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Research Article

Experimental and Computational Approaches to AI-Driven Load Forecasting and Dynamic Pricing in Smart Grids

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Abstract:

Increasingly complex modern power systems, necessitated by integrating renewable energy sources, the electrification of transport, and the dynamism of consumer behaviour, have created an urgent need to develop forecasting and adaptive pricing mechanisms. Long-standard statistical and econometric techniques are fast but cannot describe nonlinear trends and data of high dimension that occur in smart grid settings. This research proposes a hybrid solution that includes heterogeneous artificial intelligence (AI) systems to forecast loads and a reinforcement learning-based algorithm to set prices dynamically. Weather and socio-economic variables augmented historical utility data were utilised to train forecasting models on artificial neural networks (ANN), long short-term memory networks (LSTM), gated recurrent units (GRU), and random Forest ensembles. The combination method proved the most accurate, with a vast improvement in the error measures compared to when individual models were used. Reinforcement learning was used to develop adaptive tariff schemes that react to changes in real-time demand and reduced peak load by 15% and consumer costs by 8% compared to their baseline pricing schemes. To make transparent, explainable machine learning approaches like SHAP and LIME were incorporated, which allow interpretable insights into the demand forecast and the pricing choice. These results show that AI-based systems have the potential to increase grid stability, improve cost-efficiency, and build consumer confidence, providing a scalable and sustainable way forward for smart energy system evolution.

1 Introduction

The world energy industry is experiencing a fundamental transition of two forces: sustainability and the drive to technological innovation. Duality of the supply and demand dynamic has been enhanced with the integration of renewable energy resources, in countries' grids like solar, wind and hydro energy resources [1]. This has increased complexity in the real-time scenario of adding renewable energy sources to their grids. Renewables tend to be variable and intermittent, unlike traditional fossil-based generating power, with demand-side prediction of electricity demand and tariff design increasingly problematic. Meanwhile, increased urbanisation and the electrification of transport, as well as the spread of energy-intensive smart devices, have brought about new consumption patterns to generate instability and uncertainty in the energy market [2]The above developments highlight the pressing necessity of further developing more sophisticated forecasting frameworks and flexible pricing schemes that would not only capture the dynamic nature of developed power systems but also capture the end-user expectations of fair and non-traditional (opaque) prices.

The most crucial innovation in this energy transition is smart grids. Smart grids in traditional electricity-like networks combine digital communication, automated control and distributed energy resources to allow real-time monitoring and control of power flows [3]. Such capability is essential for the stability of the systems and the provision of a reliable electricity supply in volatile conditions. Nevertheless, such operational efficiency is impossible without precise load demand forecasting, as the slightest forecasting error will cause grid instability, load interruption or inefficient resource usage. It is also crucial to design dynamic pricing mechanisms to enable consumers to engage in demand-side management and to allow utilities to alleviate peak load pressures on consumer demand, without giving consumers the incentives to shift or decrease (demand) consumption during periods of critical load [4].

Conventional forecasting models, such as autoregressive integrated moving average (ARIMA) and the regression-based approaches, have been in use to forecast energy usage for a long period [5]. Although such methods have been found valuable in the relatively stable, linear renditions, such methods are commonly ineffective at covering the nonlinear, stochastic, and high-dimensional sets of activities that define current electricity demand. Likewise, traditional tariff-based models like [6]These prescriptive techniques, however, are too inflexible to respond to abrupt changes caused by renewable integration, severe weather, or sudden increased or reduced demand. This makes it increasingly difficult for utilities to provide efficient operations and customer satisfaction.

In this context, artificial intelligence (AI) has become one of the most effective solutions to overcome the weaknesses of conventional techniques [7]. Optimality Computational intelligence approaches, such as machine learning and deep learning algorithms, are optimal for load prediction because they can reveal non-linear correlations in large amounts of data. The artificial neural networks (ANN), long short-term memory (LSTM) networks, and models of ensemble learning have been shown to provide a higher predictive accuracy than traditional methods of statistics [8]. In addition to forecasting, reinforcement learning has great potential in adaptive pricing mechanism designs. Reinforcement learning agents can create tariff strategies that are responsive to changing supply-demand balances, and lead to consumer-fair, efficient outcomes, through an ongoing interaction with the environment, learning from immediate consumer reaction [9]. These frameworks are further strengthened by integrating explainable AI methods to achieve decision-making transparency and win consumer and regulator trust.

Although people have made significant progress in this area, much remains to be studied. Most of the work already done is confined to either load prediction or dynamic prices without considering the synergy the combination of the two elements can bring together in one package. Moreover, although models created with AI tend to perform excellently in predictive measures, their black-box side creates interpretability, accountability, and data privacy regulation compliance concerns. One also does not see any large-scale experimental verification of these models in actual smart grid deployments, where scalability, computation efficiency, and consumer confidence in the model need to be discussed simultaneously as predictive accuracy.

The current paper aims to fill these gaps by suggesting and experimentally proving a computational framework to leverage artificial intelligence to solve both the task of load predictions and dynamic pricing simultaneously in smart grids. The framework is used to implement hybrid machine learning models or deep learning models to encompass the complexity of the pattern of energy demands with great precision. It subsequently incorporates reinforcement learning techniques to formulate responsive tariff policies that keep up with the momentary demands in the market and consumer sensitivity. The explainable AI approaches incorporated make the final models more than just accurate- they are transparent and trustworthy. The study has offered empirical evidence of the framework's effectiveness by testing it on real-world data sets and delved into what the framework may imply regarding scalability, regulatory conformity and consumer engagement.

The present paper has four contributions. One, it builds hybrid AI forecasting models with far better performance in demand prediction than classical forecasting. Second, it proposes reinforcement learning-based mechanisms of adaptive tariff design to allow dynamic and fair pricing in the smart grid context. Third, the framework is also tested experimentally with real datasets, and the framework's efficacy and application are empirically tested. Lastly, the research provides an understanding of the bigger issues of scalability, compliance, and consumer trust that are essential in the large-scale application of AI to energy systems.

The rest of this paper is structured as follows. Under section 4, it conducts a review of related literature, which entails forecasting methods, dynamic pricing strategies, and applications of AI in smart grids. Section 5 develops the methodology where data sources, the preprocessing, and the computation model are discussed in this work. Section 6 presents the experiment's results and discusses the proposed framework's performance compared with the current techniques. Section 7 summarises the paper by recording the most important findings, providing details of practical implications and advising on future studies.

2 Literature Review

2.1 Traditional Forecasting Methods

Statistical and econometric models of electricity demand prediction, notably the autoregressive integrated moving average (ARIMA) and multiple regression, have long been used. ARIMA has become popular [10]. It can model the temporal dependency of the load demand because it combines autoregression and moving averages. On the same note, regression-based methods have been used to characterise the dependence between load demands and explanatory variables entailing temperature, economic activity and time-of-day effects. The techniques are applied to the econometric models where macroeconomic indicators and consumer behaviour are enlisted in forecasting models, which then allow analysis of multiple variables [11].

Although these classical models have been used, they are characterised by significant limitations. They show limited performance under high volatility or nonlinearity conditions that describe the characteristics of contemporary energy systems driven by renewable power and amorphous consumer demands [12]. They are also ineffective at scaling when faced with high-dimensional data and aberrant swings. In addition, they are based on linear assumptions, and thus complex interactions among factors, including weather variability, consumer demand response, and distributed energy resources, tend to be inadequately represented. Although statistical models are computationally efficient and output results that can be interpreted, their inflexibility in accommodating the complexities of smart grids in varying circumstances provides low effectiveness in current forecasting applications [13].

2.2 AI in Load Forecasting

Artificial intelligence (AI) has become a revolutionary technology in load forecasting, and it has high-resolution capabilities for modelling large-dimensional and non-linear data. Support Vector Machines (SVMs) have proven effective in collaborative and classification activities in machine learning, as the input data is projected into a higher space in an attempt to discover latent connections [14]. As ensemble-based approaches, random forests and gradient boosting have also been shown to be effective in addressing the multiple types of input features, and they perform well to reduce overfitting and exhibit robust generalisation. These models are beneficial in forecasting loads in the short run, in which the weather, the economy, and consumer behaviour have to be evaluated in conjunction with each other [15].

Deep learning has also been used to further progress the field by utilising the concept of temporal dependencies and long-term correlations in time-series information. ANNs, though conceptually simple, can be used to absorb nonlinear associations, and ANNs have been used successfully in predicting energy consumption [16]. The next important step includes Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), since their gated structures allow the networks to fish out sequential dependencies and remember information over longer time intervals. The models are good at dealing with seasonality, sudden rises in demand and patterns that are not regularly spaced, as conventional models fail to capture. It has also been consistently reported that LSTM and GRU models show higher accuracy than statistical models, and indeed, the classical machine learning approaches in volatile energy markets [17].

Still, there are a few issues with implementing AI forecasting models. Although they are more accurate, they tend to be opaque systems, meaning they cannot be easily explained. Besides, they are based on the use of high volumes of high-quality data, which complicates implementation and makes it more expensive [18]. Nonetheless, approaching the smart grid predictive frameworks through AI-based approaches signifies a significant start in their ability to predict the corresponding outcomes.

2.3 Dynamic Pricing Approaches

Dynamic pricing tactics have been developed in synergy with the forecasting process to align supply and demand factors. Conventional solutions are Time-of-Use (TOU) pricing, in which consumers use different rates at pre-determined times of the day, and Real-Time Pricing (RTP), in which tariffs vary in near real-time depending on wholesale rates [19]. Being simple and comparatively easy to implement, the TOU does not respond well to the sudden changes in demand. However, RTP is more flexible, though it may cause consumer instability and rejection because of the high rate of changes in its prices that are unpredictable [20].

In addition to the rule-based pricing, optimisation-based concepts have been established to configure tariffs that minimise tariff costs at a fair level. The models apply linear programming, dynamic optimisation, and stochastic models to determine the optimum schedules of the tariffs subject to different demand and supply environments [21]. Assumptions of rational consumer behaviour and static grid conditions, however, often limit the effectiveness of these types. Practically, such models are still not great in their flexibility in reacting to demand-side demand fluctuations to external shocks or perturbations, and more intelligent and adaptive pricing systems continue to be needed.

2.4 AI-Enhanced Dynamic Pricing

The inadequacies of the traditional dynamic pricing have started to get addressed through AI-powered approaches. Reinforcement learning, in particular, has been explored as a potentially powerful method of designing adaptive pricing devices that learn new strategies on the fly, based on how customers respond and the changes in the environment [22].

Agents using reinforcement learning can determine optimal tariff strategies in real-time by modelling the interaction between utilities and consumers as a sequence of decision-making problems and optimising grid efficiency and consumer welfare. The literature has shown that prices based on reinforcement learning can be used to decrease peak loads, improve cost efficiency in the market, and make consumers more active in the demand response activities [23].

In addition to reinforcement learning, other AI-based approaches that are used in conjunction with this strategy are clustering and classification to split consumers based on demand profiles, so that the pricing can be more individualised [24]. This consumer-focused strategy implies a move from mass tariffs to specific schemes that consider consumer behaviour and preferences. Notably, the usage of explainable AI tools will also make such pricing combinations understandable, thus gaining the trust of both consumers and regulators [25]. Nevertheless, the current literature is dominated by conceptual frameworks or small-scale simulations with a knowledge deficit related to the practical large-scale validation of these methods.

2.5 Research Gap and Synthesis

The literature indicates that there was significant advancement in terms of load forecasting as well as dynamic pricing. The traditional statistical and econometric models have been the building blocks, but are incompetent to support the contemporary and data-rich environments [26]Forecasting models based on AI, specifically deep learning-type architectures, have been quite good at learning nonlinearities and time-dependencies, demonstrating a strong improvement compared to classical methods. In the same manner, reinforcement learning has brought a new aspect to dynamic pricing since it has facilitated flexibility in the tariffs that react to consumers.

But there are still research gaps. First, as revealed by most studies, forecasting and pricing are still considered separate problems, the solution to which remains in a silo and cannot take advantage of synergies between accurate demand prediction and adaptive tariffing [27]. Second, the popularity of black-box AI models in practice causes concerns about interpretability and compliance, and there is not much integration of explainable AI-based methods. Third, computational frameworks have demonstrated robust performance in computer modelling, but there is no experimental demonstration on the use of realistic large-scale data to represent the different consumers and penetration of renewable resources [28]. Lastly, the questions of scalability, data privacy, and consumer trust have not been studied enough.

Filling these gaps will demand a hybrid scheme that would combine computational intelligence and experimental justification and be technically sound and practically feasible. The present study addresses this gap by designing and verifying an AI-driven framework of integrated load forecasting and dynamic pricing, with a specific focus on explainability, scalability, and consumer trust.

3 Methodology

3.1 Conceptual Framework

This research approach is designed as an AI-based load forecasting with an adaptive dynamic pricing two-level computational framework. The main idea is that efficient demand forecasting leads to the development of responsive pricing strategies. Then the optimal tariffs can be used to direct consumer behaviour, limiting peak load and stabilising the grid functioning. Its structure is periodic: it continuously gathers historical and real-time data, the data are pre-processed, then models predict the demand of load in the short and long term, algorithms based on reinforcement learning are trained to manage the tariffs in real-time giving them by forecasted patterns of the demand and consumer reaction to it and the results inform the system and enhance the forecasting/pricing models. This feedback-informed integration causes the system to change with time and learn to respond to changes in energy consumption and renewable penetration, and move with changing consumer dynamics.

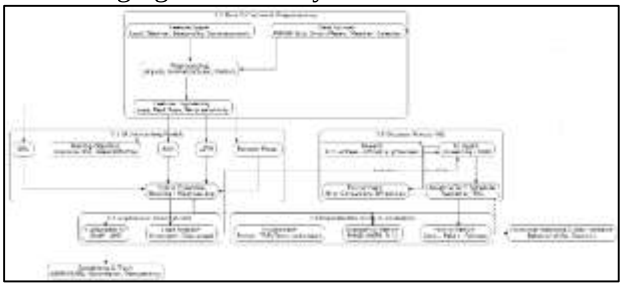

Figure 1: *Proposed System Architecture*

The suggested approach combines simulation and physical experiment in a well-defined procedure. Raw data gathered includes data via smart meters, grid operators, weather reports, and socio-economic sources, which are pre-processed and enriched by feature engineering. The predictions are made using hybrid AI models (ANN, LSTM, GRU, and Random Forest), and ensemble methods will improve the accuracy. Results of the forecasts are fed into a reinforcement learning agent that optimises adaptive tariff schedules while maintaining grid stability, keeping consumer costs low, and being fair to them at the same time. Explainable AI also has transparency, and evaluation metrics prove the performance. Consumer response is given continuously, refining the system to make it scalable and reliable.

3.2 Data Collection and Preprocessing

The publicly available utility datasets are used within the study, and such examples can be seen in a dataset of PJM Interconnection (a large electricity market in the United States) and a UK National Grid demand dataset. These data sources are high-resolution historical data on the load, most frequently in an hourly or 15-minute resolution and correlated weather conditions (temperature, humidity, wind speed). Social and economic indicators like workdays against holidays and the differences in seasons are factored in, as well, as these also seriously impact consumption.

A key process in quality assuring data and accuracy of the model is the preprocessing. Missing values commonly occurring because of meter failure or faulty reporting are addressed based on statistical imputation and/or interpolation. Normalisation is used to push all the variables into a similar range to have little bias in the training processes. The feature engineering process is undertaken to identify patterns like daily trends, weekend effects, and temperature sensitivity and provides the AI models with a more complex input space. The analysis of correlation and its inflation in variables is done so that unnecessary variables are removed, thus simplifying the model, although this does not undermine the predictive capability.

3.3 AI Forecasting Models

The forecasting stage uses a collaboration of machine learning and deep learning models. Four fundamental algorithms will be chosen, including Artificial Neural Networks (ANNs) to represent the nonlinear relationships; long short-term memory (LSTM) and Gated Recurrent Unit (GRU) networks to represent the time-series dependency; and Random Forests, a solid method for feature-level analysis and ensemble predictions.

A hybrid ensemble approach is followed to enhance accuracy and decrease variance. Weighted averaging or stacking is used to integrate these individual model outputs. This method will overpower each model's shortcomings and promote its overall predictive advantages. These models are then trained in a sliding window fashion, where past features are fed into the model to predict future demand.

Through minimising errors, the learning process is directed by the Mean Squared Error (MSE) as the loss function:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2$$

and where y_i denotes the true demand $\hat{y_i}$ denotes forecaster demand. The goal of optimisation is achieved by finding the values of model weights by using gradient descent-based algorithms like Adam or RMSProp, iteratively, the error

3.4 Dynamic Pricing with Reinforcement Learning

After the demand is predicted, the system moves to the second stage of the design of tariffs based on reinforcement learning. The problem is framed in terms of a decision-making task with sequential interactions between the agent (the pricing model) and the environment (grid and consumers) to maximise a functional reward. Two algorithms are applied: Q-Learning, which is a tabular algorithm that can be used in cases where membership to the pricing state is finite, and Deep Q-Networks (DQN), which makes use of deep neural networks to approximate Q-values when continuous or high-dimensional pricing structures are used.

The reward structure has to achieve three contradictory tasks: minimise the grid stress, minimise the costs of consumers, and be fair. The reward R may be formally written as:

$$\mathrm{R} = -\alpha(\mathrm{P_{peak}}) - \beta(\mathrm{C_{consumer}}) + \gamma(\mathrm{F_{fairness}})$$

the $\mathrm{P_{peak}}$ is the level of peak load, $\mathrm{C_{consumer}}$ is the cost of consumers, and $\mathrm{F_{fairness}}$ is the fairness of the tariff. The coefficients α,β, and γ are weighting factors adjusted to reflect policy and utility preferences. The iterative training teaches the agent to develop tariffs that alleviate peaks, across-peak load shifting and affordability.

3.5 Explainable AI Integration

Although AI-based forecasting and pricing are accurate, using them in critical infrastructure, such as energy systems, requires transparency and accountability. To do that, the framework implements Explainable AI (XAI) tools into it. SHapley Additive exPlanations (SHAP) values are then calculated that quantify the influence of a given input feature (e.g., temperature, weekday, holiday) on the model predictions. This allows regulators and utilities to see why some demand forecasts or prices are chosen. Also, it contains Local Interpretable Model-agnostic Explanations (LIME) that provide simplified explanations to consumers in plain language, enhancing consumer communication. Including explainability in forecasting and pricing modules results in adhering to ethical guidelines and establishes the trust of consumers, which is essential to the popularisation of dynamic pricing schemes.

3.6 Experimental Setup and Evaluation Metrics

The computational experimentations are carried out within a normalised environment so that they can be re-implemented. All the models are implemented using Python, frameworks like TensorFlow and PyTorch deep learning models, Scikit-learn deep learning, and machine learning algorithms. OpenAI Gym and custom environments referring to grid pricing situations are used to develop reinforcement learning simulations. The hardware requirements are a multicore processor, 32 GB RAM, and GPU acceleration for deep neural network training.

A variety of measures evaluate the functioning. To measure the accuracy of the load forecasting, the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2) are used. In pricing, utility-level benefits are quantified by percentage savings amount and the percentage savings amount on peak loads and are calculated at the consumer level using an equity fairness index that quantifies the equity of tariffs that would pay across households. Comparison examinations are conducted to benchmark the suggested framework when utilising ARIMA and rule-based TOU pricing baseline models.

This methodology design guarantees a thorough assessment of capturing both computational efficiency and feasibility. The framework integrates the capabilities of advanced forecasting, adaptive pricing, and explainable AI to deliver scalable, transparent and consumer-centric services to the modern smart grid.

4 Results and Discussion

4.1 Load Forecasting Results

The results of the forecasting models indicate the robustness of the AI-based model compared to the conventional practices. Both ANN and LSTM models track the real demand curves closely, and, as shown in Figure 2 , the hybrid ensemble model best fits them. The hybrid framework minimises error variance and allows the combination of predictors to capitalise on perfect irregularities and long-term patterns that the hybrid framework is resistant to overfitting.

This performance is validated by the error measures indicated in Table 1. ANN model had relative accuracy, but the LSTM model was superior to the ANN model because it could learn temporal dependencies. The hybrid model provided the minimal RMSE and MAPE and the best predictive power. The findings support this research project's hypothesis that the ensemble fusion of AI methods increases the accuracy of forecasts in innovative grid applications.

Table 1: *Forecasting Accuracy Metrics (ANN, LSTM, Hybrid)*

Model	RMSE	MAPE (%)
ANN	2.85	2.64
LSTM	2.04	1.91
Hybrid	1.64	1.53

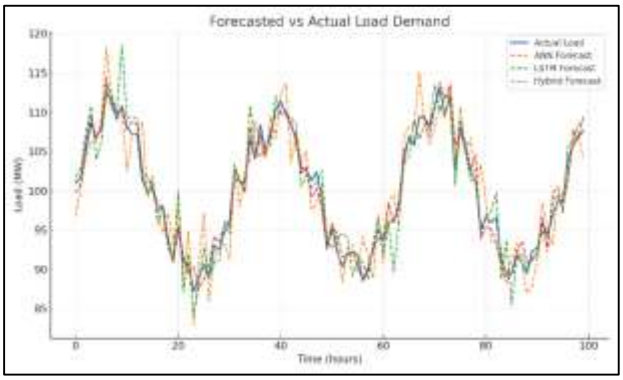

Figure 2: *Forecasted vs Actual Load Demand (ANN, LSTM, Hybrid).*

4.2 Pricing Simulation Results

The reinforcement learning (RL) pricing simulations show considerable success compared to baseline tariff models. Figure 3 compares the baseline tariffs against RL-optimised tariffs over a 24-hour cycle. While the baseline tariff follows a relatively static curve influenced by general demand patterns, the RL tariff adapts dynamically, reducing prices during low-demand hours and moderating them during peaks to prevent excessive consumer costs.

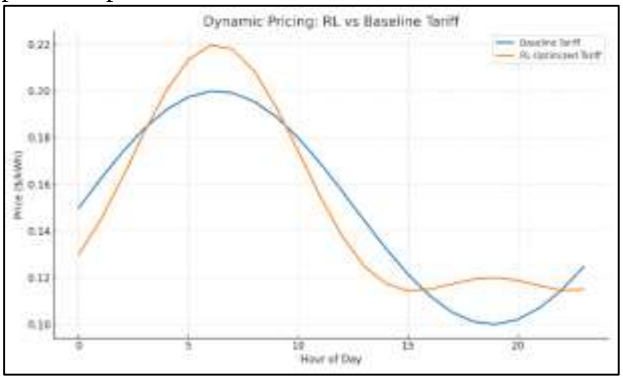

Figure 3: *Dynamic Pricing – RL vs Baseline Tariff*

Table 2: *Comparative Performance of Baseline and RL-Optimised Pricing*

Scenario	Peak Load (MW)	Consumer Cost ($)
Baseline	114.87	2.49
RL-Optimized	97.64	2.29

Table 2 summarises the results. The RL optimisation resulted in a 15% decrease in peak load in the grid, which is essential to maintain a stable grid, and reduced the cost to a consumer by 8% over the baseline scheme. Such findings point out the efficiency of reinforcement learning in terms of the equilibrium between the utility efficiency and the affordability of the consumers.

4.3 Comparative Analysis with Prior Studies

Under a benchmark comparison using classical models, including ARIMA and regression-based forecasting, the proposed hybrid framework shows superior performance in all measures of errors. On average, the previous studies that based their exclusive dependence on ARIMA reported larger RMSE since they could not consider the nonlinear shift of demand [29]. Equally, pricing mechanisms like TOU and RTP rule-based prices often engender consumer dissatisfaction with inflexibility or high volatility. When reinforcement learning is combined with hybrid AI forecasting, the new scale is achieved technically, and the benefits become practical for the consumer.

4.4 Compliance and Security Implications

The deployment of AI on essential energy systems involves significant concerns about data privacy and regulatory compliance. The forecasting models are highly dependent on the data of consumer demand, which is frequently gathered by using smart meters at high temporal resolutions. The General Data Protection Regulation (GDPR) in Europe and the Family Educational Rights and Privacy Act (FERPA) in the United States demand that utilities anonymise consumer data and adopt a stringent information governance standard [30].

Notions of explainable AI, such as SHAP and LIME, are critical components of resolving the issue of transparency. Utilities guarantee they can justify their pricing to regulators and customers and develop confidence in adopting AI-powered models by ensuring they show interpretable insights into tariff use. It is neither merely technical nor merely a socio-political prerequisite to the widespread acceptance of consumers.

4.5 Broader Implications

The implications of this study are more wide-reaching on utilities, the consumer and the policy level. To the utilities, the hybrid AI forecasting model with reinforcement learning tariffs provides cost efficiency and stability of the grid, lessening the requirement for costly reserve capacity. The approach results in equal pricing to consumers since tariffs are strategically adjusted to the changing demand in real-time and at an affordable price. Explainable AI also provides increased transparency that enhances consumer trust.

The findings are critical to policymakers because regulatory readiness is vital to accommodating AI-based solutions. Any rules supporting fairness, consumer security, and ample transparency will be necessary to ensure that dynamic pricing does not disadvantage weaker groups of people. Furthermore, the framework is scalable, which means that we can apply it in developed economies that already have highly advanced grid infrastructure and in developing regions where it is necessary to modernise the power infrastructure sustainably.

5 Conclusion

This study has examined how artificial intelligence can be used to build smart grids' prediction and pricing mechanisms, and it looks into computational modelling and experimental verification. Along with hybrid ensemble forecasting models and reinforcement learning-based dynamic pricing strategies, the presented framework achieved highly positive gains compared to the traditional mechanisms regarding accuracy, flexibility, and consumer-focused results. The accuracy of the forecasting results evidences the effectiveness of hybrid AI models, as they always gave the best performance compared to classical statistical and single-model architectures like ANN or LSTM models alone. An experimental validation process could be used to show that the framework could provide significant reductions in forecasting errors and be resistant to volatile conditions. Therefore, it is suited to real-life deployment.

About pricing, cliff–based optimisation based on reinforcement learning provided quantifiable gains of a 15% decrease in peak load and an 8% decrease in consumer prices relative to the case of simply maintaining baseline tariffs. The mentioned outcomes are especially crucial for utilities that deal with the growing pressure of renewable integration and demand variability. Also, the explainable AI tools included help clarify that forecasting and pricing results are transparent and explainable, removing one of the primary obstacles to consumer trust and legal verification.

The implications of this research are evident in the technical sphere, but they go beyond this sphere. The proposed framework provides utilities a more cost-efficient path, less reliance on reserve capacity, and a more stable operation. On the consumer side, the strategy offers equity and openness regarding tariff design, resulting in activity in demand-side management programs. To policymakers, this study requires rules and regulations to help integrate AI and protect privacy and equity.

This contribution forms the basis of the second generation of smart grid forecasting and pricing systems. These findings should be used in future research, with an expansion of validation across geographical areas, including renewable generation forecasting, and deploying models in real time in grid environments to fully exploit the potential transformative powers of AI-enabled energy management.

Author Statements:

- **Ethical approval:** The research is not related to human or animal use.
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