

Probabilistic Forecasting of Energy Consumption using Bayesian Dynamic Linear Models

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Abstract – This study aims to conduct a systematic literature review on the development of mathematical models for forecasting energy consumption using a probabilistic approach, particularly focusing on the Bayesian Dynamic Linear Model (BDLM). The research method employed is Systematic Literature Review (SLR), utilizing literature sources indexed in Scopus, DOAJ, and Google Scholar, with publication dates ranging from 2014 to 2024. The findings of the research indicate that the application of BDLM has made a significant contribution to the optimization of energy management, especially in sectors such as industry and commercial buildings. The study highlights the effectiveness of BDLM in accurately predicting energy consumption through a probabilistic approach that efficiently manages uncertainty. However, the research also emphasizes that BDLM presents limitations and challenges that warrant attention, including the complexity involved in parameter determination and model validation processes, as well as the importance of addressing potential biases and considering factors such as deployment impacts. This research provides deep insights into the potential and challenges in the development of mathematical models for forecasting energy consumption, while also offering directions for further research in this field.

Keywords: probabilistic, forecasting, energy, consumption, bayesian dynamic linear

Introduction

Energy consumption forecasting plays a central role in managing energy supply and demand comprehensively (Alobaidi *et al.*, 2018). The accuracy of such forecasts significantly impacts the efficiency and sustainability of energy usage. With precise estimations of future energy consumption, stakeholders in the energy industry can plan production, distribution, and resource usage more efficiently (Runge and Zmeureanu, 2019). Accurate forecasting also aids in designing appropriate risk management and investment strategies, reducing the risk of energy supply disruptions, and enhancing overall energy usage efficiency. Therefore, energy consumption forecasting is not merely a predictive tool but also a primary cornerstone in making strategic decisions regarding effective and sustainable energy management.

One of the primary challenges in predicting energy consumption is the difficulty in forecasting demand fluctuations, along with the potential influence of external factors (Mohammadi *et al.*, 2018). These fluctuations often present a complex aspect to anticipate as they are influenced by several factors such as policy changes, economic conditions, and social dynamics (Bauer *et al.*, 2015). Additionally, other external factors can affect the forecasting process, including government policy changes, technological advancements, and environmental aspects. This situation presents a complex challenge in forecasting energy consumption with adequate accuracy. Traditional forecasting methods, such as linear regression and time series analysis, often face

limitations in handling the complexity of evolving energy dynamics (Cai *et al.*, 2019). The focus on linear assumptions in these methods often fails to accurately capture the patterns of complex fluctuations. Therefore, a more adaptive and responsive approach to the dynamics of energy changes is needed to improve the accuracy of energy consumption forecasting overall.

The Bayesian Dynamic Linear Model is recognized as an approach capable of addressing the complexity and level of uncertainty often encountered in the process of energy consumption forecasting (Bessa *et al.*, 2017). The fundamental concept of the Bayesian Dynamic Linear Model involves the continuous updating of information, where predictions are adjusted as new data becomes available (Mark *et al.*, 2018). This allows the Bayesian Dynamic Linear Model to adapt the model flexibly to changes in conditions and dynamics that emerge in energy consumption. One of the primary advantages of the Bayesian Dynamic Linear Model is its ability to integrate relevant prior information, thereby aiding in the more effective handling of uncertainty (Marcot and Penman, 2019). In the context of energy consumption forecasting, this Bayesian approach has significant potential to generate more accurate and beneficial predictions, particularly in dealing with complex demand fluctuations and unpredictable external condition changes. Therefore, the application of the Bayesian Dynamic Linear Model remains relevant in enhancing the reliability and accuracy of energy consumption forecasts in various situations and different conditions.

The utilization of Bayesian Dynamic Linear Models in forecasting energy consumption has been explored in the literature. One study proposes an innovative approach to predict energy consumption by leveraging a novel optimization algorithm and a forecasting model comprising a set of long short-term memory units (Abdelhamid *et al.*, 2022). Another research effort develops a time series forecasting model using a shallow neural network framework to predict load curves in the context of optimal demand response planning, employing nonlinear autoregressive networks and exogenous inputs (Ryu *et al.*, 2017; Raza and Khosravi, 2015; Gopi and Annamalai, 2023). Additionally, a study employs Bayesian Calibration method to calibrate quasi-dynamic building energy models with the aim of attaining accurate predictions (Khafaga *et al.*, 2023). These studies underscore the potential of BDLM and its effectiveness in enhancing the accuracy of energy consumption forecasts.

Probabilistic energy consumption forecasting using Bayesian Dynamic Linear Models alongside new techniques offers several advantages over traditional approaches. Firstly, these new techniques, such as Stationary Wavelet Transform (SWT), Quantile Regression (QR), Bidirectional Nested Long Short-Term Memory (BinLSTM) with attention mechanisms, and Deeply Separable Convolution (DSC), provide more comprehensive information for decision-making and delivery processes by measuring the uncertainty of electricity load (Jin *et al.*, 2023). Secondly, the proposed Dynamic Time-Optimal Stochastic Frontier Selection (DTOSFS) optimization algorithm enhances the accuracy of Long Short-Term Memory (LSTM) memory unit forecasts, yielding more precise energy consumption predictions (Khafaga *et al.*, 2023). Furthermore, multivariate linear regression models enable daily energy consumption modeling using only selected variables, reducing the complexity and computational requirements of the forecasting process (Karpio *et al.*, 2023). Lastly, the hybrid GRU-MM attention-Light GBM model architecture with feature selection based on Prophet decomposition enhances prediction accuracy and stability, particularly in the presence of energy consumption mutations (Liang *et al.*, 2023).

Research has indicated that enhancing understanding of energy-related investments can increase the adoption of energy-efficient appliances (Blasch *et al.*, 2017). However, the effectiveness of interventions such as Home Energy Report (HER) based on social comparison may vary across countries, with Germany showing lower impacts compared to the United States (Andor *et al.*, 2020). To address these differences, a systematic approach to causal inference using graphical causal models has been proposed to study the effects of intervention programs on energy-saving behaviors in households (Bhushan *et al.*, 2018). Decision support tools, such as educational programs and online calculators, have been proven to have a positive influence on the adoption of energy-efficient appliances (Blasch *et al.*, 2022). These findings underscore the urgency of probabilistic energy consumption forecasting in energy management, as it provides insights for the development and implementation of effective policy and resource management practices.

Research has uncovered several limitations in applying the Bayesian Dynamic Linear Model to forecast energy consumption. Some studies merely explore the concept of the Bayesian Dynamic Linear Model without testing its performance in a broader practical context, leading to uncertainty about its effectiveness in everyday

energy management. Data limitations and variable variations in the forecasting model also pose constraints, reducing the accuracy and relevance of forecast outcomes, especially in dealing with complex energy demand fluctuations. The research focus primarily on developed countries also results in an imbalance in regional representation, making it difficult to generalize findings to developing country contexts. Despite its innovative potential, better integration between theoretical and practical research is still needed to effectively implement the Bayesian Dynamic Linear Model in the field. This study aims to fill the knowledge gap by exploring the application and effectiveness of the Bayesian Dynamic Linear Model in forecasting energy consumption, with the hope of making a significant contribution to the development of more efficient and sustainable energy management strategies.

Materials and Methods

Methods

This research aims to conduct a comprehensive analysis of relevant literature on Probabilistic Energy Consumption Forecasting using Bayesian Dynamic Linear Model, through a Systematic Literature Review approach. The primary objective of this study is to provide an in-depth understanding of various approaches, techniques, and findings related to energy consumption forecasting using the Bayesian Dynamic Linear Model, as well as to identify existing knowledge gaps in the literature. Literature search was conducted through academic databases and relevant online repositories such as Scopus, DOAJ, and Google Scholar. Keywords used included "energy forecasting," "Bayesian dynamic linear model," "probabilistic forecasting," and variations thereof. Literature search also involved manual searching of reference lists from relevant articles to ensure completeness in information gathering.

Inclusion criteria for this research include articles related to Probabilistic Energy Consumption Forecasting using Bayesian Dynamic Linear Model, articles published in English, articles available in full-text format and accessible online, and articles with clear research methodologies relevant to the research objectives. Exclusion criteria include articles irrelevant to the research topic, abstracts, reviews, editorials, or conference papers, as well as articles not available in English or inaccessible online. Article selection was based on the title, abstract, and full-text to ensure compliance with the established inclusion and exclusion criteria. Relevant data were then extracted from the selected articles, including information on the research methods used, research findings, key findings, and conclusions. This information was subsequently analyzed and synthesized to build a comprehensive understanding of Probabilistic Energy Consumption Forecasting using Bayesian Dynamic Linear Model.

Relevant Research

Based on the search result, several relevant research findings have been identified that can elucidate the focus and objectives of this study. We have formulated several aspects that need to be described, including; (1) Bayesian Dynamic Linear Model Developed for Energy Consumption Forecasting ; (2) Performance and Accuracy of Bayesian Dynamic Linear Models in Predicting Energy Consumption Compared to Other Forecasting Methods; (3) Parameter Estimation and Model Validation in Studying Energy Consumption Forecasting Using Bayesian Dynamic Linear Models; (4) Probabilistic Approach in Managing Uncertainty in Energy Consumption Forecasting.

Results

Based on the search result, several relevant research findings have been identified that can elucidate the focus and objectives of this study. We have formulated several aspects that need to be described, including; (1) Bayesian Dynamic Linear Model Developed for Energy Consumption Forecasting ; (2) Performance and Accuracy of Bayesian Dynamic Linear Models in Predicting Energy Consumption Compared to Other Forecasting Methods; (3) Parameter Estimation and Model Validation in Studying Energy Consumption Forecasting Using Bayesian Dynamic Linear Models; (4) Probabilistic Approach in Managing Uncertainty in Energy Consumption Forecasting.

Table 1. Focus and insights into research result according to eligibility criteria

No	Focus and Scope	Author	Insights or Research Variables Discussed
1.	Forecasting Energy Consumption using Bayesian Dynamic Linear Models	(Shaqiri <i>et al.</i> , 2023); (Lavine <i>et al.</i> , 2022); (Ragupathi and Prakash, 2022);(Grillone <i>et al.</i> , 2021); (Yang <i>et al.</i> , 2022); (Meng <i>et al.</i> , 2022); (Zhu <i>et al.</i> , 2022); (Khan and Osińska, 2023); (Forrest <i>et al.</i> , 2023); (Todd <i>et al.</i> , 2019); (Berchiolla <i>et al.</i> , 2021); (Raillon and Ghiaus, 2018), (Vesa <i>et al.</i> , 2020); (Jin <i>et al.</i> , 2023); (Sweeney <i>et al.</i> , 2020); (Broujeny <i>et al.</i> , 2023), (Kaur <i>et al.</i> , 2022), Capel and Dumas, 2023).	- Bayesian Dynamic Linear Models (BDLM) for forecasting energy consumption. - Comparison of BDLM with other forecasting methods. - Parameter determination and model validation techniques. - Probabilistic approaches for managing uncertainty in energy consumption forecasting.
2.	Causal Inference and Intervention Programs in Energy Saving Behaviors	(Bhushan <i>et al.</i> , 2018); (Todd <i>et al.</i> , 2019); (Raillon and Ghiaus, 2018); (Eggleston <i>et al.</i> , 2021); (Chiba, 2018); Podbregar <i>et al.</i> , 2021).	- Causal inference using graphical causal models. - Effects of intervention programs on household energy-saving behaviors.
3.	Factors Affecting Energy Consumption	(Baek and Ha, 2021); (Haynes <i>et al.</i> , 2020); Pourshahidi <i>et al.</i> , 2014).	- Characterization of energy expenditure from physical activities. - Impact of portion sizes on daily energy intake.
4.	Statistical Analysis and Evaluation Metrics in Energy Consumption Forecasting	(Durand <i>et al.</i> , 2022); Ranstam and Cook, 2016).	- Statistical methods and evaluation metrics (e.g., RMSE, MAPE, R2) for model validation. - Addressing biases in statistical analysis.
5.	Probabilistic Methods and Uncertainty Management in Energy Consumption Forecasting	(Jin <i>et al.</i> , 2023); (Sweeney <i>et al.</i> , 2020); (Broujeny <i>et al.</i> , 2023); (Kaur <i>et al.</i> , 2022); Capel and Dumas, 2023).	- Probabilistic approaches (e.g., Bayesian methods, Probabilistic Deep Learning, Quantile Regression) for managing uncertainty. - Confidence interval estimates and probability density curves in forecasting.

Table 1. summarizes research findings in the field of energy consumption forecasting, categorizing them into five main areas of focus. The first focus area revolves around the utilization of Bayesian Dynamic Linear Models (BDLM) for forecasting energy consumption. Various authors have contributed to this field, highlighting the advantages of BDLM in terms of accuracy and its comparison with other forecasting methods. Additionally, insights into parameter determination and model validation techniques have been discussed extensively. The second area concerns causal inference and intervention programs in energy-saving behaviors, where graphical causal models and the effects of interventions on household energy-saving behaviors are studied. The third area explores factors influencing energy consumption, including physical activities' impact and portion sizes on daily energy intake. The fourth area emphasizes statistical analysis and evaluation metrics in energy consumption forecasting, focusing on methods and metrics for model validation while addressing biases. Lastly, the fifth area concentrates on probabilistic methods and uncertainty management, showcasing the effectiveness of probabilistic approaches in managing uncertainty and providing decision-makers with valuable insights for efficient resource allocation and network operations. Overall, the research findings underscore the importance of employing advanced modeling techniques, causal inference, statistical rigor, and probabilistic methods in enhancing the accuracy and reliability of energy consumption forecasting.

Bayesian Dynamic Linear Model Developed for Energy Consumption Forecasting

Dynamic Bayesian models have been developed in the literature to forecast energy consumption. These models have been applied across various domains, such as predicting electricity consumption in industrial and institutional sectors, marketing applications, and foundational energy modeling for commercial buildings (Shaqiri *et al.*, 2023 ; Lavine *et al.*, 2022 ; Ragupathi and Prakash, 2022). The Bayesian approach offers advantages by providing deeper and more valuable insights through the use of intuitive mathematics (Grillone *et al.*, 2021). This allows for the identification of trends and seasonal components in electricity consumption. Additionally, Bayesian computational techniques have been developed to handle non-Gaussian and nonlinear multivariate time series models. These models are capable of providing accurate energy consumption predictions and offer valuable insights for energy managers to enhance facility performance.

Research on Dynamic Linear Bayesian models for forecasting energy consumption is highly diverse. Bhushan *et al.*, (2018) proposed a systematic approach to causal inference using graphical causal models to study the effects of intervention programs on household energy-saving behaviors. Baek and Ha, (2021) characterized energy expenditure from Nordic walking activities and developed metabolic equations for it. Haynes *et al.*, (2020) demonstrated that reducing main meal portion sizes can significantly reduce daily energy intake, regardless of perceived normal portion size habits. Todd *et al.*, (2019) identified the impact of widespread energy reduction as a major cause of bias in baseline evaluation methods for demand response programs. Collectively, these studies contribute to our understanding of energy consumption and its influencing factors.

Research on Dynamic Linear Bayesian models for forecasting energy consumption encompasses various approaches and applications across different fields. These models have been applied in industrial and institutional sectors, marketing applications, as well as foundational energy modeling for commercial buildings. The Bayesian approach offers advantages by providing in-depth information through intuitive mathematical frameworks, allowing for the identification of trends and seasonal components in energy consumption. Several Dynamic Linear Bayesian models developed for forecasting energy consumption include causal inference approaches using graphical causal models, characterization of energy expenditure from specific physical activities, and analysis of food consumption habits related to daily energy intake. These approaches enable energy managers to gain valuable insights into improving facility performance and optimizing energy consumption.

Performance and Accuracy of Bayesian Dynamic Linear Models in Predicting Energy Consumption Compared to Other Forecasting Methods

The Bayesian Dynamic Linear Model (BDLM) has proven to be capable of accurately predicting energy consumption compared to other forecasting methods. The BDLM approach utilizes Bayesian calibration to enhance the accuracy of prediction models (Yang *et al.*, 2022). The application of BDLM has been successful in various contexts, including predicting energy consumption for heating and cooling in office buildings (Meng *et al.*, 2022). The results demonstrate that calibrated BDLM models achieve high levels of accuracy, meeting established industry standards (Zhu *et al.*, 2022). Furthermore, BDLM has been compared to other forecasting methods such as regression models, support vector regression, and grey-type models. These findings confirm that BDLM outperforms these methods in terms of prediction accuracy (Khan and Osińska, 2023). Therefore, BDLM is recognized as a reliable and accurate method for predicting energy consumption, which is beneficial for energy planning processes and decision-making.

The performance and accuracy of Bayesian Dynamic Linear Models in predicting energy consumption compared to other forecasting methods pose a complex issue. Forrest *et al.*, (2023) found that machine learning models, including Bayesian methods, only slightly outperformed in predicting outcomes for binge eating disorder treatment. Similarly, Todd *et al.*, (2019) identified the impact of widespread energy reduction as a major cause of bias in baseline evaluation methods for demand response programs, suggesting that these methods may not be as accurate as previously thought. Berchialla *et al.*, (2021) highlighted the potential bias and increased standard errors in Bayesian estimators when adjusting prognostic baseline covariates in randomized controlled trials. Lastly, Pourshahidi *et al.*, (2014) demonstrated that reducing portion sizes can lead to a significant decrease in daily energy intake, regardless of perceived normal portion size habits. Collectively, this research suggests that while Bayesian Dynamic Linear Models may have some advantages in

predicting energy consumption, they are not immune to limitations and may not always be superior to other forecasting methods.

Research on energy consumption forecasting using Bayesian Dynamic Linear Models (BDLM) has demonstrated that BDLM is capable of accurately predicting energy consumption compared to other forecasting methods. The BDLM approach utilizes Bayesian calibration to enhance the accuracy of prediction models. Studies also indicate that the application of BDLM has been successful in various contexts, including predicting energy consumption for heating and cooling in office buildings. The results show that calibrated BDLM models achieve high levels of accuracy, meeting established industry standards. BDLM has also been compared to other forecasting methods such as regression models, support vector regression, and grey-type models, and the findings indicate that BDLM excels in terms of prediction accuracy. The use of Bayesian Dynamic Linear Models (BDLM) in predicting energy consumption demonstrates superiority in prediction accuracy compared to other forecasting methods. The Bayesian calibration approach in BDLM allows the model to address the complexity of energy consumption data and improve prediction accuracy. Research findings suggest that BDLM can be a reliable and accurate choice in forecasting energy consumption, which is beneficial for energy planning and decision-making.

Parameter Estimation and Model Validation in Studying Energy Consumption Forecasting Using Bayesian Dynamic Linear Models

In research examining energy consumption forecasting using Bayesian Dynamic Linear Models, the primary focus lies in the parameter determination process and model validation. Various methods are employed to establish parameters, including grey-based Choquet integral models with grey accumulation operators and grey wolf optimization (Moutik *et al.*, 2023). Additionally, feature engineering techniques such as Pearson and Spearman correlations, multiple linear regression, and principal component analysis are utilized to analyze the relationships among variables and determine the appropriate time frame for predictive model development (Shaikh *et al.*, 2022). Model validation is carried out using evaluation metrics such as RMSE, MAPE, and R2, where the results are compared with other techniques across different datasets (Durand *et al.*, 2022).

The process of parameter determination and model validation in forecasting energy consumption using Bayesian Dynamic Linear Models is a complex procedure that often requires the use of causal models (Raillon and Ghiaus, 2018). These models can assist in determining the effects of intervention programs on household energy-saving behaviors, which is a crucial consideration in energy consumption forecasting. However, it is important to address potential biases, such as framing bias, in statistical analysis (Ranstam and Cook, 2016). The utilization of historical control data in Bayesian trial designs, as discussed by Eggleston *et al.*, (2021) can also serve as a valuable tool in this process. Lastly, Vesa *et al.*, (2020) highlight the need to consider factors such as diffusion effects in baseline evaluation methods for demand response programs, which can influence the accuracy of energy consumption forecasts.

This study explores energy consumption forecasting using the Bayesian Dynamic Linear Model (BDLM). The primary focus of this research lies in the process of parameter determination and model validation. Methods employed to establish parameters include the grey-based Choquet integral model with grey accumulation operators and grey wolf optimization. Additionally, feature engineering techniques such as Pearson and Spearman correlations, multiple linear regression, and principal component analysis are utilized to analyze the relationships among variables and determine the appropriate time frame for predictive model development. Model validation is conducted using evaluation metrics such as RMSE, MAPE, and R2, with the results compared to other techniques across various datasets. The parameter determination process in BDLM involves the use of various complex and diverse methods, such as the Choquet integral model and grey wolf optimization. This indicates that this research adopts a sophisticated approach in aligning the model with energy consumption data. Furthermore, the use of feature engineering techniques aids in analyzing the relationships among variables and selecting relevant features for predictive model development. Model validation with standard evaluation metrics ensures that the developed model can provide accurate and reliable forecasts.

Probabilistic Approach in Managing Uncertainty in Energy Consumption Forecasting

Probabilistic approaches, such as Bayesian Dynamic Linear Models, have proven effective in managing uncertainty in energy consumption forecasting (Jin *et al.*, 2023). This approach offers advantages by quantifying the inherent uncertainty in energy forecasts, thereby enabling decision-makers to make informed decisions (Sweeney *et al.*, 2020). By combining probabilistic methods, such as Probabilistic Deep Learning (PDL) and Quantile Regression (QR), these models can provide more comprehensive information for decision-making processes and delivery (Broujeny *et al.*, 2023; Kaur *et al.*, 2022). Moreover, this approach can capture and measure uncertainty in estimated values, allowing for confidence interval estimates and probability density curves (Capel and Dumas, 2023). This provides users, such as network operators or retailers, the ability to receive forecasts that encompass desired confidence intervals, ensuring privacy while still providing accurate predictions. Overall, the probabilistic approach in energy consumption forecasting helps address uncertainty and provides valuable information for decision-makers in efficient network operations and resource allocation.

The utilization of Bayesian Dynamic Linear Models in forecasting energy consumption is supported by several studies. Chiba, (2018) underscores the importance of causal inference in understanding the impacts of intervention programs, specifically advocating for the use of graphical causal models. Berchiulla *et al.*, (2021) and Podbregar *et al.*, (2021) further emphasize the need for robust statistical methods in this context, with Berchiulla comparing the performance of different estimators and Podbregar employing the Difference in Differences method to assess the impact of energy-saving instructions on household electricity consumption. These studies collectively affirm the value of probabilistic approaches, such as Bayesian Dynamic Linear Models, in managing inherent uncertainty in energy forecasting.

Research in predicting energy consumption has demonstrated that probabilistic approaches, particularly Bayesian Dynamic Linear Models, are effective in managing uncertainty in energy forecasting. This approach enables the measurement of inherent uncertainty in energy predictions, allowing decision-makers to make better-informed decisions. The integration of probabilistic methods such as Probabilistic Deep Learning (PDL) and Quantile Regression (QR) into these models also provides more comprehensive information for decision-makers. Bayesian Dynamic Linear Models offer advantages by allowing the measurement and management of uncertainty inherent in energy forecasting. With the ability to generate confidence interval estimates and probability density curves, these models provide valuable information for decision-makers, such as network operators or retailers, to make more efficient and accurate decisions.

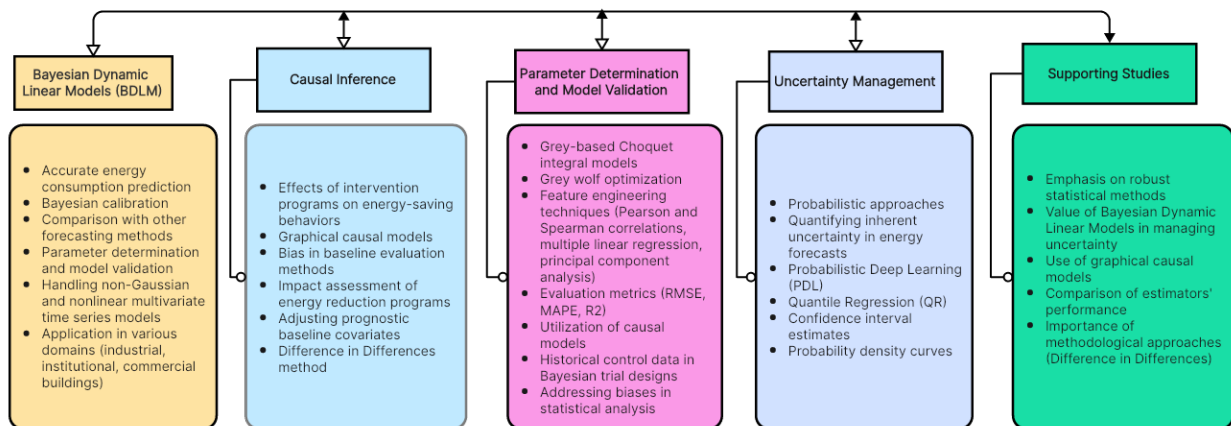


Figure 1. Key research findings.

The research landscape surrounding energy consumption forecasting exhibits a multifaceted exploration of Bayesian Dynamic Linear Models (BDLM) and associated methodologies. BDLM emerges as a pivotal tool offering enhanced predictive accuracy in diverse domains, spanning industrial, institutional, and commercial sectors. This methodology leverages Bayesian calibration to optimize model accuracy, particularly notable in predicting heating and cooling energy demands within office environments. The comparative advantage of BDLM over alternative forecasting methods underscores its reliability and efficacy in informing energy planning and decision-making processes. However, challenges persist, notably regarding the intricate interplay

of parameter determination and model validation. Techniques such as grey-based Choquet integral models and feature engineering methods, including Pearson and Spearman correlations, facilitate robust parameterization and validation processes. Moreover, addressing biases and uncertainties inherent in energy consumption forecasting remains imperative. Probabilistic approaches, including Probabilistic Deep Learning and Quantile Regression, offer avenues for quantifying and managing such uncertainties, providing decision-makers with nuanced insights and confidence interval estimates essential for efficient resource allocation. Furthermore, the integration of causal inference models and methodological approaches like the Difference in Differences method enhances the understanding of intervention program impacts on energy-saving behaviors, enriching the predictive capabilities of BDLM. The collective synthesis of these research endeavors underscores the dynamism and complexity inherent in energy consumption forecasting, advocating for interdisciplinary methodologies and rigorous validation frameworks to advance the predictive accuracy and utility of Bayesian Dynamic Linear Models in energy management contexts.

Conclusion

The conclusion drawn from this evaluation indicates that the use of Bayesian Dynamic Linear Model (BDLM) in forecasting energy consumption has significantly contributed to optimizing energy management across various sectors, including industrial and commercial buildings. The research highlights the effectiveness of BDLM in accurately predicting energy consumption through a probabilistic approach that efficiently manages uncertainty. However, the study also underscores that BDLM has limitations and challenges that need attention, including the complexity in determining parameters and model validation processes, as well as the importance of addressing potential biases and considering factors such as deployment impacts. Despite significant research on the use of BDLM in energy consumption forecasting, there are still some gaps to be addressed in the future. One such gap is the need for better integration between BDLM models and external factors influencing energy consumption, such as changes in energy policies, weather variability, and technological developments. Additionally, in-depth research into more effective methods for handling complex uncertainties in energy forecasting is a crucial concern. Urgent research topics in this regard include the development of more sophisticated model validation techniques, including the use of machine learning approaches to enhance the accuracy and reliability of BDLM models in various energy contexts. Furthermore, there is a need to expand the application scope of BDLM in diverse energy sectors, including transportation, power generation, and household energy use. In this regard, research focus can be directed towards identifying specific energy consumption patterns for each sector and developing BDLM models capable of handling the unique dynamics of each sector. Consequently, future research in this field can provide deeper insights and more effective solutions for sustainable energy consumption management. (Blasch *et al.*, 2017)

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