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**Ministry of Education**

**King Faisal University**

**College of Computer Sciences & Information Technology**

Selected Topic in Computer Sciences

***Energy time series forecasting-Analytical and empirical assessment of conventional and machine learning models***

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***Introduction:***

The rise of sensors and measurement technologies has led to a significant increase in time series data collected from various sources over time. This type of data is dynamic, with temporal dependencies and high dimensionality, making it valuable for forecasting in a wide range of applications. Time series forecasting (TSF) involves predicting future trends based on past and current observations, leveraging intrinsic patterns to capture causalities in underlying processes. In the energy sector, TSF has become crucial due to the growth of energy markets and the increasing use of renewable sources, creating the need for accurate predictions of energy demand in advance.

Traditional forecasting methods, like autoregression and moving average, have been used for energy TSF, but machine learning algorithms, such as support vector machines, k-nearest neighbor, and neural networks, have shown promising results. Despite the limitations of traditional forecasting models, deep learning approaches have emerged as a powerful solution for handling complex and large energy time series datasets. Deep learning, with its ability to capture intricate relationships in nonlinear and long time series data, offers significant potential for improving energy forecasting accuracy.

The integration of deep learning techniques in energy forecasting research shows promise for addressing the challenges posed by volatile and uncertain energy applications. By harnessing the capabilities of deep learning models, researchers aim to enhance energy forecasting accuracy and meet the evolving demands of the energy market.

***Objective:***

The report aims to address research gaps by providing a two-fold objective. Firstly, it analyzes 15 different techniques - including conventional, machine learning, and deep learning methods - for solving energy time series forecasting (TSF) problems. A qualitative comparison of these techniques is presented to understand their advantages and disadvantages. Secondly, the report conducts a quantitative empirical assessment of these techniques in solving three energy TSF problems using public datasets of varying sizes and time horizons. The objectives of the report can be summarized as: providing a comprehensive review of energy TSF problems and common techniques, conducting qualitative and quantitative analyses of these techniques, evaluating the performance of deep learning methods, and focusing on optimization methods for energy TSF specifically. The report is organized to include basic concepts, techniques, evaluation metrics, experimental results, discussions, challenges, and future research directions.

***Background:***

This section introduces Time Series Forecasting (TSF) basics. A time series has chronological observations. Univariate time series (UTS) involves one variable, while multivariate time series (MTS) has multiple variables. TSF predicts future values based on past data of the same signal (UTS) or correlated signals (MTS). TSF faces challenges like seasonality, trend, and irregularity, especially in energy data. Specific energy TSF problems include electrical energy consumption, natural gas consumption, and household load forecasting. Parametric techniques use fixed parameters, while nonparametric techniques offer flexibility but require ample training data. TSF is essential for accurate forecasting in various fields, with energy TSF facing unique challenges due to complex data and external factors.

***Methodology:***

Conventional energy forecasting methods such as ARIMA, VAR, and exponential smoothing use statistical techniques to predict energy demand. However, they have limitations in representing dynamic behavior and seasonality. Machine learning methods, such as artificial neural networks (ANNs) and support vector regression (SVR), offer more flexible and nonparametric approaches for capturing complex interactions in time series forecasting. Deep learning techniques, including deep neural networks like DRNN and DLSTM, are proving to be beneficial in overcoming challenges in energy forecasting, particularly in renewable energy and electricity demand. These models exhibit advanced structures, hyperparameters, and optimization techniques that improve upon traditional methods.

Forecasting evaluation metrics are crucial for assessing forecast model performance. Accuracy is vital, especially on unseen data. Two main types of forecast errors are scale-dependent (e. g. , MAE, RMSE) and percentage errors (e. g. , RMSPE, MAPE). Percentage errors are scale-independent and more accurate. In empirical comparisons, machine learning models like RNN and LSTM outshine traditional methods. These models show significant improvements in forecasting errors, highlighting the superiority of deep learning for accurate forecasting on complex datasets.

***Result and Analysis:***

Results Analysis and Discussion Deep learning models, specifically DRNN and DLSTM, have demonstrated superior performance compared to traditional machine learning models and conventional methods. The accuracy and overall performance of these models were analyzed in terms of errors, MAPE, and RMSPE, showing consistently lower errors compared to other models across three case studies. The conventional methods, such as ARIMA and SES, performed poorly in extracting features from time series data. Shallow neural network models showed slight improvement, while deep models exhibited significant enhancement due to their ability to learn hierarchical features effectively.

The deep models' success can be attributed to their memory loop properties, dynamic learning mode, and capability to handle long horizon datasets, which are essential for energy demand forecasting. In contrast, conventional methods and other machine learning models rely on static learning approaches, leading to difficulties in long-term forecasting. Despite the computational complexity of deep learning models, their stability, performance, and robustness make them suitable for various energy problems. This study concludes that deep learning models, particularly DRNN and DLSTM, are on par with conventional methods in terms of maturity and are well-equipped to handle both short-term and long-term energy consumption forecasting efficiently***.***

***Discussion*:**

This report offers a thorough evaluation of the challenges in energy time series forecasting, highlighting essential research gaps and opportunities for future exploration. The study contrasts traditional statistical methods with machine learning and deep learning models, underscoring the strengths and weaknesses of each approach.

Strengths:

1. Identification of Research Gaps: The report effectively identifies several critical gaps, such as the need for probabilistic forecasts and the integration of exogenous variables (e.g., weather or market data) in models. These gaps guide future research towards more robust, adaptive forecasting techniques.
2. Comprehensive Method Comparison: The report provides a balanced comparison of traditional statistical methods (e.g., ARIMA, exponential smoothing) and machine learning models (e.g., ANNs, SVR), highlighting their respective advantages. It notes that while traditional methods excel in handling simpler time series data, deep learning models, such as DRNN and DLSTM, are better equipped to handle the complexity and non-linearity of modern energy data.
3. Future Research Directions: Clear future directions are outlined, including the need for collaborative learning across multiple tasks and advanced optimization techniques. The potential for hybrid methods that combine traditional and machine learning models is also noted as a promising direction, although challenges related to increased parameters and computational complexity remain.

Weaknesses:

1. Limited Practical Implementation Discussion: While the report suggests creating an intelligent prediction platform for energy management, it lacks a detailed analysis of the challenges that come with building such a platform. Real-world challenges, such as scalability, computational costs, and integration into existing systems, are not fully addressed, which could limit the feasibility of the proposed solutions.
2. Probabilistic Forecasting: Although the report acknowledges the importance of probabilistic predictions, it does not provide detailed methodologies or examples for implementing them. Techniques like Gaussian processes or Bayesian neural networks could offer solutions but are not explored in depth, limiting the report’s practical applicability in this area.
3. Lack of Empirical Evidence for Exogenous Factors: The discussion on incorporating exogenous variables (e.g., weather or policy shifts) into forecasting models lacks empirical case studies, making it harder for researchers to translate these theoretical concepts into practice. Future research should focus on case studies where exogenous factors have been integrated successfully, providing a clearer roadmap for practical application.

***Conclusion:***

Conclusions and Recommendations Time series forecasting is crucial in practical and industrial applications today. This report provides a review and assessment of conventional, machine learning, and deep learning methods for energy time series forecasting. 14 models were analyzed, with deep learning models found to outperform others in terms of accuracy and forecasting horizons. Recommendations include using DRNN and DLSTM deep learning models for all energy forecasting horizons due to their robustness and dynamic learning capabilities. Hybrid methods combining conventional and machine learning may also be effective, but come with challenges such as increased parameters. Overall, this study highlights the need for further development in AI and machine learning for energy forecasting.