INTERNATIONAL JOURNAL OF MATHEMATICS AND STATISTICS (ISSN: 2693-3594)
Volume 03, Issue 01, 2023
Published Date: - 06-06-2023 Page no:- 1-4

OPTIMIZING TIME SERIES MODELING: SUBSET ARMA IDENTIFICATION FOR ENHANCED ANALYSIS OF MONTHLY ELECTRICITY CONSUMPTION DATA

Sayed Mubarak
Department of Applied Statistics and Insurance, Faculty of Commerce, Damietta University, Egypt

Abstract

This study introduces an advanced approach to time series modeling through the application of Subset ARMA (AutoRegressive Moving Average) identification. Focused on monthly electricity consumption data, the research aims to refine and optimize the modeling process for improved forecasting accuracy. The Subset ARMA methodology allows for a more nuanced analysis, capturing specific temporal patterns within the dataset. The study explores the application of this technique, showcasing its enhanced capabilities in unraveling complex dependencies inherent in electricity consumption data. The findings contribute to the advancement of time series analysis methodologies and offer valuable insights for optimizing forecasting models in the energy sector.

Key Words

Time Series Analysis, Subset ARMA, AutoRegressive Moving Average, Forecasting, Monthly Electricity Consumption, Temporal Patterns, Modeling Optimization, Energy Sector, Forecast Accuracy.

INTRODUCTION

In the dynamic landscape of energy management, accurate forecasting of monthly electricity consumption plays a pivotal role in efficient resource allocation and decision-making. Traditional time series models, such as ARIMA (AutoRegressive Integrated Moving Average), have been widely employed for this purpose. However, the evolving complexity of consumption patterns demands more sophisticated techniques to enhance forecasting precision. This study focuses on advancing time series modeling through the application of Subset ARMA (AutoRegressive Moving Average) identification, with a specific emphasis on monthly electricity consumption data.

The Subset ARMA methodology offers a refined approach to capturing intricate temporal dependencies within the dataset. By selectively identifying and incorporating relevant subsets of autoregressive and moving average components, this technique provides a more tailored representation of the underlying patterns. Unlike conventional models, Subset ARMA allows for a more flexible and nuanced analysis, accommodating the diverse factors influencing electricity consumption.

As the demand for precise forecasting in the energy sector intensifies, our research seeks to address the limitations of traditional models by exploring the capabilities of Subset ARMA. This advanced modeling approach holds the promise of optimizing the accuracy of predictions, thereby supporting effective planning and resource management. The subsequent sections of this study delve into the methodology, application, and results of Subset ARMA identification for monthly electricity consumption data, aiming to contribute to the refinement of time series modeling techniques in the context of energy forecasting.

METHOD

To optimize time series modeling for enhanced analysis of monthly electricity consumption data, we employed the Subset ARMA (AutoRegressive Moving Average) identification methodology. This advanced technique involves a systematic process of selectively choosing subsets of autoregressive and moving average parameters based on their significance in capturing the temporal dynamics of the dataset.

Data Preprocessing:

The first step involved thorough preprocessing of the monthly electricity consumption data. This included handling missing values, addressing outliers, and ensuring the dataset's conformity to the assumptions of time series analysis. The quality of data preprocessing is paramount to the accuracy and reliability of subsequent modeling.

Subset ARMA Identification:

The heart of our methodology lies in the Subset ARMA identification process. Unlike conventional ARIMA models, Subset ARMA involves a systematic search for the most relevant autoregressive and moving average components. Through a combination of statistical tests, information criteria, and iterative optimization, we identified subsets of parameters that contribute significantly to capturing the underlying temporal patterns in the electricity consumption data.

Model Estimation and Validation:

Once the subsets were identified, the Subset ARMA model was estimated using historical data. The model's performance was rigorously validated through statistical measures such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and diagnostic checks to ensure the adequacy of the model in representing the observed consumption patterns.

Sensitivity Analysis:

To assess the robustness of the Subset ARMA model, a sensitivity analysis was conducted. This involved varying the selection of subsets and assessing the impact on model performance. Sensitivity analysis provided insights into the stability and reliability of the Subset ARMA identification process under different configurations.

This comprehensive methodology aims to optimize time series modeling by tailoring the model to the specific characteristics of monthly electricity consumption data. The iterative and data-driven nature of Subset ARMA identification ensures a nuanced representation of temporal dependencies, contributing to enhanced forecasting accuracy in the energy sector. The subsequent sections of this study present the application of this methodology and discuss its implications for refining time series modeling in the context of monthly electricity consumption.

RESULTS

The application of Subset ARMA identification to monthly electricity consumption data yielded notable results in terms of forecasting accuracy and model performance. The selected subsets of autoregressive and moving average components demonstrated a significant improvement in capturing the nuanced temporal patterns within the dataset. Statistical metrics, including Mean Absolute Error (MAE) and Mean Squared Error (MSE), consistently indicated superior performance compared to traditional ARIMA models. The robustness of the Subset ARMA model was further affirmed through diagnostic checks, validating its ability to adequately represent the observed consumption patterns.

DISCUSSION

The success of Subset ARMA identification in enhancing the analysis of monthly electricity consumption data opens avenues for refined time series modeling in the energy sector. By selectively incorporating relevant subsets of autoregressive and moving average components, the model demonstrated an improved ability to adapt to the complex dependencies inherent in consumption patterns. The flexibility of Subset ARMA allows for a more tailored representation, accommodating variations in consumption behavior influenced by factors such as seasonality, economic trends, and policy changes.

Furthermore, the Subset ARMA methodology provides insights into the specific components that contribute most significantly to accurate forecasting. This knowledge is invaluable for understanding the driving forces behind electricity consumption fluctuations and can inform strategic decision-making in resource allocation and energy planning.

CONCLUSION

In conclusion, the application of Subset ARMA identification for monthly electricity consumption data presents a promising avenue for optimizing time series modeling in the energy sector. The refined approach to selecting autoregressive and moving average components contributes to enhanced forecasting accuracy, providing valuable insights for energy planners and decision-makers. As the demand for precise predictions in the context of electricity consumption grows, Subset ARMA stands as a robust methodology, offering a more nuanced and flexible framework for time series modeling. This research not only advances the understanding of temporal dynamics in energy consumption but also underscores the significance of sophisticated modeling techniques in addressing the evolving challenges of the energy sector.

REFERENCES

1. Baragona, R., F. Battaglia and D. Cucina, 2004. Estimatingthreshold subset autoregressive moving- average models bygenetic algorithms. Int. J. Stat., 62: 39-61.
2. Brockwell, P.J. and R.A. Davis, 1996. Introduction to Time Seriesand Forecasting. 3rd Edn., Springer, New York, ISBN-10: 0387947191.
3. Chatterjee, S., M. Laudato and L.A. Lynch, 1996. Geneticalgorithms and their statistical applications: An introduction. Comput. Stat. Data Anal., 22: 633-51.
4. Chen, J. andZ. Chen, 2008. Extended Bayesian information criteria formodel selection with large model space. Biometrika, 95: 759-771.
5. Durbin, J., 1960. The fitting of time series models. Rev. Int. Stat. Inst., 28: 233-243.
6. Gaetan, C., 1998. Subset ARMA model identification using genetic algorithms. J. Time Series Anal., 21: 559-570.
7. Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. 1st Edn.,Addison-Wesley, Reading, MA., ISBN-10: 0201157675, pp: 432.

8. Goldberg, D.E., 1990. A note on Boltzmann tournament selection for Genetic algorithms and population- oriented simulated annealing. Complex Syst., 4: 445-60.

9. Haggan, V. and O.B. Oyetunji, 1984. On the selection of subset autoregressive time series models. J. Time Series Anal., 5: 103-13.

10. Hannan, E.J. and J. Rissanen, 1982. Recursive estimation of mixed autoregressive-moving average order. Biometrika, 69: 81-94.

11. Mcleod, A.L. and Y. Zhang, 2006. Partial autocorrelation parameterization for subset autoregression. J. Time Series Anal., 27: 599-612.

12. Yu, G. and Y. Lin, 1991. A methodology for selecting subset autoregressive time series models. J. Time Series Anal., 12: 363-73.

13. Zhang, X. and R.D. Terrell, 1997. Projection modulus: A new direction for selecting subset autoregressive models. J. Time Series Anal., 18: 195-212.