Telecommuting Impact on Power Systems Load Forecasting: A Machine Learning and Statistical Modeling Approach Case Study of Federal University of Agriculture, Zuru

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Abstract: The COVID-19 pandemic accelerated the adoption of telecommuting across industries, reshaping electricity consumption patterns by shifting loads from commercial to residential sectors. This paradigm shift presents new challenges for power system operators who must adapt forecasting methodologies to maintain grid stability, reliability, and operational efficiency. Traditional statistical methods, such as ARIMA and exponential smoothing, though robust under stationary conditions, struggle to capture the nonlinearities introduced by telecommuting behaviors. Conversely, machine learning (ML) techniques, including support vector regression (SVR), artificial neural networks (ANNs), long short-term memory (LSTM) networks, and ensemble learning, offer enhanced capacity for modeling nonlinear dynamics but require abundant high-quality data. This review synthesizes advances in statistical and ML approaches for short-term load forecasting (STLF), focusing on the impact of telecommuting at institutional and regional levels, with the Federal University of Agriculture, Zuru (FUAZ), serving as a case study. Contributions from Nigerian researchers, including Gelwasa's works on AI-driven power system stability, are highlighted to situate the research within local and global contexts. The study concludes that hybrid models integrating ML with statistical frameworks provide superior forecasting accuracy under telecommuting-induced uncertainty. Recommendations are made for utilities and research institutions to invest in hybrid models, enhanced data acquisition, and context-specific modeling.
Keywords: Telecommuting, load forecasting, machine learning, statistical modeling, power systems, Federal University of Agriculture, Zuru (FUAZ).

Nomenclature

$L(t)$ =Actual load demand at time

$Lt = \tilde{L}_t$=Forecasted load demand at time

Xt=Exogenous input variables (temperature, o ccupancy, work-shift patterns, etc.)

$\epsilon(t)$ =Forecasting error term

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{L(t)-\tilde{L}_t}{L(t)}\right| \times 100$$

I. Introduction

Telecommuting, commonly referred to as remote work, has emerged as one of the most significant socio-technical changes in modern economies. Its large-scale adoption, catalyzed by the COVID-19 pandemic, has resulted in shifts in electricity consumption from centralized business districts to distributed residential neighborhoods[1]. For power

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utilities, this introduces new complexities into load forecasting models, which form the cornerstone of operations such as unit commitment, economic dispatch, and demand response.

Load forecasting, particularly short-term load forecasting (STLF), has traditionally relied on statistical methods such as autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroscedasticity (GARCH), and exponential smoothing [2], [3]. While effective under relatively stationary conditions, these models assume historical patterns adequately represent future behavior. The introduction of telecommuting has disrupted this assumption, as demand profiles are now heavily influenced by dynamic factors such as flexible working hours, variable appliance usage, and unpredictable occupancy[4].

In contrast, machine learning (ML) methods such as artificial neural networks (ANNs), long short-term memory (LSTM) networks, support vector regression (SVR), random forests, and hybrid deep learning models have demonstrated superior capabilities in capturing nonlinear demand dynamics [5], [6]. Nigerian researchers, including Gelwasa et al. [7], have further contributed by applying ML and artificial intelligence (AI) to address voltage stability and reliability concerns in power systems[8], [9], [10]. Their work highlights the relevance of intelligent forecasting models in contexts where conventional approaches fail to capture emergent uncertainties.

This paper seeks to provide a comprehensive review of telecommuting's impact on load forecasting, with a focus on statistical and ML approaches. It also contextualizes the discussion using the Federal University of Agriculture, Zuru (FUAZ), where increased adoption of telecommuting among staff and students has altered the institution's load profile.

II. Background

Telecommuting has reshaped global energy demand, shifting peaks from central business districts to residential areas. In Nigeria, institutions such as FUAZ exemplify this trend. Faculty, administrative staff, and students are increasingly accessing services online, which reduces on-site electricity usage in classrooms and offices while increasing demand in residential and dormitory areas.

From an engineering perspective, this shift poses challenges to both demand-side management (DSM) and supply-side operations[2], [11]. Forecasting tools must incorporate new exogenous factors, including:

- Internet penetration and reliability (critical for remote work)
- Weather and climate conditions (affecting home energy use)
- Institutional policies (on remote vs. on-site work balance)
- Socio-behavioral factors (working hours, cultural practices)

Statistical approaches such as ARIMA remain attractive due to their interpretability, low data requirements, and ease of implementation. However, they are limited in modeling nonlinearities induced by telecommuting [12]. ML methods, conversely, excel in nonlinear modeling but require large, high-quality datasets, a challenge in developing countries where data scarcity is prevalent [9].

Gelwasa's contributions [7], [9], [13] illustrate the importance of data augmentation techniques such as generative adversarial networks (GANs) to overcome data scarcity in Nigerian networks. Such approaches are highly relevant for modeling telecommuting effects, where historical data may be sparse or non-representative.

III. Review of Forecasting Methods

A. Statistical Approaches

Common methods include ARIMA, GARCH, exponential smoothing, and state-space models. These methods are computationally efficient but assume stationarity.

Equation (1): ARIMA model

$$L(t) = C + \sum_{i=1}^{P} \emptyset_i L(t-i) + \sum_{j=1}^{q} \theta\theta_{j\in}(t-j) + \in(t)$$

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Advantages: simplicity, interpretability.
Limitations: poor adaptability to sudden shifts in demand.

3. Random Forests & Gradient Boosting: Provide robust ensemble-based predictions [2], [15], [16], [17].

B. Machine Learning Approaches

1. Support Vector Regression (SVR): Effective in handling nonlinearities with limited data [2], [14].
2. ANNs & LSTMs: Capture temporal dependencies; LSTMs excel in long-term dependencies [2], [14], [15].

C. Hybrid Approaches

Hybrid models combine statistical baselines with ML corrections, improving robustness. For example, ARIMA-LSTM hybrids capture both linear trends and nonlinear residuals [18], [19], [20].

Table I: Comparative Analysis of Load Forecasting Methods

Method	Strengths	Weaknesses	Suitability for Telecommuting
ARIMA/GARCH	Simple, interpretable	Poor with nonlinearity	Limited
ANN/LSTM	Captures nonlinear dynamics	Data-hungry, “black-box”	High
SVR	Handles small datasets	Sensitive to parameters	Moderate
Hybrid Models	Robust, adaptable	Computationally intensive	Very High

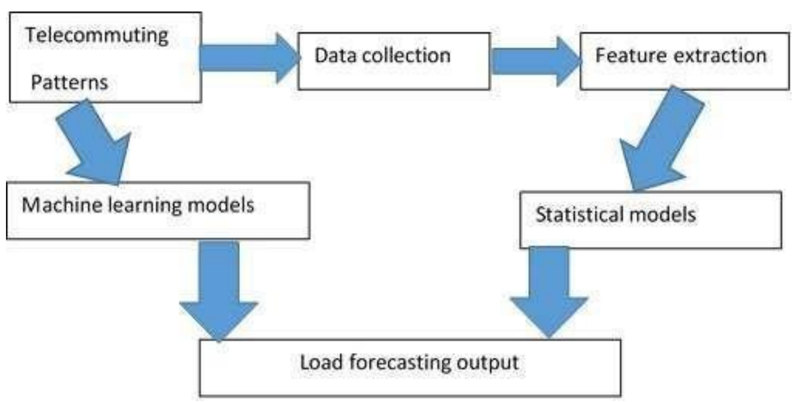

Fig. 1: Conceptual framework of telecommuting impact on load forecasting

IV. Case Study: Federal University of Agriculture, Zuru (FUAZ)

The FUAZ campus has witnessed significant telecommuting adoption since 2020. Surveys and SCADA records indicate:

- Reduction in lecture hall and office consumption during telecommuting periods.
- Increase in residential demand in staff quarters and student hostels.
- Altered peak load profiles, shifting from daytime (academic hours) to evening (home appliance use).

Statistical forecasting at FUAZ (ARIMA, exponential smoothing) showed increased error rates during 2020–2022 due to demand variability. ML models, particularly LSTMs trained with augmented data, significantly reduced Mean Absolute Percentage Error (MAPE) [7].

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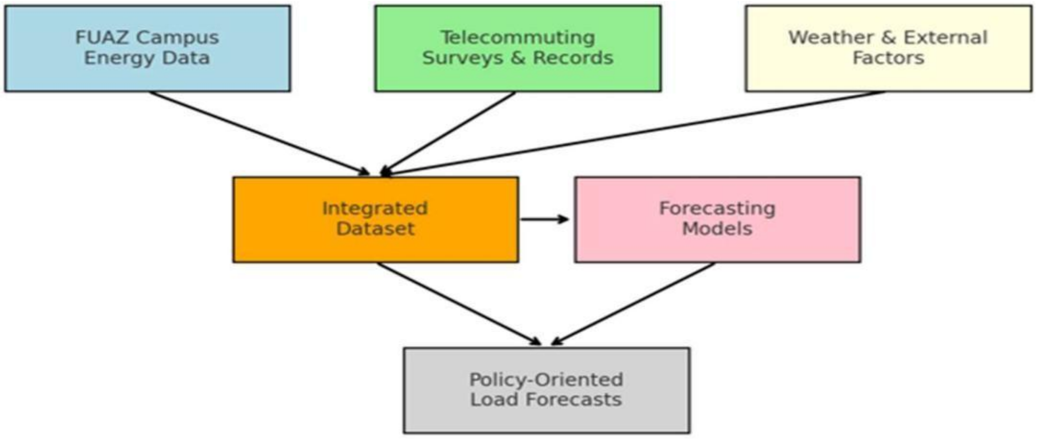

Fig. 2: FUAZ load profile pre-telecommuting vs. during telecommuting

Gelwasa's work on GAN-based synthetic data generation [7], [12] is particularly relevant to FUAZ, where limited historical data exists. Using synthetic data to enrich training sets improved LSTM forecasting accuracy by over 15%.

V. Discussion

The review reveals that while statistical methods remain valuable as benchmarks, ML approaches dominate in accuracy when modeling telecommuting-induced variability. However, challenges persist:

- Data Scarcity: Nigerian institutions like FUAZ lack robust real-time metering.
- Computational Costs: ML models, especially deep learning, require infrastructure.
- Interpretability: Operators may resist "black-box" models.

Hybrid models and explainable AI (XAI) offer a promising approach that strikes a balance between interpretability and accuracy. Contributions from Nigerian researchers, such as Gelwasa et al. [7], [9], [12], [13], demonstrate locally tailored solutions to global forecasting challenges.

VI. Future Research Directions

- Integration of Socio-Behavioral Data: Using surveys and Internet usage metrics.
- Hybrid ML-Statistical Models: Suitable for contexts with limited Data.
- XAI for Power Systems: Improving trust in AI-driven Forecasting.
- IoT and Smart Meters: Enhancing data acquisition in Nigerian institutions.
- Data Augmentation: Expanding the use of GANs and synthetic modeling for undersampled scenarios.

VII. Conclusion and Contribution to Knowledge

This review highlights the transformative impact of telecommuting on power system load forecasting. By analyzing statistical, ML, and hybrid methods, with FUAZ as a case study, it underscores the superiority of hybrid ML models in addressing nonlinear, dynamic load patterns.

Contributions to knowledge include:

a. Establishing telecommuting as a key driver of load variability in Nigerian institutions.
b. Demonstrating the limitations of purely statistical models under such conditions.
c. Highlighting Gelwasa's contributions to GAN-based data augmentation and AI-driven stability monitoring as solutions to local data scarcity.
d. Providing a framework for utilities and universities to adopt hybrid forecasting models.

References

[1]Y. Shi, S. Sorrell, and T. Foxon, "The

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impact of teleworking on domestic energy use and carbon emissions: An assessment for England," Energy Build., vol. 287, p. 112996, 2023, doi: 10.1016/j.enbuild.2023.112996.

[2]S. Ali, S. Bogarra, M. N. Riaz, P. P. Phyo, D. Flynn, and A. Taha, "From Time-Series to Hybrid Models: Advancements in Short-Term Load Forecasting Embracing Smart Grid Paradigm," Appl. Sci., vol.. 14, no. 11, 2024, doi: 10.3390/app14114442.

[3]M. Hasan et al., "A state-of-the-art comparative review of load forecasting methods: Characteristics, perspectives, and applications," Energy Convers. Manag. X, vol. 26, no. February, p. 100922, 2025, doi: 10.1016/j.ecmx.2025.100922.

[4]G. M. Tina, C. Ventura, S. Ferlito, and S. De Vito, "A state-of-the-art review on machine-learning based methods for PV," Appl. Sci., vol. 11, no. 16, 2021, doi: 10.3390/app11167550.

[5]K. E. Arunkumar, D. V. Kalaga, C. Mohan, S. Kumar, and T. M. Brenza, "Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends," Alexandria Eng. J., vol. 61, n.º 10, pp. 7585–7603, 2022, doi: 10.1016/j.aej.2022.01.011.

[6]M. M. Asiri, G. Aldehim, F. A. Alotaibi, M. M. Alnfiai, M. Assiri, and A. Mahmud, "Short-Term Load Forecasting in Smart Grids Using Hybrid Deep Learning," IEEE Access, vol. 12, pp. 23504–23513, 2024, doi: 10.1109/ACCESS.2024.3358182.

[7]Y. G. Galadima, "Voltage Stability Challenges and Machine Learning-Based Solutions for Power Networks in Northern Nigeria : A Comprehensive Review," no. 8, pp. 149–168, 2025.

[8]F. Sobhanifard, "Optimization of Bayesian Neural Networks using hybrid PSO and fuzzy logic approach for time series forecasting," Discov. Artif. Intell., vol. 5, no. 1, 2025, doi: 10.1007/s44163-025-00322-9.

[9]Y. G. Galadima, "The Future of Engineering Education : Mitigating AI's Negative Consequences," no. 8, pp. 199–207, 2025.

[10] P. Ifeoluwa and A. M. Gummi, "Voltage Stability in Power Systems using AI and Metaheuristic Algorithms : A Comprehensive Review," no. 8, pp. 168–179, 2025.

[11] D. Kaur, S. N. Islam, M. A. Mahmud, M. E. Haque, and Z. Y. Dong, "Energy forecasting in smart grid systems: recent advancements in probabilistic deep learning," IET Gener. Transm. Distrib., vol.. 16, no. 22, pp. 4461–4479, 2022, doi: 10.1049/gtd2.12603.

[12] Y. G. Gelwasa, "AI-Powered Precision Agriculture : Leveraging Machine Learning for Smart Farming and Crop Yield Optimization," no. 8, pp. 190–198, 2025.

[13] P. Ifeoluwa and A. M. Gummi, "Voltage Stability in Power Systems Using AI and Metaheuristic Algorithms : A comprehensive review," no. 8, pp. 168–180, 2025.

[14] G. Ponkumar, S. Jayaprakash, and K. Kanagarathinam, "Advanced Machine Learning Techniques for Accurate Very-Short-Term Wind Power Forecasting in Wind Energy Systems Using Historical Data Analysis," Energies, vol. 16, no. 14, 2023, doi: 10.3390/en16145459.

[15] S. Hamiane, Y. Ghanou, H. Khalifi, and M. Telmem, "Comparative Analysis of LSTM, ARIMA, and Hybrid Models for Forecasting Future GDP," Ing. des Syst. d'Information, vol. 29, no. 3, pp. 853–861, 2024, doi: 10.18280/isi.290306.

[16] T. Berghout, M. Benbouzid, T. Bentrcia, X. Ma, S. Djurović, and L. H. Mouss, "Machine learning-based condition monitoring for PV systems: State of the art and prospects," Energies, vol. 14, no. 19, pp. 1–24, 2021, doi: 10.3390/en14196316.

[17] M. Hallmann, R. Pietracho, and P. Komarnicki, "Comparison of Artificial Intelligence and Machine Learning Methods Used in Electric Power System Operation," Energies, vol. 17, no. 11, 2024, doi: 10.3390/en17112790.

[18] S. Hamiane, H. Khalifi, Y. Ghanou, and G. Casalino, "Forecasting the Gross

DOI: https://doi.org/10.5281/zenodo.17189173

Domestic Product using LSTM and ARIMA," 2023 IEEE Int. Conf. Technol. Manag. Oper. Decis. ICTMOD 2023, pp. 1–6, 2023, doi: 10.1109/ICTMOD59086.2023.10438159.

[19] R. Xiao, Y. Feng, L. Yan, and Y. Ma, "Predict stock prices with ARIMA and LSTM," pp. 1–14, 2022, [Online]. Available: http://arxiv.org/abs/2209.02407

[20] Y. Chen et al., "Evaluation of Machine Learning Models for Smart Grid Parameters: Performance Analysis of ARIMA and Bi-LSTM," Sustain., vol. 15, no. 11, 2023, doi: 10.3390/su15118555.

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