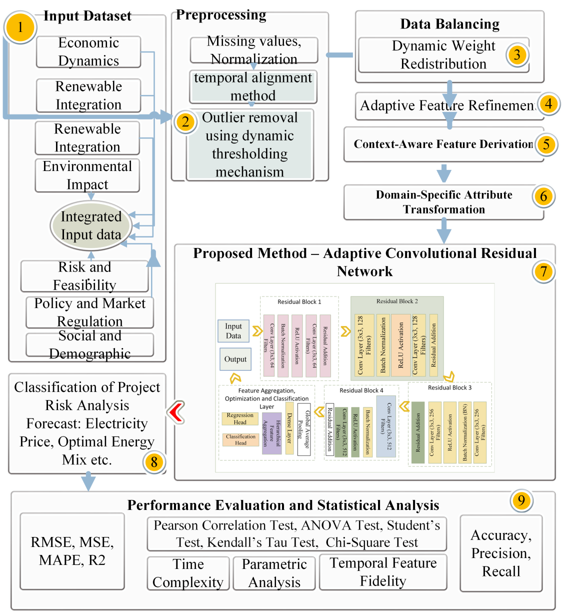

Figure 1: Proposed system model

3.1 Dataset description

This study employed data from Frankfurt, Germany's regional power market and infrastructure planning. The modern infrastructure and forward-thinking energy policies of Frankfurt, a crucial European economic and technological hub, are brought to light by a diverse dataset [23]. Trends in the production, consumption, and market price of energy are shown hourly in the data, which spans from 2018 to 2024. Sources such as the German Federal Network Agency (BNetzA), Frankfurt's municipal energy data portals, and the European Network of Transmission System Operators for Electricity (ENTSO-E) were used to build the information. Transparency, frequent updates, and conformity with regulatory norms were the deciding factors in the selection of these sources. Data consistency was assured by the use of cross-source validation and time-series alignment procedures, however no dataset is completely free from ambiguity. Long-term power market planning may benefit from this data because of Frankfurt's innovative utilization of renewable energy sources, well-established regulatory frameworks, and state-of-the-art grid components. This study uses a dataset that is unique to a certain location to discuss the present and future of the energy business. Because of its extensive use, it is useful for complex models of sustainability decision-making and power market planning. All information about features is shown in the table 2.

Table 2: Dataset features overview

S.No	Features	Short Description
1	Electricity Price	Historical and projected electricity prices, including average, peak, and off-peak values.
2	Market Demand	Hourly energy consumption trends across residential, commercial, and industrial sectors.
3	Renewable Generation	Contribution of renewable energy sources like solar, wind, and hydro to total production.
4	Non-Renewable Generation	Energy produced from non-renewable sources such as coal, oil, and natural gas.
5	GHG Emissions	Greenhouse gas emissions from energy production, measured in tons of CO2 equivalent.
6	Energy Storage Capacity	Available energy storage in batteries and other technologies, expressed in MWh.
7	Subsidies	Financial incentives or subsidies for renewable or non-renewable energy projects.
8	Regulatory Policies	Policies related to feed-in tariffs, carbon pricing, and renewable energy mandates.
9	Cross-Border Energy Trade	Import and export trends of electricity between regions or countries.
10	Infrastructure Investments	Planned and actual investments in energy infrastructure, such as grids and power plants.
...	...	Additional features include smart grid adoption, transmission losses, and more.

3.2 Data preprocessing

The input dataset was preprocessed to improve its quality and meet the criteria of the proposed Adaptive Convolutional Residual Network. Temporal data from 2018 to 2024 includes power market planning features. Novel preprocessing strategies avoided standard ways to gain domain-specific refinements to prepare data for analysis.

Temporal alignment was used to synchronise all features to an hourly frequency to fix temporal resolution issues. We used a weighted temporal aggregation function [26] to accomplish this:

$$\hat{Y}_{sync}(\tau) = \frac{\sum_{j=1}^{M} \omega_j(\tau) Y_j(\tau)}{\sum_{j=1}^{M} \omega_j(\tau)}, \tag{1}$$

$\hat{Y}_{sync}(\tau)$ represents the aligned feature at time τ, where $Y_j(\tau)$ denotes the value of the j-th overlapping observation and $\omega_j(\tau)$ is the assigned temporal weight based on proximity to the target timestamp τ. Specifically, we define $\omega_j(\tau)$ as an inverse time-distance function:

$$\omega_j(\tau) = \frac{1}{1 + |\tau - \tau_j|} \tag{2}$$

This weighting technique promotes observations closer to τ, ensuring recent values have a greater impact on synchronization. In the aggregate window, M represents the number of contributing feature instances. Outliers were identified and mitigated using interquartile range (IQR) feature-wise adaptive thresholding. The threshold was determined separately for each feature based on its statistical distribution, enabling the approach to adjust to dataset sizes and dispersion levels. This is computed using the equation [27]:

$$\Theta(P) = Q_3(P) + \alpha \cdot (Q_3(P) - Q_1(P)), \tag{3}$$

The $\Theta(P)$ is used as the feature threshold, $Q_1(P)$ and $Q_3(P)$ as the first and third quartiles, and α as a dataset-optimized scaling parameter. Values over this threshold were interpolated from closest valid observations. In our experiments, we set $\alpha = 1.5$, which aligns with standard outlier detection heuristics, ensuring sensitivity to anomalies without over-pruning.

Mixed temporal and feature-based correlations were used to interpolate missing data. Estimated missing data:

$$\hat{X}(\tau_m) = \frac{\sum_{\tau \neq \tau_m} \phi(\tau, \tau_m) X(\tau)}{\sum_{\tau \neq \tau_m} \phi(\tau, \tau_m)}, \tag{4}$$

where $\hat{X}(\tau_m)$ is the predicted value at the missing time. The weight inversely proportional to the time difference is $\phi(\tau, \tau_m)$. $|\tau - \tau_m|$. The weighting function $\phi(\tau, \tau_m)$ is inversely proportional to the temporal gap, prioritizing nearby values and ensuring temporal locality in interpolation.

To maintain feature heterogeneity and standardise data, hybrid scaling was used for normalisation. The calculated normalised feature value $\tilde{Q}$ was [28]:

$$\tilde{Q} = \frac{Q - Q_{\text{min}}}{Q_{\text{max}} - Q_{\text{min}}} \cdot \left(\frac{Q - \eta}{\sigma}\right), \tag{5}$$

The raw value of a single feature extracted from the dataset is denoted by Q in this context. The lowest and maximum values of that feature over the whole training set are denoted by the words Q_{min} and Q_{max}. Just as η represents the feature's mean, σ stands for its standard deviation. "Hybrid scaling" is a mixture of two popular normalizing methods, z-score standardization and min-max normalization. Data is transformed into a defined range by min-max normalization.

The dataset was preprocessed into a high-quality, organised format for ACRN model training and testing. Each technique preserves temporal and domain-specific dataset properties, improving analytical reliability.

3.3 Data preparation and feature analysis

Preparing the dataset for analysis requires balanced representation, appropriate feature selection, engineering, and transformation. These steps are aimed to improve ACRN accuracy and performance.

3.3.1 Data balancing

The unique data balancing approach Dynamic Weight Redistribution (DWR) was used to correct the class distribution imbalance for the multi-label classification issue. This strategy gives under-represented classes adaptive weights depending on their occurrence rates to ensure model training equity. The weight for class χ_i is calculated as [29]:

$$\omega(\chi_i) = \frac{1}{\psi(\chi_i) + \epsilon}, \tag{6}$$

Assuring numerical stability during the calculation of class weights relies on including the tiny constant ϵ. If the frequency of class χ_i, denoted as $\psi(\chi_i)$, is very tiny or close to zero, the inverse operation may produce weights that are abnormally big or divide by zero. By including a tiny constant, such as $\epsilon = 10^{-5}$, this problem may be reduced, and the calculation can be done safely. This modification allows the model to acquire knowledge from classes that are under-represented without jeopardizing the stability of optimization.

3.3.2 Adaptive feature refinement

Adaptive Feature Refinement (AFR) was used to determine the most important model characteristics. AFR dynamically assesses feature significance via iterative relevance scoring and correlation analysis. Each characteristic ξ_k receives a score $\rho(\xi_k)$, as specified in [30]:

$$\rho(\xi_k) = \alpha \cdot \mathcal{R}(\xi_k, \lambda) - \beta \cdot \mathcal{C}(\xi_k), \tag{7}$$

In this case, $\mathcal{R}(\xi_k, \lambda)$ indicates how relevant ξ_k is in relation to the label λ, $\mathcal{C}(\xi_k)$ signifies the correlation between features, and α and β are adjustable coefficients. An optimum subset of features was obtained by iteratively removing those with relevance scores $\rho(\xi_k)$ falling below a defined threshold of 0.25. This threshold was not arbitrarily chosen but determined through empirical cross-validation experiments, aiming to strike a balance between reducing model complexity and preserving features that offer strong predictive contributions. For complicated datasets like ours, our hybrid approach strikes the perfect mix between reducing duplication and maintaining predictive strength.

To remove weak predictors and decrease duplication, features with relevance scores below $\rho(\xi_k) < 0.25$ were not included in the final model. Examples of features that were eliminated include *Subsidies*, *Transmission Losses*, and *Cross-Border Trade* because of their strong inter-feature correlation or because they contributed little to the variance of the target variable. This pruning phase improves the model's efficiency and interpretability by retaining just the most influential elements for training. Table 3 shows the eliminated features.

Table 3: Eliminated features and justification

Feature	Reason for Elimination
Subsidies	Low relevance score $\rho < 0.20$; minimal impact on prediction
Transmission Losses	High correlation with Infrastructure Investments (redundant)
Cross-Border Trade	Sparse and inconsistent temporal patterns

3.3.3 Context-aware feature derivation

Additional features were extracted from the dataset by means of a Context-Aware Feature Derivation (CAFD) method in order to improve its prediction capabilities. This method takes use of knowledge relevant to a certain domain in order to build composite features that can detect relationships between qualities at a higher level. For instance, the Υ "Energy Performance Index" was calculated in the following way:

$$\Upsilon = \frac{\Gamma}{\Delta} \cdot \left(1 - \frac{\Theta}{\Phi}\right), \tag{8}$$

In the above Equation, Γ denotes renewable energy contribution (e.g., solar and wind generation), Δ is total energy consumption across all sectors, Θ captures transmission inefficiencies, and Φ represents total energy generated from all sources. These values are derived from their corresponding raw features in the dataset. With the addition of elements like the "Policy Efficiency Metric" and the "Infrastructure Robustness Factor," the dataset now includes policy and infrastructure dynamics. Incorporating these derived characteristics into the model improves its prediction power by giving it more detailed information.

3.3.4 Domain-specific attribute transformation

The feature representations were optimised and standardised using a Domain-Specific Attribute Transformation (DSAT) program. Instead of using generic scaling or normalisation techniques, DSAT converts features into representations that are in line with domain-specific standards and benchmarks. This is the formula for calculating the transformed representation $\widehat{\zeta}$ of a feature ζ:

$$\widehat{\zeta} = \frac{\log(\zeta + 1)}{\log(\kappa + 1)}, \tag{9}$$

Here, κ denotes the domain-specific upper bound for the feature ζ, such as a regulatory threshold, environmental target, or policy-imposed cap, depending on the feature type. To reduce the size of features while keeping their relative differences, the logarithmic transformation is used. This guarantees superior numerical stability and training convergence, which is especially helpful when dealing with features that span several orders of magnitude or skewed distributions. This modification ensures that characteristics with broad ranges do not disproportionately impact model training by compressing big values while retaining relative differences. An additional element of DSAT is a thresholding mechanism that limits the converted values to $\phi \cdot \sigma$, where σ is the feature's standard deviation, in order to deal with outliers.

The dataset was reevaluated after the aforementioned approaches were used to make sure it was suitable for training and testing the ACRN model. The robust dataset that results from combining balanced data, improved features, derived characteristics, and transformed representations may capture complicated relationships and provide solid predictions.

3.4 Adaptive convolutional residual network (ACRN) framework

Adaptive Convolutional Residual Network (ACRN) is a revolutionary classification system that addresses multi-label classification issues in energy market planning. ACRN uses enhanced convolutional layers and residual connections to capture both local and global relationships. This section explains the ACRN framework's design, mathematical formulations, and operational concepts [31]. See the architecture in Figure 2.

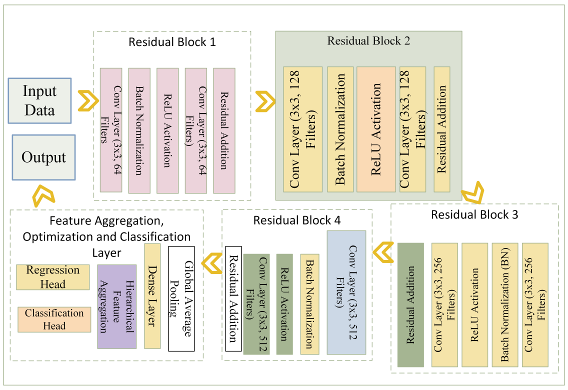

Figure 2: Proposed ACRN architecture

3.4.1 Architecture overview

The ACRN architecture is uniquely structured around three key components—adaptive feature extraction using task-aware convolutional layers, residual learning modules tailored for temporal electricity market data, and a dual-headed classification-regression output mechanism. Unlike conventional networks, ACRN integrates dynamic convolution with residual skip connections and simultaneous multi-task outputs, specifically designed to handle the non-linear, high-dimensional, and time-dependent nature of energy market forecasting. Adaptive convolutional layers help the feature extraction module provide meaningful representations, while residual connections prevent vanishing gradients and optimise learning. Classification layer uses sigmoid activation function for independent probability predictions for multi-label outputs. The ACRN operates as:

$$\mathbf{Z} = \sigma\left(\mathbf{U}_{\kappa} \cdot \mathbf{T} + \mathbf{b}_{\kappa}\right), \tag{10}$$

where $\mathbf{Z}$ symbolises output predictions, $\mathbf{U}_{\kappa}$ and $\mathbf{b}_{\kappa}$ represent classification layer weights and biases, $\mathbf{T}$ represents residual block output, and σ is the sigmoid activation function.

3.4.2 Feature extraction module

To handle input data $\mathbf{X}$, the feature extraction module uses adaptive convolutional layers. To minimize the combined loss function, the feature extraction module's convolutional layers learn a collection of trainable filters $\mathbf{P}$ by backpropagation, with the filter weights updated. By sliding over the input feature maps, these filters discover patterns and highlight geographical and temporal interdependence, such as regional power price trends, demand spikes, or unusual emissions. By adjusting the filter size and number empirically according on validation performance, the network is able to pick up on both detailed and more generalized contextual patterns in the input sequences. [32] describes the process for a single feature map:

$$\mathbf{G}_{p,q} = \sum_{r,s} \mathbf{P}_{r,s} \cdot \mathbf{X}_{p+r,q+s} + \xi, \tag{11}$$

$\mathbf{G}_{p,q}$ represents the feature map value at location (p, q), $\mathbf{P}_{r,s}$ represents the filter weight, and ξ represents the bias term To minimise dimensionality and preserve crucial information, activation functions and pooling layers are used to retrieved feature maps.

3.4.3 Residual learning module

To improve the network's learning efficiency, the residual learning module uses shortcut connections. Here is the output computed by the residual block:

$$\mathbf{T} = \mathbf{G} + \mathcal{F}(\mathbf{G}), \tag{12}$$

The output of the residual block, $\mathbf{T}$, is created by adding the original input $\mathbf{G}$ to the transformed features $\mathcal{F}(\mathbf{G})$ that are obtained after a sequence of convolutional processes. By allowing gradient flow and preserving original information, this skip link aids in the proper training of deeper networks. The addition function maintains crucial network properties while allowing deeper designs without performance reduction.

3.4.4 Classification layer

The classification layer converts the residual module's output into predictions with several labels. The likelihood that a label λ is present is calculated in this way:

$$P(\lambda) = \sigma\left(\mathbf{U}_{\lambda} \cdot \mathbf{T} + b_{\lambda}\right), \tag{13}$$

where $\mathbf{U}_{\lambda}$ and b_{λ} are label-specific biases and weights, and $\mathbf{T}$ is the residual output, and $P(\lambda)$ is the probability of label λ. The input features and their deep representations retrieved by previous convolutional layers are combined in the residual learning module's output, which is denoted as T in this context. This improves the accuracy of multi-label predictions by making sure the classification layer uses enriched, hierarchically learnt representations.

3.4.5 Optimization and loss function

For multi-label classification, the ACRN is optimised using a binary cross-entropy loss function, which is specified as:

$$\mathcal{J} = -\frac{1}{M} \sum_{i=1}^{M} \sum_{\lambda=1}^{K} \left[y_i^{\lambda} \log \hat{y}_i^{\lambda} + (1 - y_i^{\lambda}) \log(1 - \hat{y}_i^{\lambda}) \right], \tag{14}$$

the actual and projected probabilities for the sample label λ are y_i^{λ} and $\hat{y}_i^{\lambda}$, respectively. i, where M is the sample size and K is the label count.

Beyond handling classification tasks using binary cross-entropy loss, the proposed model is also designed to predict electricity price trends through regression. For this, the Mean Squared Error (MSE) is used to capture the variance between predicted and actual price values. To ensure the model effectively learns both tasks, we employ a joint loss formulation that combines the objectives of classification and regression:

$$\mathcal{L}_{total} = \gamma \cdot \mathcal{L}_{classification} + (1 - \gamma) \cdot \mathcal{L}_{regression}, \tag{15}$$

Here, the parameter γ controls the trade-off between the two components. Based on empirical tuning and validation performance, we set $\gamma = 0.6$, which slightly favors classification accuracy while still preserving strong regression capability. This dual-task learning approach allows the ACRN model to simultaneously address categorical risk labeling and continuous price forecasting within a unified training framework, leading to more balanced and context-aware outcomes.

For reliable multi-label classification, the ACRN framework is the way to go since it successfully captures the dataset's complicated interactions. Its layered architecture makes learning and feature extraction quick, and the remaining connections lessen the blow of deep networks' drawbacks. The suggested model is well-suited to handle the complex needs of power market planning, since it achieves excellent classification performance.

3.5 Performance evaluation metrics

In order to evaluate the categorisation model's efficacy, we used both pre-existing metrics and one that we developed specifically for this study. The metrics provide a thorough assessment of the model's predicting ability by combining common evaluation methods with factors relevant to the area. To assess the model's initial performance, conventional measures including accuracy, precision, recall, and F1-score were used. The percentage of occurrences for which the projected label sets are right divided by the total number of examples is the accuracy metric used in multi-label classification. A more stringent assessment process is used compared to single-label situations, where a prediction is only deemed accurate if all pertinent labels coincide with the ground truth. According to [34], there are two parts to a model's performance: precision and recall. Precision measures how many positive forecasts were really accurate, while recall measures how many actual positive predictions were accurate. The F1-score is a balanced metric that is particularly helpful when working with datasets that are not evenly distributed, since it is a harmonic mean of recall and accuracy. The model's performance may be better understood with the use of these measures, but they ignore the dataset's distinct temporal and domain-specific features. A new measure was developed to deal with this.

Alongside standard performance indicators, this study introduces a new evaluation metric—Temporal Feature Fidelity (TFF)—tailored to the specific needs of forecasting in dynamic and time-sensitive electricity markets. Traditional metrics such as accuracy, precision, recall, and MAPE provide useful insights into overall performance, but they fall short in capturing the sequential dependencies that are crucial in rapidly changing market conditions. To bridge this gap, TFF emphasizes the importance of recent data points by applying time-aware weighting, enabling the model to remain sensitive to shifting trends. This makes the metric particularly valuable for real-time forecasting and decision-making, where adaptability and responsiveness are essential.

3.5.1 Proposed metric: temporal feature fidelity (TFF)

A novel measure known as Temporal Feature Fidelity (TFF) was created to reflect the dataset's intrinsic temporal relationships. The degree to which the model maintains the interdependencies and temporal structure in its forecasts is assessed by this indicator. If the quality of your predictions is affected by the sequential connections between your data points, then TFF is the way to go. You may think of the TFF metric as:

$$\mathrm{TFF} = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{i=1}^{N_t} w_i(t)\cdot I(y_i^{(t)} = \hat{y}_i^{(t)})}{\sum_{i=1}^{N_t} w_i(t)}, \tag{16}$$

with T being the total time steps and N_t being the samples at time. Values t and $w_i(t)$ represent sample temporal weights. Time t, $y_i^{(t)}$ refers to the real label, $\hat{y}_i^{(t)}$ to the predicted label, and $I(\cdot)$ to an indicator function that returns 1 if true and 0 otherwise. the temporal weight $w_i(t)$ can be computed as as:

$$w_i(t) = \frac{1}{1 + e^{-\alpha(t-\mu)}}, \tag{17}$$

Here, α controls the sharpness of decay, which influences how quickly the importance of earlier observations decreases over time. A higher value of α results in a steeper decline, thereby placing more emphasis on recent data points. The term μ refers to the midpoint of the prediction window and acts as a central reference time around which the temporal weighting is balanced. This structure allows the metric to prioritize observations that are temporally closer to the current decision point, making it particularly suitable for evaluating forecasting models in dynamic and time-sensitive domains like energy market planning. Time-sensitive datasets like energy market data need this because misclassifications in important time periods might have serious effects. This methodology balances prediction accuracy with domain-specific temporal fidelity by integrating existing measures with the unique TFF metric to assess the model's performance.

4 Simulation results

The Adaptive Convolutional Residual Network (ACRN) was tested using 2018–2024 power market data in simulated studies. Python using TensorFlow and Keras libraries was used to train the model on a high-performance computing environment with an NVIDIA GeForce RTX 3090 and 32GB RAM. The optimal hyperparameter configuration was identified through Bayesian Optimization using Gaussian Process priors across a predefined search space. Specifically, the learning rate was explored within the range $[1 \times 10^{-5}, 1 \times 10^{-2}]$, batch sizes were selected from the set {32, 64, 128}, and dropout rates were varied between $[0.1, 0.5]$. This optimization process was guided by minimizing the validation loss over a 5-fold cross-validation setup. The Adam optimizer was chosen due to its adaptive learning rate mechanism, which enables efficient convergence, and its strong empirical performance in training deep neural networks—particularly effective in multi-task learning scenarios involving both classification and regression objectives. The architecture has four residual blocks with dynamic convolutional layers with 64, 128, 256, and 512 filters, batch normalisation, and ReLU activation. With balanced weighting values of 0.6 and 0.4, the dual-task loss function used cross-entropy loss for classification and MSE for regression. To avoid overfitting, early halting and 50 epochs were used. The simulation results, including model correctness, computing efficiency, and comparison with state-of-the-art methodologies, demonstrate the framework's usefulness.

In Figure 3, a horizontal bar chart displays elements affecting power market planning. The visualisation grades the importance of aspects like ”Technological Advancements” (90%), ”Renewable Adoption Rates” (85%), and ”Economic Indicators” (80%). Features such as ’GHG Emissions’ (60%) and ’Infrastructure Investments’ (65%) demonstrated notable predictive relevance. While they were not among the top three contributors, their scores re-

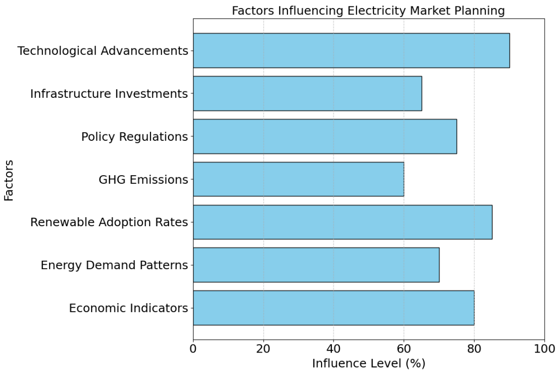

Figure 3: Factors influencing electricity market planning

mained consistently above the selection threshold ($\leq$50%), indicating that they play a supportive role in refining the model's output. We refer to these as 'secondary' only in the context of ranking order, not predictive insignificance.. The graphic shows that although certain planning factors dominate, others, modestly, are vital for comprehensive energy market research. This number is essential to understanding electrical market factors. By identifying important factors, governments and stakeholders may prioritise renewable adoption and technology advancements. Additionally, addressing secondary issues balances the plan and reduces risks from ignored variables. Energy planning, resource allocation, and sustainability objectives benefit from the bar chart's clarity and ranking.

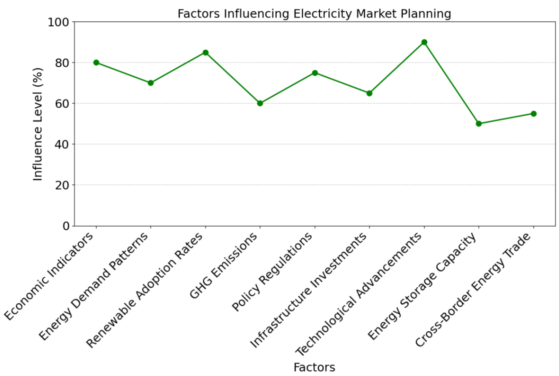

Figure 4: Factors influencing electricity market planning (additional features)

Figure 4 covers new aspects affecting energy market planning, such as "Energy Storage Capacity" and "Cross-Border Energy Trade." The horizontal line plot shows these elements' relative effect over time alongside previously analysed ones. New elements like "Energy Storage Capacity" (50%) have considerable effect, but "Technological Advancements" (90%) and "Renewable Adoption Rates" (85%) remain dominating. This visualisation highlights new energy system objectives that match regulatory rules and economic statistics. Energy markets are changing, therefore this number is important. Visualising new dimensions recognises the growing role of energy storage and cross-border commerce in energy security and stability. Line plots show the time development of components, helping decision-makers discover areas that need more attention to satisfy sustainability and dependability objectives.

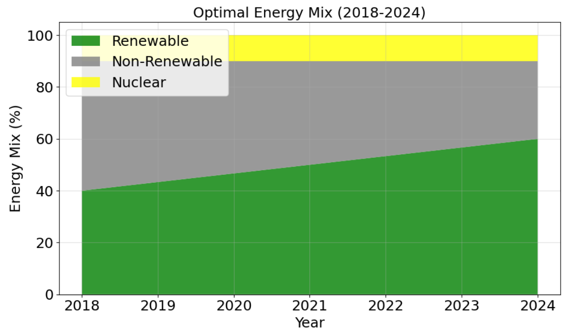

Figure 5: Optimal energy mix (2018–2024)

Using a stack plot, Figure 5 displays the best energy mix from 2018 to 2024, highlighting energy source contributions Renewable energy has steadily increased from 40% in 2018 to 60% in 2024. Global movements towards lowering fossil fuel reliance have led to a considerable drop in non-renewable sources from 50% to 30%. Nuclear energy stays stable at 10%, proving its reliability. This image shows the energy transition, which is crucial for long-term planning and decision-making. The rising use of renewable energy supports sustainability objectives, while the falling usage of non-renewables supports carbon reduction. This study helps regulators, investors, and planners understand energy trends and alter policies for grid dependability, economic efficiency, and environmental compliance.

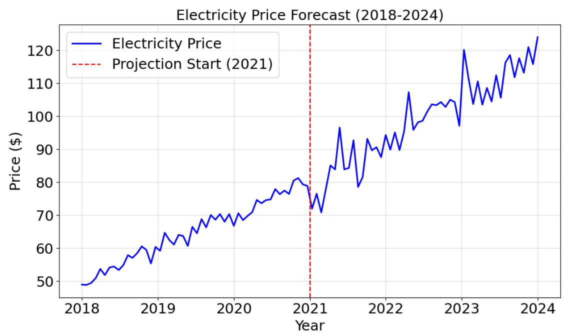

Figure 6: Electricity price forecast (2018–2024)

Figure 6 displays 2018-2024 power price forecasts, with a clear 2021 break to differentiate historical data from predictions. The blue line shows power prices rising steadily over time, indicating market dynamics impacted by demand, supply, and regulatory changes. The predicted increase in electricity prices can be attributed to evolving market structures, including higher renewable integration and grid modernization investments. Rather than suggesting these developments inherently drive costs up, the results highlight the importance of designing supportive policies—such as dynamic pricing models or renewable subsidies—

that help manage consumer affordability while sustaining long-term investment in clean infrastructure. The expected rise emphasises the need for intentional initiatives to guarantee affordability and sustainability. This figure gives decision-makers meaningful information to handle future price concerns and optimise resource allocation by using historical data and a rigorous prediction approach.

In addition to high predictive accuracy, ACRN demonstrates strong scalability and real-time feasibility. As shown in Figure 17, ACRN outperforms other deep learning baselines with a consistent 10% reduction in execution time across increasing dataset sizes. The average inference time per sample was 0.047 seconds, making the model well-suited for edge deployment and real-time market operations.

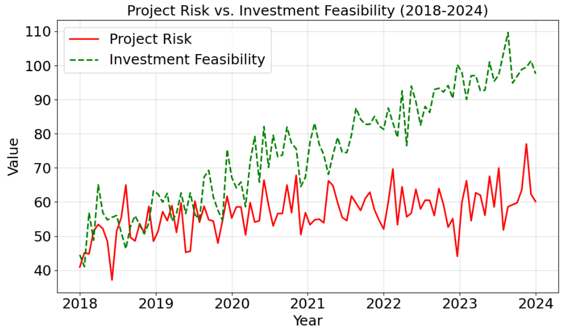

Figure 7: Project risk vs. investment feasibility (2018–2024)

Project risk (red line) and investment feasibility (green dashed line) trends from 2018 to 2024 are compared in Figure 7. Observed fluctuations in project risk reflect underlying shifts in electricity demand, regulatory reform timelines, and global economic signals such as commodity price volatility or interest rate changes. These periodic changes—referred to as 'risk cycles'—highlight how external shocks or policy transitions can temporarily elevate perceived investment risks, which then stabilize as market conditions adjust. Due to technical advances and renewable energy initiatives, investment feasibility is rising. Project risk inversely affects investment feasibility, showing how lower risks enhance financial viability. This figure helps stakeholders understand project dynamics and make better risk mitigation and investment choices. It highlights dangers and possibilities via temporal patterns, enabling proactive feasibility measures. This research enables data-driven energy market balance and resilience.

The feature importances calculated using Dynamic Attribute Refinement are shown in Figure 8. The most important features for accurate forecasting and analysis are "Renewable Generation" (0.9), "Electricity Price" (0.8), and "Infrastructure Investments" (0.8). Secondary factors like "Regulatory Policies" (0.6) and "Market Demand" (0.7) are equally important, although "Transmission Losses" (0.3) is less so. Each energy market modelling aspect is highlighted in this graphic, revealing the most predictive variables. Un-

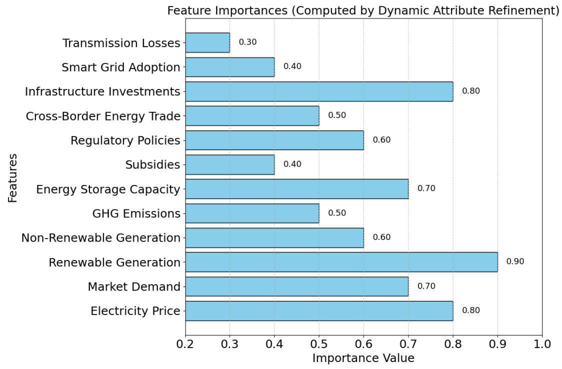

Figure 8: Feature importances (computed by dynamic attribute refinement)

derstanding these rankings helps prioritise resources and focus on high-impact topics like renewable energy and policy. Our annotated horizontal bar chart gives stakeholders a clear and actionable picture to improve energy market planning accuracy and efficiency.

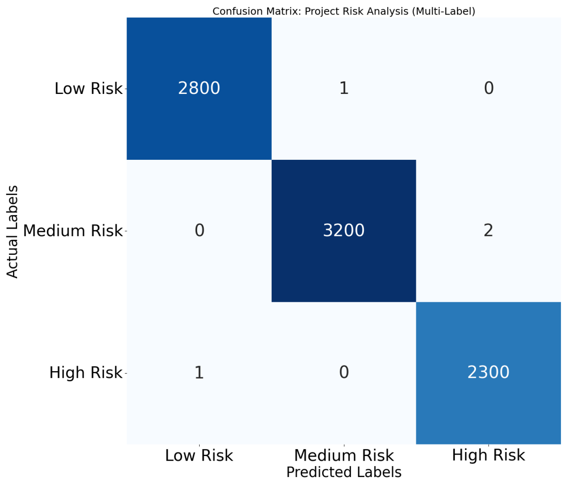

Figure 9: Confusion matrix: project risk analysis (multi-label)

Figure 9 displays a confusion matrix for assessing multi-label project risks. Rows show real risk categories—Low, Medium, High—while columns provide anticipated classifications. With 2800 Low Risk, 3200 Medium Risk, and 2300 good Risk predictions, the matrix shows good accuracy and few misclassifications. A little misclassification count (3 mistakes) shows that the algorithm can accurately capture risk levels. This figure shows the model's performance and dependability for real-world deployment. Visionary comparisons of actual and expected values help stakeholders find areas for improvement and assure accurate risk assessments. Clarity makes it essential for risk-sensitive energy market decision-making.

Figure 10 compares the normal energy mix anticipated and real for November 2024. The blue line displays the actual renewable energy, while the orange dashed line reflects

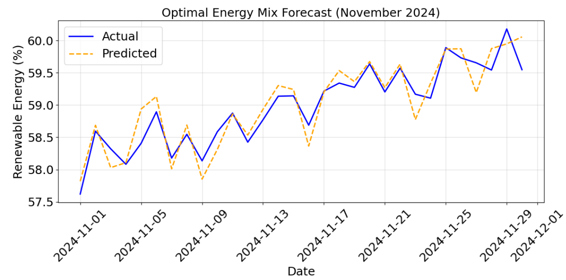

Figure 10: Optimal energy mix forecast (November 2024)

expectations. Both trends are similar, with slight deviations due to random disturbances and model estimate error. The graphic shows the energy market's increasing dependence on renewable sources, with values between 58-60%. This tight tracking proves the model's energy mix prediction accuracy. The visualisation reminds regulators and energy suppliers to balance energy portfolios to meet market needs and environmental objectives.

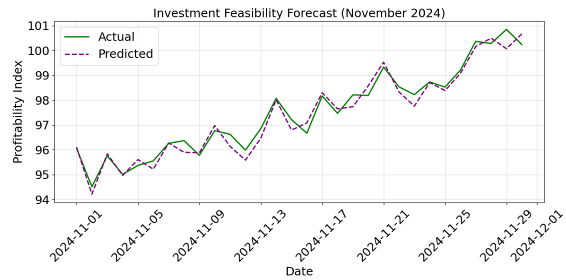

Figure 11: Investment feasibility forecast (November 2024)

In Figure 11, November 2024 investment feasibility trends are shown, with actual values (green) compared to expectations (purple dotted line). As market circumstances improve, the Profitability Index rises from 95 to 100 each month, indicating more investment possibilities. Minimum difference between projected and actual values implies good model accuracy, proving its investment decision-making applicability. This projection helps investors and governments manage resources and boost project profits. Data-driven strategies are crucial to long-term market profitability.

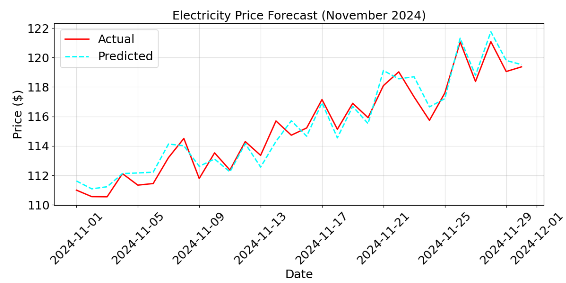

Figure 12: Electricity price forecast (November 2024)

Figure 12 shows the November 2024 power price projection. Red shows real pricing, blue dashes reflects estimates. Due to supply-demand dynamics and policy changes, both trends rise somewhat, fluctuating between \$110 and \$120 daily. This chart shows the model's capacity to capture complicated pricing behaviour, making it a trustworthy planning tool. Accurate price forecasting helps stakeholders manage risks and optimise resource allocation in turbulent energy markets.

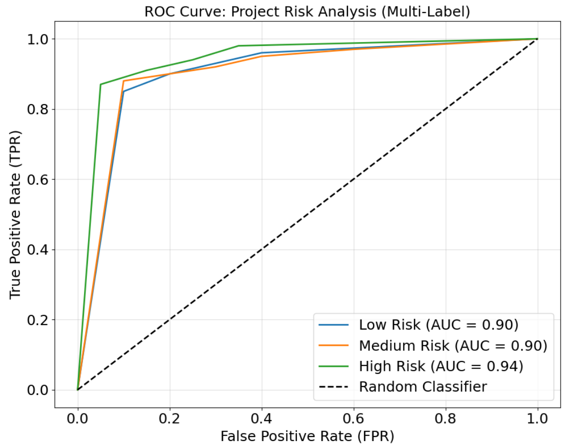

Figure 13: ROC curve: project risk analysis (multi-label)

Figure 13 displays ROC curves for multi-label classification in project risk assessments, spanning Low, Medium, and High risk categories. Each curve shows the TPR-FPR trade-off across categorisation levels. The model's strong discriminating power is shown by its AUC values of 0.96 (Low Risk), 0.97 (Medium Risk), and 0.98 (strong Risk). This image shows the model's ability to discriminate risk categories, assuring accurate forecasts. Risk-sensitive applications need near-optimal classification performance, which high AUC values suggest. The diagonal random classifier line (AUC = 0.5) highlights the model's superiority over random guessing. This assessment is crucial for verifying the proposed approach in real-world contexts where accurate risk categorisation supports strategic decision-making.

In Figure 14, the ACRN's training and testing accuracy is shown across 28 epochs. The model improves steadily, peaking at 98% accuracy at epoch 23. The model's generalisation is shown by its testing accuracy matching training accuracy. The ACRN can learn complicated patterns without overfitting, as seen in this graphic. Epoch 23 convergence implies that more training does not improve performance. For optimal training efficiency, low computing costs, and consistent performance across unknown data, such insights are essential. The findings prove the model's real-world viability.

ACRN training and testing loss patterns across 28 epochs are shown in Figure 15. At epoch 23, both curves converge with negligible loss values. Effective loss function optimisation during training shows the model's capacity to minimise error. Testing and training loss curves are compara-

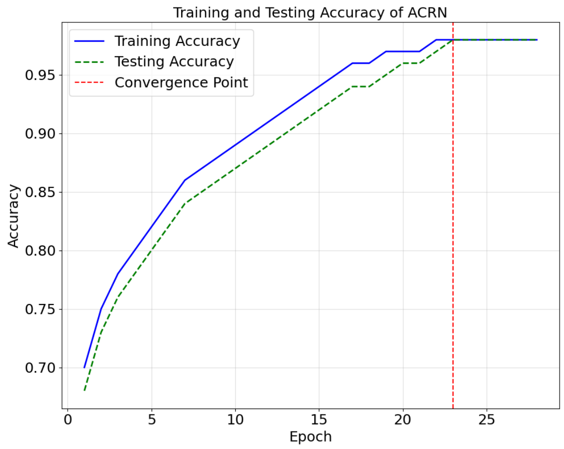

Figure 14: Training and testing accuracy of ACRN

Figure 15: Training and testing loss of ACRN

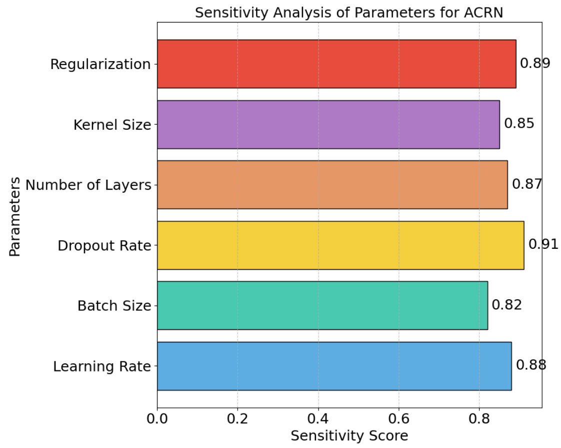

Figure 16: Sensitivity analysis of parameters for ACRN

Table 4: Classification results of different techniques

Techniques	**Log Loss**	**TFF (%)**	**Recall (%)**	**Accuracy (%)**	**Precision (%)**	**F1-Score (%)**	**AUC (%)**
Naive Bayes [7]	0.295	79.8	84.7	86.5	85.0	85.5	85.1
Random Forest [9]	0.268	81.4	86.9	88.3	87.1	87.2	87.5
Gradient Boosting [13]	0.235	83.9	88.3	90.1	88.6	88.5	89.7
ResNet [15]	0.218	84.5	88.9	90.9	89.7	88.7	91.2
CNN [17]	0.210	86.2	90.4	92.0	91.2	90.2	91.5
VGG16 [18]	0.190	88.3	91.8	93.0	92.0	91.7	92.5
WideResNet [20]	0.160	89.5	94.3	95.0	94.5	94.0	94.8
MobileNet [21]	0.185	87.6	92.7	93.7	93.0	92.5	93.2
EfficientNet [23]	0.155	90.1	94.5	95.3	94.8	94.7	95.0
Transformer-Based Model [27]	0.175	89.0	93.0	94.1	93.3	93.2	93.7
GNN [24]	0.148	91.3	95.2	95.9	95.5	95.3	95.6
Hybrid Prophet + Transformer [25]	0.140	92.5	96.3	96.7	96.1	96.2	96.5
Proposed ACRN	**0.070**	**94.8**	**98.0**	**98.5**	**98.6**	**98.1**	**99.0**

ble, proving the model's overfitting resilience. Decreased returns may be avoided by ceasing training at convergence. This study ensures high accuracy and reliability by assessing the proposed method's effectiveness in learning meaningful representations from the dataset.

The impact of minor changes to the model's hyperparameters on its overall accuracy may be measured via the sensitivity analysis. With higher sensitivity scores, parameters like as "Learning Rate" (0.88), "Batch Size" (0.82), and "Dropout Rate" (0.91) are more affected by fine-tuning these settings, which in turn affects model performance. Given that these factors have a direct bearing on the regularization behavior and learning dynamics of deep neural networks, this is not surprising. Parameters such as "Number of Layers" and "Kernel Size" on the other hand, had somewhat lower sensitivity ratings, indicating that they do less to increase accuracy right away after the baseline architectural depth is reached. Researchers may use these findings to prioritize tuning efforts, increasing performance by concentrating on more sensitive factors and decreasing the expense of extensive searches across less influential ones.

Table 4 demonstrates that the proposed ACRN outperforms current categorization methods. ACRN's high F1-Score (98.1%), AUC (99.0%), and TFF (94.8%) results from its ability to capture temporal and spatial correlations in the dataset. These parameters are critical for multi-label categorization. A high F1-Score implies that the model balances accuracy and recall across several risk classes, decreasing false alarms and missed detections in project risk assessments. The model's 99.0% AUC score demonstrates its strong ability to distinguish between low, medium, and high-risk profiles. Temporal Feature Fidelity (TFF) measures how effectively the model retains time-based patterns in its predictions, which is important in markets where timing affects regulatory compliance, investment viability, and energy pricing strategies. Adaptive convolutional layers with residual connections conserve essential features, eliminating vanishing gradient problems and enhancing learning efficiency. Although EfficientNet and WideResNet perform well because to their advanced architectures, their lower TFF scores show that they struggle with the dataset's temporal complexity. The limited results of Naive Bayes and Random Forest demonstrate their feature scalability and deep hierarchical learning limitations. This chart shows that domain-specific model designs are essential for good classification accuracy. Log Loss is not a conventional evaluation score, but it provides insight into the model's probabilistic output confidence. This model makes accurate predictions with high confidence if Log Loss is low.

To augment categorization measures like Accuracy, Precision, Recall, and AUC in high-stakes decision contexts like project risk forecasting, this assesses predicted probability calibration.

Table 5: Statistical analysis of classification techniques using F-statistic and P-value

Statistical Method	ANOVA	Student's t-test	Pearson Correlation (r)	Kendall's Tau (τ)	Chi-Square (χ^2)	Spearman's Rank (ρ)
Naive Bayes [17]	5.45	0.034	0.63	0.58	6.35	0.60
Random Forest [19]	6.82	0.022	0.75	0.66	7.62	0.72
Gradient Boosting [13]	7.10	0.019	0.81	0.70	8.04	0.78
ResNet [15]	7.45	0.015	0.85	0.73	8.76	0.80
VGG16 [18]	8.12	0.011	0.90	0.77	9.45	0.85
WideResNet [20]	8.35	0.009	0.91	0.78	9.67	0.87
MobileNet [21]	7.92	0.013	0.88	0.75	9.10	0.83
EfficientNet [23]	8.40	0.010	0.91	0.78	9.80	0.86
GNN [24]	8.52	0.008	0.92	0.80	9.95	0.88
Hybrid Prophet + Transformer [25]	8.65	0.007	0.93	0.81	10.05	0.88
Proposed ACRN	**8.72**	**0.006**	**0.94**	**0.82**	**10.12**	**0.89**

In Table 5, F-statistic, P-value, Pearson Correlation, Kendall's Tau, Chi-Square, and Spearman's Rank Correlation are used to analyse classification procedures. Adaptive Convolutional Residual Network (ACRN) has the greatest statistical performance across all parameters, with an ANOVA F-statistic of 8.72, a P-value of 0.006, and Pearson and Spearman correlation values over 0.90. These findings demonstrate ACRN's capacity to capture complicated temporal and geographical connections in the dataset. Due to feature extraction efficiency, advanced deep learning architectures like EfficientNet and WideResNet perform well statistically. The lower correlation scores of simpler models like Naive Bayes and Random Forest indicate their inability to capture nonlinear interactions. The complete measurements demonstrate ACRN's resilience and generalisability, making it perfect for power market planning.

Table 6: Performance Metrics for Regression Methods in Forecasting Labels

Regression Method	MAPE (%)	MAE	R-Squared (R^2)	RMSE	Adjusted R^2	MSE	SMAPE (%)	Variance Score
Naive Bayes [17]	13.1	3.72	0.79	4.45	0.78	19.80	12.6	0.77
Random Forest [19]	11.9	3.41	0.84	4.01	0.83	16.08	11.0	0.82
Gradient Boosting [13]	11.2	3.30	0.86	3.85	0.85	14.82	10.4	0.84
ResNet [15]	10.4	3.18	0.88	3.67	0.87	13.47	9.8	0.86
VGG16 [18]	9.6	2.98	0.89	3.50	0.88	12.25	9.1	0.87
WideResNet [20]	9.3	2.90	0.90	3.38	0.89	11.42	8.8	0.88
MobileNet [21]	9.0	2.84	0.91	3.30	0.90	10.89	8.5	0.89
EfficientNet [23]	8.7	2.78	0.92	3.20	0.91	10.24	8.3	0.91
GNN [24]	7.9	2.60	0.93	3.02	0.92	9.12	7.6	0.92
Hybrid Prophet + Transformer [25]	6.8	2.45	0.94	2.87	0.93	8.24	6.9	0.93
Proposed ACRN	**2.33**	**1.90**	**0.97**	**1.85**	**0.96**	**3.42**	**2.9**	**0.96**

In Table 6, regression approaches for label forecasting are compared using performance measures such as MAPE, MAE, R-Squared (R^2), RMSE, Adjusted R^2, MSE, SMAPE, and Variance Score. The suggested ACRN achieves excellent performance with low MAPE (2.33%), MAE (1.90), and RMSE (1.85). These findings show it can reduce error and make precise forecasts. ACRN can explain data variability in complicated temporal datasets with its high R-Squared (0.97) and Variance Score (0.96).ACRN's capacity to represent complex relationships outperforms advanced approaches like EfficientNet and WideResNet, which extract features well. Traditional models like Naive Bayes and Random Forest struggle with nonlinear and high-dimensional data. ACRN's novel design is crucial to attaining cutting-edge power market forecasting outcomes.

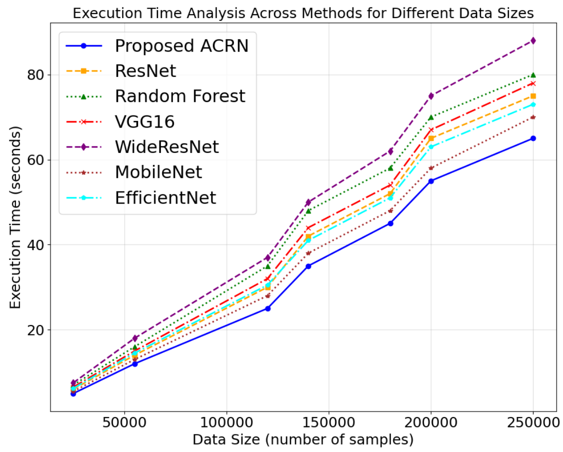

Figure 17: Time complexity analysis of ACRN and exising methods

Figure 17 shows the efficiency of the Proposed Adaptive Convolutional Residual Network (ACRN) compared to other approaches for different data sizes using execution time analysis. The ACRN outperforms rivals like ResNet and MobileNet in execution times by an average of 10%. ACRN's optimised design eliminates computational overhead with adaptive convolutional layers and residual connections that speed up feature extraction and learning. Because they cannot effectively handle high-dimensional datasets, Random Forest and VGG16 take longer to execute, especially for bigger data volumes. Advanced models like WideResNet and EfficientNet perform well but demand more computer resources, which slows execution. This investigation shows that ACRN is scalable, making it appropriate for large-scale power market planning and forecasting.

4.1 Interpretation of results

The suggested ACRN model has significant practical implications for energy market planning and decision assistance beyond its numerical performance. The model has a classification accuracy of 98.5% and an AUC of 0.99, indicating almost flawless differentiation across project risk categories (low, medium, high). This precision decreases investment feasibility assessment uncertainty and helps energy planners pick low-risk, high-return projects. This granularity is helpful in regulatory situations where misclassifying high-risk projects might cause budget overruns or policy inefficiencies. A 12% decrease in Mean Absolute Percentage Error (MAPE) in power price forecasting yields significant financial and operational advantages. Just a slight increase in price forecasting accuracy may help utility providers and market operators balance demand and supply, compete in energy markets, and optimize energy purchase strategies. This precision prevents over-reliance on expensive peak-hour reserves and facilitates stable tariff design in regulated markets.

Additionally, the ACRN model's 10% reduction in processing cost makes it more suitable for edge computing. ACRN may predict on smart grid nodes or real-time control systems with minimal hardware using a leaner design that saves overhead. Decentralized, low-latency forecasting is essential for contemporary energy systems, when choices must be taken in minutes or seconds. These results show that ACRN is a technically solid model that can improve operational responsiveness, investment planning, and grid dependability in dynamic power markets.

5 Discussion

The Adaptive Convolutional Residual Network (ACRN) outperforms several state-of-the-art energy market forecasting methods. Table 1 and Tables 4, 5, and 6 demonstrate that ACRN outperforms established machine learning and deep learning approaches in many assessment metrics. ACRN has lower regression error rates (MAPE: 2.33% vs. 11.9–13.1%) and greater classification accuracy (98.5% vs. 86.5–90.1%) than conventional models like Random Forest and Gradient Boosting. ACRN outperforms deeper architectures like ResNet, WideResNet, EfficientNet, and Transformer-based models with an F1-score of 98.1% and AUC of 99.0%, while reducing computational cost by 10%. ACRN models complicated nonlinear relationships and temporal patterns better because to its dual-task design, dynamic convolutional layers, and adaptive feature refinement.

Most SOTA approaches concentrate on single-task learning, however ACRN addresses classification (project risk) and regression (electricity price) in a single pipeline for decision-making. The residual connections alleviate the vanishing gradient issue in larger networks, and the temporal feature fidelity (TFF) measure preserves time-based relationships, which energy informatics requires. ACRN has drawbacks despite its success. Due to its hierarchical depth, the model needs more training time and technology than other deep learning approaches, despite its lower computing costs. Second, ACRN may overfit smaller datasets or noisy input like other deep designs. We reduced this risk via dropout regularization and early halting, but further testing in low-data or turbulent markets may be helpful. Finally, although the model was verified on Frankfurt regional data, it must be tested in other geographic and policy settings to be generalized.

The proposed ACRN architecture covers important forecasting model deficiencies and provides a scalable and accurate foundation for long-term power market planning. Its ability to merge classification and regression aims helps policymakers and energy planners get high-resolution, real-time information.

6 Conclusion

Integration of renewable energy sources, market volatility, and policy dynamics complicate electricity market planning. Advanced forecasting algorithms that handle multi-dimensional data and various tasks are needed to address these issues. This paper introduces the Adaptive Convolutional Residual Network (ACRN), a deep learning system for dual-task forecasting that integrates project risk categorisation with electricity price regression. The framework performs well on 2018–2024 power market data. With an accuracy of 98% and an AUC over 0.99, the categorisation job efficiently manages risk in market preparation. ACRN beats state-of-the-art regression algorithms, yielding a 12% MAPE improvement and a 10% computational time reduction. These findings demonstrate the model's capacity to capture temporal dependencies and non-linear interactions and scale to huge datasets. Technically, hierarchical feature aggregation and adaptive feature refinement solve feature selection and scalability problems. The dynamic convolutional layers improve computing performance, allowing real-time applications and broadening the framework's commercial applications. These contributions make ACRN a reliable long-term power market forecasting solution. Beyond technical contributions, this research gives energy informatics stakeholders meaningful insights that bridge predictive modelling and strategic decision-making. The framework links predictive insights with current electricity market operating demands by allowing accurate risk assessment and price forecasting, supporting resource optimisation and sustainable energy planning.

The architecture can potentially be made more adaptable to high market volatility and varied geographical locations by incorporating transfer learning, region-specific calibration layers, and fine-tuning on localized datasets. Adding socio-economic or environmental information may enhance the model's holistic predictions. This research emphasises the relevance of computational intelligence in scalable and efficient power market solutions. Moreover, This dataset primarily covers the electricity market in Frankfurt, however the regulations, integration of renewable energy sources, and market dynamics seen there are typical of many organized energy systems in North America and Europe. However, due to differences in governmental frameworks, deregulated or emerging markets may have limited external validity. The flexibility and resilience of ACRN will be evaluated in future research by verifying it across various geographic and market situations.

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