Load Forecasting in Electrical Grids: Analysis of Methods and their Trends

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Abstract. Main objective of this study is to analyze the progression of load forecasting methodologies for electrical grids, with a focus on identifying trends in performance metrics such as Mean Absolute Percentage Error (MAPE) over time. This analysis evaluates various forecasting approaches, including statistical methods, artificial intelligence, fuzzy logic, ensemble methods, and hybrid systems, to understand their evolution and current state. To achieve the stated goals, the systematic review of scientific studies and articles that have the necessary metrics was conducted. From them, it was determined which models were used and what forecasting errors corresponded to them. Also, the publications reviewed within this study were distributed over time to take into account the dynamics of changes in the results. The most important results are the obtained graphs of the dynamics of forecast of error changes for different models by years, as well as the possible ranges of variation of this error. The results show that, although increasingly complex models are being developed, their accuracy gain remains inconsistent in different application contexts, provided that a single-type architecture is used. Hybrid models demonstrate a significant increase in accuracy, and, therefore, superiority over a single-type architecture. The significance of the obtained results is in the clear illustration of the development of the accuracy of forecasting models. They allow us to determine the optimal vector of evolution of subsequent studies, namely, what type of model should be used to forecast the grid load. This study proves the prospects of using hybrid methods in the area under consideration as well.
Keywords: load forecasting, electrical grids, analysis, fuzzy systems, neural networks, hybrid models, performance metrics, artificial intelligence, machine learning.

DOI: https://doi.org/10.52254/1857-0070.2025.1-65.02
UDC: 519.23:004.85:621.311

Prognoza sarcinilor în rețelele electrice: analiza metodelor și tendințelor lor

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Rezumat. Obiectivul principal al acestui studiu este de a analiza și identifica progresia metodologiilor de prognoză a sarcinii pentru rețelele electrice, cu accent pe identificarea tendințelor în metrici de performanță, cum ar fi eroarea procentuală medie absolută în timp. Această analiză evaluează diverse abordări de prognoză, inclusiv metode statistice, inteligență artificială, logica fuzzy, metode de ansamblu și sisteme hibride, pentru a înțelege evoluția și starea lor actuală. Pentru atingerea scopurilor declarate, a fost efectuată o revizuire sistematică a studiilor și articolelor științifice care au metricile necesare. Din acestea s-a determinat ce modele au fost folosite și ce erori de prognoză le corespundeau. De asemenea, publicațiile revizuite în cadrul studiului au fost distribuite în timp -pentru a ține cont de dinamica modificărilor rezultatelor. Cele mai importante rezultate sunt graficele obținute ale dinamicii modificărilor erorilor de prognoză pentru diferite modele pe ani, precum și posibilele intervale de variație a acestei erori. Rezultatele arată că, deși sunt dezvoltate modele din ce în ce mai complexe, câștigul lor de precizie rămâne inconsecvent în diferite contexte de aplicație, cu condiția să fie utilizată o arhitectură de tip unic. Cu toate acestea, modelele hibride demonstrează o creștere semnificativă a preciziei și, prin urmare, superioritate față de o arhitectură de tip unic. Semnificația rezultatelor obținute este în ilustrarea clară a dezvoltării acurateței modelelor de prognoză. Acestea ne permit să determinăm vectorul optim de evoluție al studiilor ulterioare, și anume, ce tip de model ar trebui utilizat pentru a prognoza sarcina în rețeaua electrică. De asemenea, acest studiu demonstrează perspectivele utilizării metodelor hibride în zona luată în considerare.
Cuvinte-cheie: prognoza încărcăturii, rețele electrice, analiză, sisteme fuzzy, rețele neuronale, modele hibride, metrici de performanță, inteligență artificială, machine learning.

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Прогнозирование нагрузки в электрических сетях: анализ методов и их развития

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Аннотация. Основная цель данного исследования – проанализировать развитие методологий прогнозирования нагрузки в электрических сетях, уделяя особое внимание выявлению тенденций в оценках показателей качества, например, такой как средняя абсолютная процентная ошибка во времени. Этот анализ оценивает различные подходы к прогнозированию, включая статистические методы, искусственный интеллект, нечеткую логику, ансамблевые методы и гибридные системы, чтобы понять их эволюцию и текущее состояние. Для достижения поставленных целей был проведен систематический обзор научных публикаций, имеющих необходимые метрики. Из них было определено, какие модели использовались и какие ошибки прогнозирования им соответствовали. Также публикации, рассмотренные в рамках исследования, были распределены по времени – для учета динамики изменения результатов. Важнейшими результатами являются полученные графики динамики изменения ошибки прогноза для разных моделей по годам, а также возможные диапазоны изменения этой ошибки. Результаты показывают, что, хотя разрабатываются все более сложные модели, их прирост точности остается непоследовательным в разных контекстах применения при условии использования однотипной архитектуры. Однако гибридные модели демонстрируют существенное увеличение точности, а значит и превосходство над однотипной архитектурой. Значимость полученных результатов заключается в наглядной иллюстрации развития точности моделей прогнозирования. Они позволяют определить оптимальный вектор проведения последующих исследований, а именно, какой тип модели следует использовать для прогнозирования нагрузки в электрической сети. Также данное исследование доказывает перспективность использования гибридных методов в рассматриваемой области.

Ключевые слова: прогнозирование нагрузки, электрические сети, анализ, нечеткие системы, нейронные сети, гибридные модели, показатели производительности, искусственный интеллект, машинное обучение.

INTRODUCTION

Load forecasting is a cornerstone of efficient power grid management, influencing decisions from operational planning in the short term to infrastructure investments over extended horizons. The accuracy of these forecasts has profound implications for grid stability, renewable energy integration, and cost optimization. As the field evolves, advancements in computational methods and data availability have driven remarkable improvements in forecasting precision.

Despite significant advancements, challenges remain in achieving reliable forecasts across varying time scales. Short-term load forecasting demands models capable of handling rapid fluctuations, while long-term forecasting requires capturing broader trends and seasonality. These differing goals often necessitate diverse modeling approaches, yet the fundamental methodologies be they statistical, artificial intelligence (AI), or hybrid-share notable similarities. This overlap provides a unique opportunity to unify the evaluation of these methods across forecasting horizons.

The literature [1, 2, 3] demonstrates a rich evolution of load forecasting methodologies. Early statistical models such as ARIMA and polynomial regression provided foundational techniques for addressing forecasting challenges.

Despite substantial advancements in load forecasting methodologies, there is a significant lack of clarity surrounding the consistency and reliability of reported performance results. A closer examination of the available literature and dataset information reveals considerable dispersion in reported metrics, particularly MAPE.

The heterogeneity of datasets used in these studies further complicates the interpretation of results. While some models are applied to well-prepared, extensive datasets – such as DBN with a MAPE of 0.21 on a curated dataset – others rely on limited or inadequately described datasets. For example, ARIMA-based models and polynomial regression approaches often utilize datasets spanning only one to two years, potentially limiting their predictive accuracy and generalizability.

This dispersion of results and lack of standardization in dataset preparation, feature engineering, and evaluation criteria introduce doubts about the reliability of reported advancements. Hybrid models, often touted for their superior performance, exemplify this issue.

The purpose of this study is to analyze and critically evaluate research trends in electrical load forecasting, focusing on the methodologies used, performance indicators achieved, and data sets used.

PROBLEM FORMULATION

The evolution of load forecasting methodologies has been shaped by decades of research, with statistical methods, artificial intelligence, fuzzy logic systems, machine learning ensemble methods, and hybrid approaches each contributing uniquely to addressing the complexities of modern power grids. These methodologies exhibit distinct performance trends and dependencies on dataset characteristics, which are crucial for understanding their strengths, limitations, and future potential.

Statistical methods, such as Time Series Regression (TSR) and ARIMA, were foundational in load forecasting but show limited advancements over time. For instance, TSR achieved a MAPE of 6.959 when applied to hourly industrial energy consumption data over six weeks [34], illustrating the constraints of traditional statistical approaches in adapting to modern grid demands. These methods often struggle with complex, dynamic datasets, and their performance has remained largely stagnant despite advancements in computational capabilities.

In contrast, AI-based models, including Artificial Neural Networks (ANN) and Deep Neural Networks (DNN), have shown gradual improvements, particularly when applied to feature-rich datasets. For example, Deep Learning models achieved a competitive MAPE of 1.00 by leveraging sensor-driven data [1], while DNN demonstrated adaptive learning capabilities with a MAPE of 0.21 in medium-term forecasting scenarios. These advancements highlight the adaptability of AI methods to diverse forecasting challenges, though their performance remains highly dependent on the quality of the datasets.

Fuzzy logic systems have emerged as a powerful alternative, particularly in handling non-linearity and uncertainty. Adaptive Neuro-Fuzzy Inference System (ANFIS) have achieved significant accuracy improvements, with MAPEs as low as less than 1. Similarly, Fuzzy Neural Networks (FNN) with Takagi-Sugeno inference models reported MAPEs ranging from 1.06 to 1.72 when trained on historical data segmented by day type and seasonality [93]. These results underscore the effectiveness of fuzzy systems in addressing complex forecasting scenarios.

Dataset characteristics play a pivotal role in determining the performance of load forecasting models. Short-duration datasets often constrain model performance, as seen in TSR and ANN models trained on six weeks of data, which struggled to achieve low MAPEs. In contrast, models trained on longer datasets, such as FNN using seven years of historical data, achieved significantly lower MAPEs. Furthermore, feature engineering and preprocessing have emerged as critical factors in enhancing model accuracy. Models incorporating diverse features, such as weather patterns and industrial activity data, consistently outperform those relying on limited inputs.

Despite these advancements, challenges persist in ensuring consistency and reproducibility in load forecasting. Dispersion highlights the dependency on dataset preparation and experimental conditions, particularly for hybrid systems that often rely on tailored datasets. Such reliance complicates the reproducibility and generalizability of reported outcomes, emphasizing the need for standardized frameworks.

Looking ahead, the success of hybrid and ensemble models illustrates the potential of integrating diverse methodologies. By combining neural networks with fuzzy logic, hybrid models capitalize on the strengths of individual techniques.

Additionally, exploring novel methodologies that integrate multiple approaches while addressing the challenges of dataset dependencies and reproducibility will be crucial for achieving breakthroughs in forecasting accuracy. Such advancements are essential for ensuring the stability and sustainability of modern power grids, particularly as they integrate renewable energy sources and face increasing demand variability.

In general, the classification of electrical load forecasting by modeling methods can be presented structurally, as shown in Fig. 1.

OVERVIEW OF FORECAST METHODS AND MODELS

A detailed review of a number of published studies reveals clear patterns and recurring themes in the field of load forecasting. Studies have been categorized based on their main contribution and methodology, and similar approaches have been grouped together for clarity.

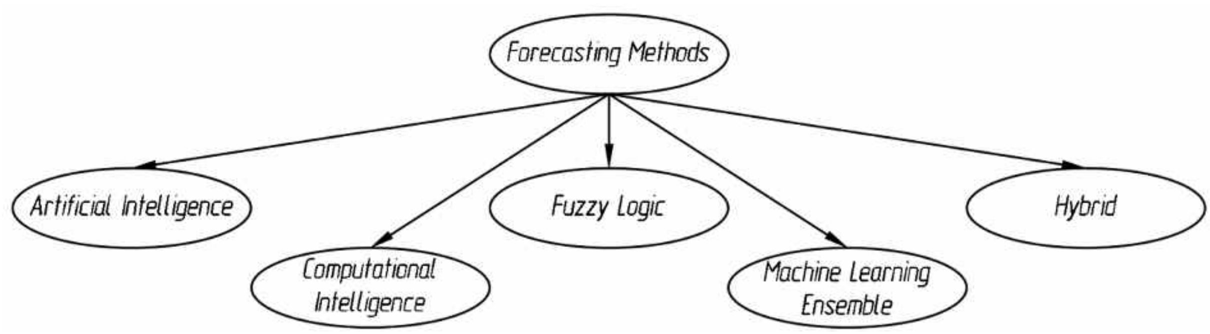

Fig. 1. Classifications of load forecasting according to modeling techniques.

- **AI** methods [1-49] have transformed load forecasting by providing advanced solutions for analyzing non-linear relationships and improving prediction accuracy. These methods can be broadly categorized into several subtypes, each tailored to address specific aspects of forecasting challenges (fig. 2.).

One prominent subcategory is **Deep Learning Models**, which have proven highly effective for processing large datasets and identifying complex patterns. Their ability to model non-linear dependencies has made them a cornerstone for load forecasting, particularly in scenarios requiring high accuracy and adaptability. These models have demonstrated exceptional performance and low RMSE values, highlighting their precision and versatility across various forecasting tasks.

Deep Neural Networks (DNNs), while closely related to Deep Learning Models, are classified separately due to their broader applicability and focus on hierarchical data representations. DNNs have achieved MAPE values ranging from 3.45 to 8.85, depending on the complexity of the dataset and forecasting horizon. These models are particularly effective in tasks requiring high-level abstraction and complex feature extraction.

Recurrent Neural Networks (RNNs), another major subcategory, are specifically designed to handle sequential data. Their unique architecture allows them to capture temporal dependencies, making them particularly suitable for forecasting tasks where historical trends and patterns play a critical role. LSTM, a popular RNN variant, has achieved MAPE values as low as 0.0535, demonstrating its ability to handle multi-temporal and short-term load forecasting with exceptional accuracy.

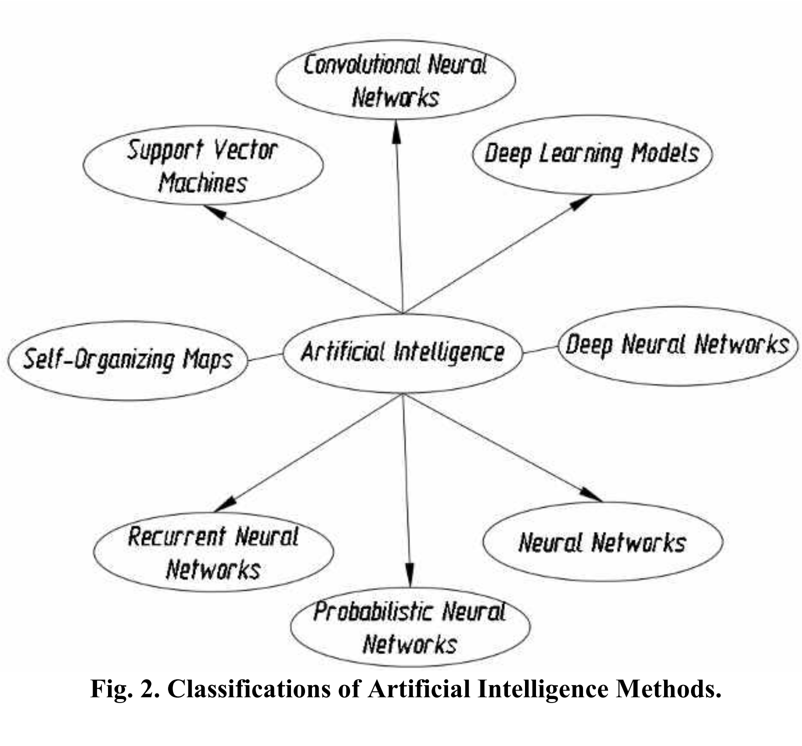

Fig. 2. Classifications of Artificial Intelligence Methods.

Table 1

AI Methods data

Ref. №	Year	Model Name	Performance
1	2013	IoT-DL	MAPE: 1.00
	2019	DBN	MAPE: 0.21
	2020	LSTM-RNN	MAPE: 0.0535
	2019	SDA	MAPE: 2.47
	2021	FCRBM	MAPE: 1.43
	2020	DNN	MAPE: 9.77
	1978	LSTM-RNN	MAPE: 8.18
	2017	DNN	MAPE: 8.84
	2007	LSTM-RNN	MAPE: 22
	2019	SVM	MAPE: 1.790
	2019	ANN + RBF	MAPE: 1.950
2	2020	DBN	MAPE: 3.864, RMSE: 341.601
	2005	SOM	MAPE: 1.93
	2012	SOM	MAPE: 2.32
	2019	R-ANN	MAPE: 1.57
3	2019	KP-SVR	MAPE: 1.79
	2011	ANN-MLP	MAE: 0.01, MAPE: 0.03
	1995	Adaptive NN	MAPE: 6
	1998	ANN-Input ID	MAPE: 1.67
	2007	Autonomous NN	MAPE: 1.75
	2012	SOM-STLF	MAPE: 2.18
	2015	SVR	MAPE: 1.78
	2016	DCANN + UDCANN	MAPE: 8.28
	2016	BP-ANN	MAPE: 1.65
	2016	NN-LV	MAE: 3.63, MAPE: 10.3
	2017	MLP-Sectors	MAPE: 1.41
	2019	Multi-scale CNN	MAPE: 3.74
	2020	MCRN + k-d Tree	MAPE: 4.59
	2021	Adaptive RNN	MAPE: 0.24
	2002	ANN	MAPE: 2.87
	2013	LS-SVM	MAPE: 1.76
	2015	LSSVM	MAPE: 1.07
	2017	SDA	MAPE: 2.47
	2019	DRL	MAPE: 3.47
	2021	DBNN	MAPE: 2.05
4	1988	SLA Forecasting	MAPE: 3
5	1995	ANN	MAPE: 2.66
6	1997	Cascades ANN	MAPE: 4.197
	1997	ANN	MAPE: 2.7
7	1997	ANN + Deficit Module	MAPE: 3-5
8	1997	ANN: Linear, RBF, MLP, Elman	MAPE: 3.03-4.04; 2.95-4.04; 2.93-3.4; 2.87-3.6
9	1997	ANN	MAPE: 1.86
10	1998	MLP	Weekly MAPE range: ~3.01-5.92; Best weekday (Tuesday): MAPE ~0.2-2.0.
11	1998	MLP + ANN	MSE: 1.04
12	2000	FFNN	MAPE: 1.1-3.2

Ref. №	Year	Model Name	Performance
13	2000	FNN + BP	MAPE: 1.52-1.7
14	2001	SVM + RBF	MAPE: 1.95
15	2004	ANN	MAPE: 1.89
16	2005	MLP-SPF	MAPE: 0.86-1.4
17	2009	ANN	MAPE: 1.585-5.747
18	2010	ANN	MAPE: 0.10-1.25
19	2010	PNN	MAPE: 1.0419-1.5373
20	2010	ANN	MAPE: 2.81, MAE: 168.04 MW
21	2011	FFNN	MAPE: 3.5
	2011	Elman NN	MAPE: 1.3
	2011	RBFNN	MAPE: 1.3
22	2011	ANN	MAPE: 4.11-14.46
23	2011	BPN	MAPE: 1.30, MAXPE: 2.27, SDAPE: 0.59
24	2012	SVR	MAPE: 3.6
	2012	DESVR	MAPE: 1.6
	2012	BPNN	MAPE: 1.5
25	2013	MLP	MAPE: 2.47
26	2013	RBFNN	MAPE: 1.86
27	2013	ANN 10N	MAPE: 5.74-7.39
	2013	ANN 20N	MAPE: 6.16-9.28
	2013	ANN 30N	MAPE: 7.62-8.5
28	2014	GRNN	RMSRE: 0.53
	2014	SVM	RMSRE: 3.16
	2014	BP	RMSRE: 2.59
29	2014	ANN	MAPE: 1.252
	2014	GMDH	MAPE: 0.959
30	2014	ANN	MAPE: 4.20-23.5
31	2015	ANN	MAPE: 1.89-2.78
32	2015	BP	MAPE: 3.43
	2015	BP 2xhidden layer	MAPE: 3.97
	2015	GABP	MAPE: 3.97
	2015	RBF	MAPE: 3.46
	2015	GRNN	MAPE: 4.72
33	2016	ANN	MAE: 1,936; MAPE: 3.293; RMSE: 2,035
34	2016	DNN	MAPE 3.2. RRMSE: 4.1
	2016	SNN	MAPE 4.36. RRMSE: 5.86
35	2016	DNN + ReLU	MAPE: 3.45-8.85. RMSRE: 4.36-10.69
	2016	DNN + RBM	MAPE: 3.20-8.84. RMSRE: 4.10-10.62
36	2016	NN	MAPE: 6.29-10.465
	2016	Decision Tree	MAPE: 5.204-12.309
37	2016	D-PNN	MAPE: 1.56
	2016	ANN	MAPE: 1.82
	2016	SVM	MAPE: 2.15
	2016	GMDH	MAPE: 1.87
38	2017	LSTM-RNN	MAPE: 8.18-9.14
39	2017	LSTM	MAPE: 21.99
40	2019	MLP	MAPE: 1.125 -3.4
41	2019	Stacked LSTM	MAPE: 6.407
	2019	SVR	MAPE: 6.840
	2019	BPNN	MAPE: 6.805

Ref. №	Year	Model Name	Performance
42	2019	BP	MAPE: 4.44-6.42
	2019	RBF	MAPE: 1.69-3.69
	2019	Elman NN	MAPE: 2.88-5.30
	2019	LSTM	MAPE: 1.55-3.4
43	2019	LSTM	MAPE: 0.88-1.15
44	2020	GRU	MAPE: 4.6377. RMSE: 1910.02
	2020	CNN	MAPE: 3.3890. RMSE: 1406.77
	2020	BPNN	MAPE: 4.4681. RMSE: 1841.63
45	2020	SVR	MAPE: 6.93
46	2020	LSTM-RNN	MAPE: 1.49-1.52
47	2020	LSTM	Single-step Forecasting: MAPE: 1.52. Multi-step Forecasting (24-hour horizon): MAPE: 4.79
	2020	GRNN	Single-step Forecasting: MAPE: 3.05. Multi-step Forecasting (24-hour horizon): MAPE: 5.33
	2020	ELM	Single-step Forecasting MAPE: 3.44. Multi-step Forecasting (24-hour horizon): MAPE: 6.86
48	2020	LSTM	MAPE: 0.073

Probabilistic Neural Networks (PNNs) stand out for their adaptability to dynamic environments. Their probabilistic framework enables them to handle uncertainties in forecasting, providing reliable predictions even under fluctuating conditions. For example, PNNs such as Deep Belief Networks (DBNs) have achieved MAPE values as low as 0.21, showcasing their precision and resilience in unpredictable scenarios.

Convolutional Neural Networks (CNNs), traditionally used in image and spatial data analysis, have been effectively adapted to load forecasting. CNNs have achieved MAPE values as low as 3.39%, demonstrating their capability to improve forecasting accuracy in scenarios involving complex interactions between variables.

Support Vector Machines (SVMs) are widely applied in both regression and classification tasks within load forecasting. By leveraging various kernel functions, SVMs excel at mapping data into higher-dimensional spaces, enabling precise predictions. Reported MAPE values for SVMs are around 1.79, reflecting their effectiveness in diverse forecasting applications.

Artificial Neural Networks, which encompass traditional feedforward architectures, remain fundamental in AI-based load forecasting. Their flexibility and simplicity have made them a reliable choice for many applications, with performance metrics such as MAPE values as low as 1-2% in medium-term forecasting scenarios. ANNs continue to be foundational in the development of more advanced hybrid models.

Finally, **Self-Organizing Maps** (SOMs) specialize in clustering and visualization, playing a crucial role in exploratory analysis. By segmenting load patterns, SOMs help uncover hidden structures in the data, with MAPE values reported around 1.93 to 2.32, making them valuable tools for preprocessing and improving the organization of large datasets.

Together, these subcategories of AI-based methods form the backbone of modern load forecasting techniques. Their collective strengths—ranging from handling sequential and spatial data to adapting to uncertainty and uncovering hidden patterns—enable energy providers to meet the growing complexity of forecasting tasks with improved precision and reliability.

Computational Intelligence (CI) [2, 3] methods remain one of the least widely adopted approaches in load forecasting when compared to AI and Fuzzy Logic Methods. While CI methods, such as Evolutionary Algorithms, Swarm Intelligence, and Metaheuristics, offer robust tools for optimization and exploration of complex solution spaces, they are not as commonly implemented for direct load prediction. This distinction arises from the inherent focus of CI methods on optimization rather than forecasting, positioning those more as auxiliary tools than standalone solutions.

One of the primary reasons for the limited adoption of CI methods is their design philosophy. Techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) excel in optimizing parameters or solving multi-objective problems but lack inherent capabilities for time-series prediction.

As a result, these methods are typically integrated into hybrid models where they optimize parameters for statistical or AI-based forecasting methods. For instance, a Hybrid Genetic Algorithm (HGA) can optimize the hyperparameters of Support Vector Machines (SVM) or ANN, enabling these predictive models to achieve higher accuracy. However, this reliance on hybridization adds complexity, which can deter their widespread use in practical applications.

Table 2

CI Methods data

Ref. №	Year	Model Name	Performance
2	2002	AIS	MAPE: 2.038
	2013	MGGP	MAPE: 1.5716
	2002	AIN	MAPE: 2.038
3	2003	GA	MAPE: 1.56
	2009	HGA	RMSE: 7.73, MAPE: 0.76
	2018	Grasshopper	MAPE: 1.4.
	2020	E-ELITE	MAPE: 1.18

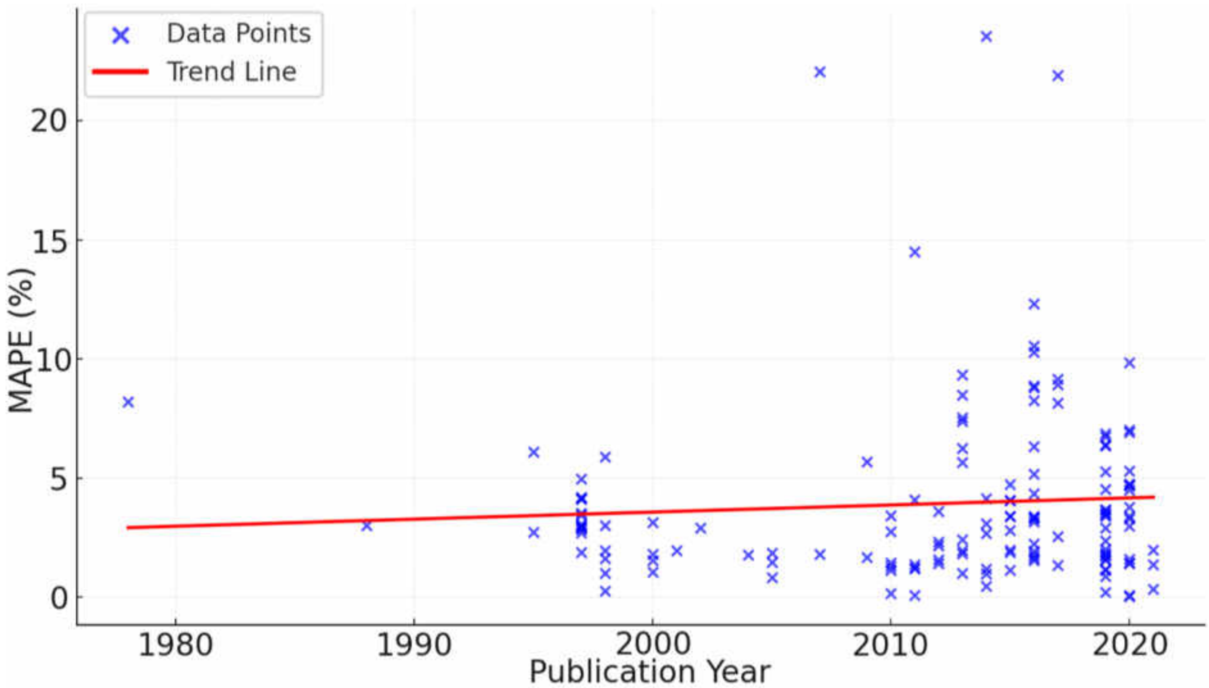

Fig. 3. MAPE Trends over Years for Artificial Intelligence methods.

Another challenge associated with CI methods is their limited interpretability. While AI models, such as Neural Networks, often face similar criticisms for being "black boxes," CI methods are particularly abstract in their outputs, as they focus solely on providing optimized solutions. This lack of transparency reduces their appeal in scenarios where interpretability is essential for decision-making.

Overall, CI methods occupy a niche role in load forecasting, primarily as tools for fine-tuning and optimizing other forecasting methodologies. Their potential remains significant, particularly in hybrid applications where they complement the strengths of AI or statistical models. Great example of this is [49] where GA used in microgrids for battery load and scheduling forecasting. Detailed methodology described in [49].

Fuzzy Logic Systems [2, 3, 50-66] are widely recognized for their ability to manage uncertainty and imprecision in load forecasting, offering a flexible alternative to traditional deterministic methods. By leveraging membership functions and rule-based reasoning, these systems excel in applications where input data may be incomplete, noisy, or ambiguous.

Recent studies have highlighted a diverse range of applications and innovations in Fuzzy Logic Systems. In [52] demonstrated the effectiveness of fuzzy clustering combined with splines, achieving a MAPE of 1 and reducing errors in load curve modeling. Similarly, [58] employed fuzzy linear regression to model uncertainty in electricity demand, achieving a MAPE of 3.68. Another notable contribution is the fuzzy logic-based similar-day approach outlined in [59], which achieved a highly competitive MAPE of 0.85-9.4.

Improvements in Type-1 and Type-2 Fuzzy Logic Systems have further extended their capabilities. Type-1 and Type-2 Fuzzy Logic Systems (IT1FL and IT2FL) for daily load forecasting, reporting MAPE values of 1.6078 and 1.3445 [63], respectively. These advancements demonstrate the effectiveness of Type-2 systems in handling variability and noise in complex forecasting environments.

Several studies have also integrated exogenous variables to enhance the predictive power of fuzzy systems. In [50] introduced a fuzzy logic-based approach combining similar-day analysis with exogenous factors like weather data, achieving a MAPE of 2.53. Another study, combined fuzzy logic with weather data to improve long-term load forecasting, demonstrating the adaptability of fuzzy systems in dynamic environments [53].

Clustering and regression techniques have also been widely explored [54]. Fuzzy time series analysis, reporting MAPE values near 3, highlighting the versatility of fuzzy approaches in capturing temporal patterns.

The Mamdani fuzzy logic model [62], incorporated weather data into its rule-based framework, achieving a MAPE of 0.5-1 for short-term forecasts. Meanwhile in a multi-TSK (Takagi-Sugeno-Kang) [66] predictor model, reporting an impressive Mean Relative Error (MRE) of 1.2296.

These advancements underscore the adaptability of Fuzzy Logic Systems across various forecasting scenarios. However, challenges persist. The design and tuning of fuzzy membership functions, rule bases, and input variables often require significant domain expertise and computational resources. Additionally, the performance of fuzzy systems is heavily dependent on the quality of input data and the comprehensiveness of the rule base. Despite these, Fuzzy Logic Systems remain a valuable tool in load forecasting, particularly in applications where interpretability and flexibility are critical. Their ongoing refinement, as demonstrated by recent research, ensures that they will continue to play a significant role in addressing the complexities of energy demand forecasting in the future.

Table 3

Fuzzy Logic Systems data

Ref. №	Year	Model Name	Performance
2	2017	Fuzzy Model	MAPE: 2.3
	2016	Fuzzy-LTLF	MAPE: 6.9
3	2009	Fuzzy Controller	MAPE: 2.2
	2014	Fuzzy Regression	MAPE: 3.68
	2018	Adaptive Fuzzy	MAPE: 0.13
	2005	Fuzzy Logic	MAPE: 1.71
	2020	Fuzzy Clustering	MAPE: 3.66
50	1998	Fuzzy Similarity Analysis	MAPE: 2.53
	1998	Fuzzy Previous Day + Similar Day	MAPE: 4.22
51	1999	Simplified Fuzzy	MAPE: 3.809
52	2003	Fuzzy Clustering + Splines	MAPE: 1.76
53	2006	Fuzzy Linear + Weather Factors	MAPE: 0.7
54	2006	Fuzzy Logic	MAPE: 3
55	2010	GA + TSK	MAPE: 0.36
56	2010	GA + TSK	MAPE: 2.04
57	2010	Fuzzy AHP	MAPE: 0.87-2.30

Ref. №	Year	Model Name	Performance
58	2011	Fuzzy Linear Regression	MAPE: 3.68
59	2012	Fuzzy Similar Day FISDM	MAPE: 0.84-9.37
60	2015	Fuzzy Time Series	MAPE: 2.6-5.1
61	2016	Fuzzy Logic Model	MAPE: 6.98-8.36. APE: 23.33
62	2017	HFCM-TM	MAPE: 0.478-1.048
63	2018	IT1FL	MAPE: 1.6078
	2018	IT2FL	MAPE: 1.3445
64	2018	FL + Gaussian Membership	MAPE: 1.51
65	2018	Fuzzy Logic System	MAPE: 0.6244
66	2019	Multiple TSK Predictors	MAPE: 1.2296. RMSE: 7.351

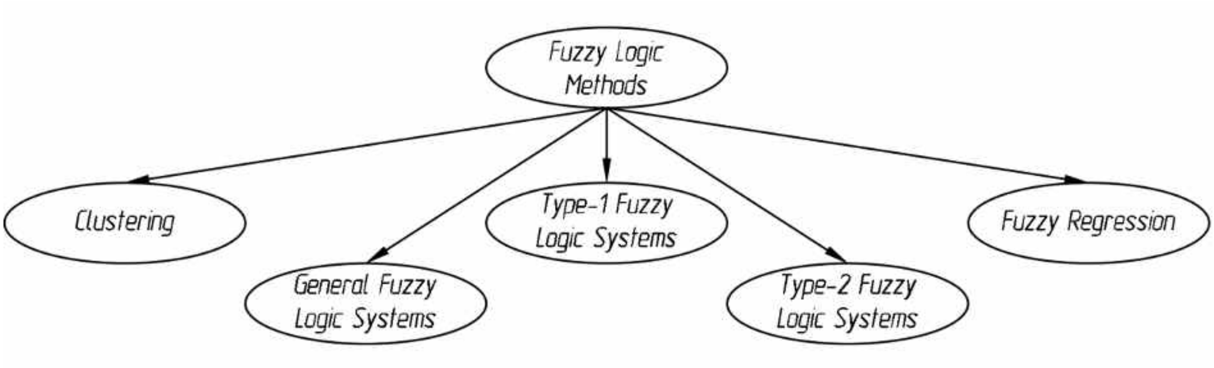

Fig. 4. Classifications of Fuzzy Logic Systems.

- **Ensemble methods** [1, 3, 67-69] have become a cornerstone of modern load forecasting due to their ability to improve prediction accuracy and robustness by combining multiple models. By leveraging the strengths of diverse base predictors, ensemble techniques reduce variance, minimize bias, and enhance the stability of forecasts. This section focuses exclusively on ensemble methods as standalone approaches, excluding their hybrids with other methodological frameworks.

Bagging (Bootstrap Aggregating) is a widely adopted ensemble technique that trains multiple models on different subsets of the data and combines their predictions to reduce variance and prevent overfitting. Within the dataset, Bagging Neural Networks [69] demonstrated impressive performance, achieving a MAPE between 1.42 and 1.50. Similarly, Bagged Regression Trees exhibited a slightly higher MAPE range of 1.93 to 2.44, highlighting the method's versatility across different predictive models. Bagging-based methods are particularly effective in short-term load forecasting, where data variability can significantly impact prediction accuracy.

Boosting algorithms iteratively refine weak learners by correcting their previous errors, resulting in a strong predictive model. Boosted Regression Trees [1] exemplify the power of boosting in load forecasting, with RMSE values of 0.1389 and 0.1734 for predictive and corrective components, respectively. Another notable study on BoostNN [69] combined boosting with neural networks, achieving a MAPE of 1.46 to 1.47. These results underscore the effectiveness of boosting in capturing complex, nonlinear patterns in load data while minimizing bias and improving accuracy.

Stacking ensembles combine the outputs of multiple base models using a meta-model trained to optimize the final prediction. The COSMOS ensemble [3] introduced a novel stacking framework, achieving a MAPE of 6.97. This approach demonstrates the potential of stacking in integrating diverse algorithms, enabling the model to harness complementary strengths of base predictors. While stacking is computationally intensive, its ability to enhance forecasting accuracy makes it a valuable approach in scenarios requiring robust predictions.

The rise of deep learning has inspired the development of ensemble methods incorporating advanced neural networks. Deep Belief Network (DBN) Ensembles from [1] achieved a MAPE of 5.93, providing adaptive forecasting capabilities that leverage hierarchical feature extraction.

Similarly, Ensemble LSTM models combined ARIMA, SVR, and LSTM networks to achieve superior performance in capturing long-term dependencies in load patterns. These deep learning ensembles excel in addressing the complexity of real-world load data, particularly in dynamic and high-dimensional forecasting scenarios.

Table 4

Ensemble Methods data

Ref. №	Year	Model Name	Performance
1	2016	DBN Ensemble	MAPE 5.93
3	2020	COSMOS Ensemble	MAPE: 6.97
	2020	Ensemble HMMs	MAPE: 7.07
	2018	ML Ensemble	RMSE: 0.03, MAPE: 15.7
67	2015	BagNN	MAPE: 1.5-1.75
68	2017	BoostNN	MAPE: 1.42-1.43
69	2020	Bag-BoostNN	MAPE: 1.35-1.43
	2020	BagNN	MAPE: 1.42-1.5
	2020	BoostNN	MAPE: 1.46-1.47
	2020	BagRT	MAPE: 1.93-2.44

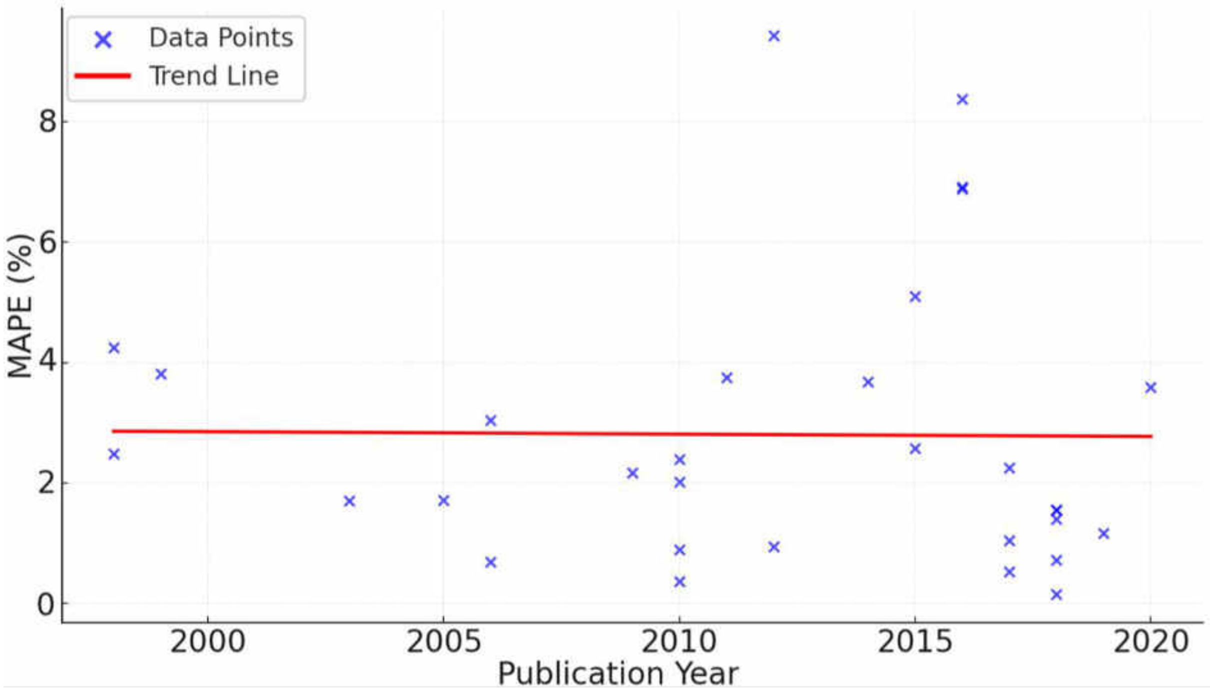

Fig. 5. MAPE Trends over Years for Fuzzy Logic Systems.

Ensembles of Hidden Markov Models demonstrated their utility in forecasting by capturing temporal dependencies and probabilistic transitions in load data. With a reported MAPE of 7.07, these models are particularly well-suited for medium-to long-term forecasting applications, where temporal correlations and uncertainty play a significant role.

An analysis of ensemble methods over the past decade reveals a clear trend of decreasing MAPE values, reflecting continuous advancements in ensemble techniques and their application. Early models such as COSMOS [3] reported MAPE values near 7, while more recent studies like Bagging Neural Networks and BoostNN [69] achieved MAPEs below 1.5. This improvement highlights the increasing sophistication of ensemble algorithms and their capacity to adapt to complex data environments.

Despite these advancements, ensemble methods as standalone approaches have certain limitations compared to their hybrid modifications. While hybrid models that combine ensembles with other approaches, such as statistical techniques, neural networks, or fuzzy logic systems, have demonstrated exceptional accuracy and robustness, pure ensemble methods often fall short in capturing the full complexity of load data. This comparative weakness results in a smaller pool of non-hybrid ensemble applications in the field. Their reliance on combining similar predictive models inherently limits their ability to address diverse and nonlinear dependencies present in load forecasting tasks.

Table 5

Statistical Methods data

Ref. №	Year	Model Name	Performance
3	2001	ARIMA + Operator Estimation	MAPE: 1.98
	2011	MA-C-WH	MAPE: 2.88
	2018	SARIMAX	MAPE: 0.7
	2008	Bayes	MAPE: 1.61
	2005	GARCH	MAPE: 9
	2009	GARCH	MAPE: 2.56
	1998	NPR	RMSE: 2.64, MAPE: 3.57
	2010	LSWR	MAPE: 1.34
	2016	Straightforward Models	MAPE: 1.35
	2020	PAR	MAPE: 1.62
	2006	Euclidean Similarity	MAPE: 1.3
	2012	Grey-STLF	MAPE: 3.27
	2015	Pattern-Based LF	MAPE: 2.97
	2017	South Korea Techniques	MAPE: 2.13
	2020	QRF + Temp/Humidity	MAPE: 1.37
	2005	Periodic TS	MAPE: <3
	2013	Seasonal-Trend	MAPE: 2.09
	2016	Time-series LF	RMSE: 0.03, MAPE: 14.8
8	1997	AR, ARX, ARIMA, ARMAX	MAPE: 3.60-4.07. RMSE: 20.84
70	1997	Regression + Weather Factors	MAPE: 2. Error standard deviation: 1.2-5.8
71	1997	Regression Models (Hourly)	MAPE: 2.45-4.49.
12	2000	ARIMAX	MAPE: 1.1-3.3.
18	2010	ARIMA	MAPE: 2.62-5.27, ANFIS: 10.21-18.72
20	2010	SAM	MAPE: 1.88, MAE: 110.21 MW
22	2011	ARIMA	MAPE: 13.05-19.13
	2011	AR	MAPE: 4.26-13.26
23	2011	Lifting Scheme + ARIMA	MAPE: 0.87, 0.66
	2011	ARIMA	MAPE: 1.03, 0.92
72	2011	Moving Average	MAPE: 3.84, Mean Error: 30.55 MW. 30-day Mean Error: 174.47 MW
73	2012	SPAM	MAPE: 1.88. MAE(MW): 110.21
74	2012	SARIMA	MAPE: 1.5
75	2013	OLS_LR	MAPE: 0.389, 0.918, 5.360, 4.677, 2.377
29	2014	HWT	MAPE: 2.045
76	2014	MT (Middle term)	MAPE: 8
	2014	ST (Short term)	MAPE: 5
	2014	MTD (MT detrending)	MAPE: 6
33	2016	ATSR	MAE: 3,894; MAPE: 6.959; RMSE: 4,127
34	2016	ARIMA	MAPE 9.97. RRMSE: 15.61

Ref. №	Year	Model Name	Performance
	2016	DSHW	MAPE 3.65. RRMSE: 5.47
77	2016	PLSR	MAPE: 1.34
77	2016	PCR	MAPE: 1.44
78	2018	SARIMA	MAPE: 3.91
79	2019	ARIMAX	MAPE: 2.86
80	2019	ARIMA	MAPE: 9.047, 10.787
	2019	SARIMA	MAPE: 9.532, 10.324
45	2020	MLR	MAPE: 6.9
	2020	FIR	MAPE: 7.86
46	2020	KSLF	MAPE: 1.99-2.27
69	2020	ARMA	MAPE: 2.21
81	2020	ARIMA	MAPE: 13.73. RMSE: 190
	2020	SARIMA	MAPE: 10.7. RMSE: 200
82	2023	GLMLF-B	MAPE: 3.73, MAE: 210 MW, RMSE: 249.74 MW
	2023	GAMLF-SL	MAPE: 2.18, MAE: 123 MW, RMSE: 148 MW
	2023	GAMLF-SLE	MAPE: 2.004-2.58

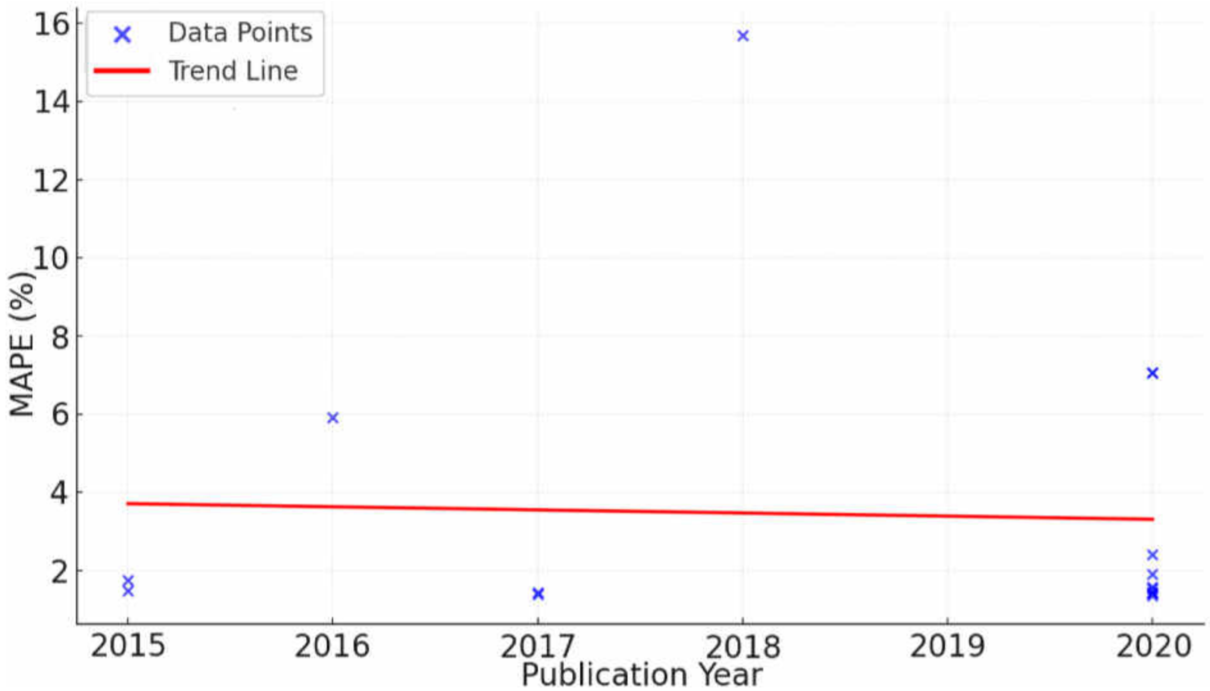

Fig. 6. MAPE Trends over Years for Ensemble methods.

- **Statistical methods** [3,8,12,18,20,22, 23,29,33,34,45,46,69-82] have historically been the cornerstone of load forecasting, providing foundational techniques for time-series analysis and prediction. These methods are based on mathematical modeling and have long been favored for their simplicity, interpretability, and computational efficiency. Widely applied techniques such as ARMA, ARIMA, and SARIMA (Seasonal ARIMA) have formed the basis for many forecasting systems, particularly in scenarios where the relationships between features are relatively straightforward and stationary.

Articles reveals the extensive application of statistical methods in load forecasting, spanning several decades. Early models, such as ARMA combined with Polynomial Regression [3] and Weighted Recursive Least Squares (WRLS), were among the first attempts to adapt these techniques for dynamic and online forecasting scenarios. These models performed effectively in capturing short-term temporal patterns, with early implementations achieving satisfactory performance metrics, including low MAPEs. For instance, ARIMA models with operator estimation achieved a MAPE of 1.98, demonstrating the adaptability of statistical methods to specific problem domains.

Over time, advancements such as SARIMA models [74,81] have enabled better handling of seasonality in load data. These models, which explicitly incorporate periodic components into their structure, have shown strong performance in forecasting daily and hourly loads, with MAPE values as low as 0.7–1.88. Additionally, approaches like Multivariate Adaptive Regression Splines introduced non-linear regression capabilities, further expanding the applicability of statistical methods to more complex forecasting tasks.

Despite these advancements, statistical methods face inherent limitations in their ability to process a large number of features. These models generally assume linearity and stationarity, which makes them less effective in capturing non-linear or dynamic patterns that are increasingly prevalent in modern energy systems. Furthermore, the need for extensive preprocessing such as deseasonalization and detrending adds complexity to their implementation, particularly when dealing with high-dimensional datasets or incorporating external factors like weather or socioeconomic variables.

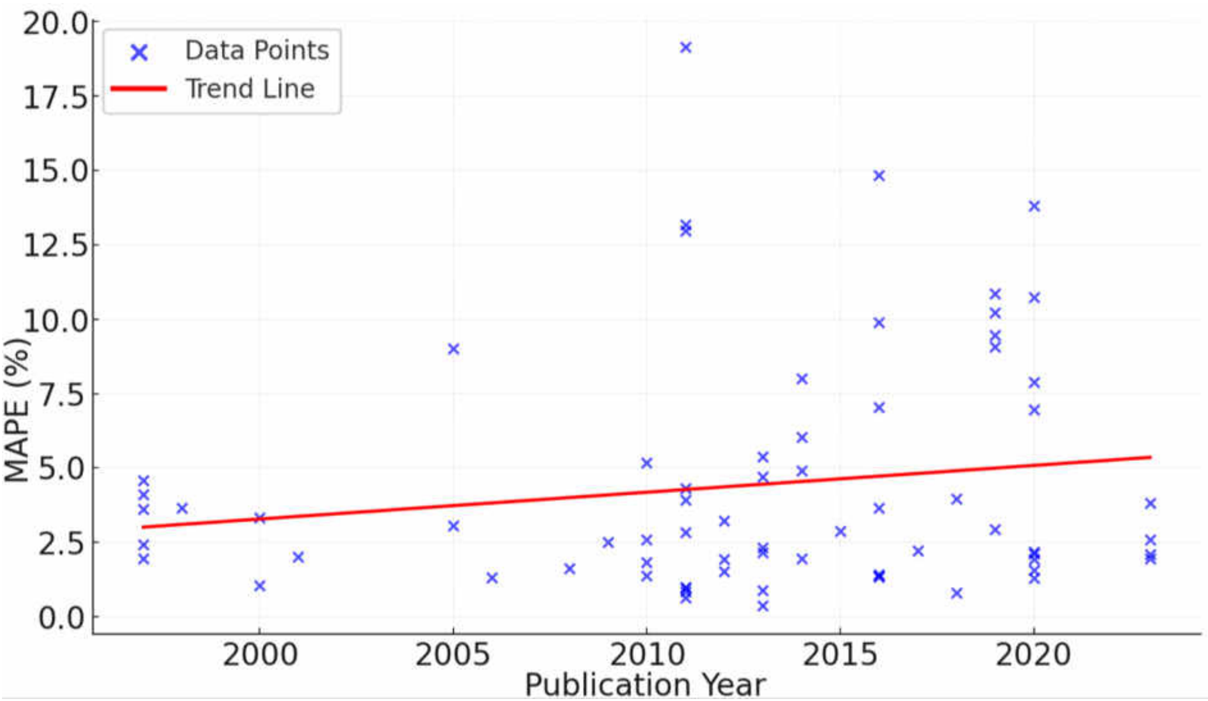

Fig. 7. MAPE Trends over Years for Statistical methods.

An analysis of the dataset indicates a notable trend in the performance of statistical methods over the years. While MAPEs reported in early studies were often low, this can be attributed to the simplicity of the datasets and limited scope of those studies. As the volume of research has grown and datasets have become more complex, MAPEs have generally increased. However, the overall trend in MAPE values suggests that statistical methods have largely maintained their performance levels over time. This stability reflects the maturity and reliability of these approaches, even as the complexity of forecasting challenges has evolved.

- **Hybrid methods** [1-3,15,17,18,20,33, 35,43,44,48,83-125] represent the most significant and diverse category in load forecasting research, combining strengths from multiple methodologies to address the challenges of modern energy systems. By integrating techniques such as AI, Fuzzy Logic, statistical models, and signal processing, hybrid models offer unparalleled flexibility, adaptability, and accuracy. One of the defining advantages of hybrid methods is their flexibility. By combining complementary approaches, hybrid models overcome the limitations of individual methods.

For instance, statistical models like ARIMA excel in capturing temporal dependencies but struggle with non-linearities, which hybrid approaches address through integration with machine learning or optimization techniques. A notable example is ARIMA + K-means Clustering, which leverages clustering to refine ARIMA predictions, achieving a MAPE of 5.1. Hybrid methods have also demonstrated substantial improvements in accuracy, particularly through the integration of AI and Fuzzy Logic. Recent advancements include models like LSTM-RNN + CNN, which combine the temporal strengths of recurrent neural networks with the spatial feature extraction capabilities of convolutional networks, achieving a MAPE of 1.34. Similarly, SAE + ELM (Stacked Autoencoders + Extreme Learning Machines) reported an MRE of 2.92, showcasing the ability of hybrid AI models to handle high-dimensional and dynamic datasets.

Table 6

Hybrid Methods data

Ref. №	Year	Model Name	Performance
1	2020	EMD + DL Ens.	MAPE 3.00
	2020	LSTM-RNN + CNN	MAPE 1.34
	2015	CNN + LSTM	MAPE 10.16
	2017	EWT + LSTM + Elman	MAPE: 10.93
	2019	ANFIS	MAPE: 2.876
2	2014	FCM + RBF	MAPE: 4.04
	2018	ACO + GA Fuzzy	MAPE: 3.9
	2013	SVM + FOA	MAPE: 3
	2009	GA + SVR	MAPE: 0.76; RMSE: 7.73; Max Error: 20.88
	2014	SVR + FA	MAPE: 1.8051
	2016	SVM + HS	MAPE: 4.579
	2016	SVM + FOA	MAPE: 3.679
	2009	SVM + GA	MAPE: 0.76
	2017	SVM + PSO	MAPE: 1.92
	2016	SVM + ABC	MAPE: 0.5268
	2005	SVM + SA	MAPE: 1.76
	2013	ANN + FOA	MAPE: 1.149; MSE: 1.421
	2014	K-means + ANN	MAPE: 15.34 (Data Set A), 16.69 (Data Set B)
	2002	ANN + AIS	MAPE: 2.52
	2017	WNN + Pre-filtering	MAPE: 2.41
	2013	ANN + FOA	MAPE: 1.149
	2016	ANN + FA	MAPE: 1.1808
	2013	ANN + CT	MAPE: 0.4935
	2014	ANN + NFIS	MAPE: 0.000396
	2010	ANN + AIS	MAPE: 2.457
	2015	ANN + WT	MAPE: 1.111
	2009	ANN + PSO	MAPE: 1.9882
	2018	ANN + GA	MAPE: 0.020
	2020	EMD + PSO + SVR	MAPE: 2.7510; RMSE: 0.0595; MAE: 0.0414
	2016	GHSA + FTS + LS-SVM	MAPE: 3.709; MAE: 14.358; RMSE: 18.180
	2018	GA + NARX	MAPE: 1.12; RMSE: 1.39; Variance: 0.00036

Ref. №	Year	Model Name	Performance
	2018	EMD + KF + BA-SVM	MAPE: 1.9052
3	2013	ARMA + GARCH	RMSE: 7.4, MAE: 0.2, MAPE: 14.5
	2000	ANN + Non-linear	MAPE: 0.8
	2020	ARIMA + K-means	MAPE: 5.1
	2012	SARIMA + PSO	RMSE: 4.9, MAPE: 2.19
	2013	SARIMA + SVM	RMSE: 9.4, MAPE: 2.73
	2008	HSPO + ARMAX	MAPE: 1.06
	2010	ARMA + GARCH + Wavelet	MAPE: 1.16
	2018	Non-linear + TS	MAPE: 0.81
	2002	MLP + SOM	MAPE: 1.15
	2009	NN + PSO	MAPE: 1.98
	2009	NN + CGA	MAPE: 1.46
	2013	SVR + DEKF + RBFNN	MAPE: 0.6
	2013	MFES + EMD	MAPE: 2.42
	2016	WT + Ensemble	MAPE: 2.02
	2017	EMD + DL	MAPE: 0.67
	2018	EV Impact Model	MAPE: 4.53
	2018	SSA + Reconstruction	MAPE: 0.59
	2019	Copula + DNN	MAPE: 2.36
	2019	MOFTL + ANN	MAPE: 4.59
	2019	BRNN + DBN	RMSE: 28.5, MAPE: 1.95
	2019	OP-ELM + LSTM	RMSE: 0.06, MAE: 0.05, MAPE: 0.13
	2020	MIMO + LSSVM	MAPE: 2.10
	2020	FFNN + Clustering	MAPE: 7.00
	2020	DBM + RBM	MAPE: 3.86
	2020	Fuzzy Clustering + K-means	MAPE: 1.63
	2004	Hybrid STLF	RMSE: 0.62, MAPE: 0.43
	2006	Hybrid FNN	MAPE: 1.96
	2008	ANN + Fuzzy + ARMA	MAPE: 1.85
	2010	SVM + ACO	MAPE: 1.98
	2013	WT + ANN	MAPE: 1.60
	2013	CB-FWNN	RMSE: 3.31, MAPE: 0.87
	2014	WT + GP	RMSE: 1.96, MAPE: 3.12
	2015	ANN + SSA-SVR	MAPE: 0.19
	2016	ELM + LM	MAPE: 0.21
	2016	Two-stage Adaptive	MAPE: 1.64
	2016	ANN + Clustering	MAPE: 3.5
	2016	Seasonality + ANN	MAPE: 0.85
	2016	EMD + PSO + SVR	RMSE: 0.06, MAE: 0.04, MAPE: 2.75
	2017	FFNN + PSO	MAPE: 1.41
	2017	GNN + WD-ELMAN	MAPE: 2.4
	2018	RF + EEMD	MAPE: 4.45
	2018	3-Stage Hybrid	MAPE: 17.6
	2018	2-Step Optimization	MAPE: 2.53
	2018	DWT + EMD + RVFL	MAPE: 2.08
	2018	Multiple Hybrids	MAPE: 1.91
	2019	LSTM + CLD	MAPE: 3.38
	2019	GA + PSO + BPNN	MAPE: 1.25
	2019	PSO + GSA	MAPE: 0.79
	2019	EEMD + ELM + GOA	MAPE: 0.46

Ref. №	Year	Model Name	Performance
	2019	GA + PSO + ANFIS	MAPE: 6.78
	2020	CEEMD + SSA	MAPE: 1.74
	2020	Hybrid SVM	MAPE: 0.04
3	2020	IAGA + SVR	MAPE: 20.4
	2020	Wavelet + NN	MAPE: 1.52
	2020	PSO + ANFIS	MAPE: 9.86
	2020	EGA + STLF	MAPE: 3.06
	2021	Wavelet + LSTM	RMSE: 0.93, MAPE: 2.67
	2021	FCM + RF + DNN	RMSE: 0.03, MAE: 0.08.
	2021	CNN + BiGRU	RMSE: 4.22, MAPE: 5.08
	2022	TCN + DenseNet	RMSE: 0.91, MAE: 0.87.
	2022	WNN + SAMF	RMSE: 0.79, MAPE: 1.08
	2023	HFSM + LSTM	MAPE: 2.21
83	1994	Hybrid Fuzzy-NN	MAPE: 0.65, 0.97, 1.22
84	1998	ARTMAP	MAPE: 6.5
85	1998	FNN + TS Inference	MAPE: 1.67
86	1998	ANN + GA	MAPE: 3.83
87	1998	NNIC	MAPE: 1.72-2.41
88	2000	Adaptive Load Model	MAPE:5.07
15	2004	AIFNN	MAPE: 1.619
	2004	GA + ANN	MAPE: 1.837
89	2004	FNN	MAPE: 3.5
90	2006	HFNNs	MAPE: 1.3024 - 5.3129
91	2008	Fuzzy-Neural	MAPE: 3.5
92	2008	ANFIS	MAPE: 0.66, 2.21, 1.03, 1.87, 0.04, 0.19, 0.99, 1.32
17	2009	Mamdani Fuzzy Logic +ANN	MAPE: 1.549-2.231
18	2010	ANFIS	ANFIS: 10.21-18.72
20	2010	Hybrid Model	MAPE: 2.14, MAE: 126.73 MW
93	2011	SR-SVR + CABC	MAPE: 2.387
94	2011	SVR + HCIA	MAPE: 1.766
95	2012	T2SDSA-FNN	MAPE: 1.4446, 2.0428
96	2012	LSSVM + FOA	MAPE: 1.305. MSE: 2476
	2012	LSSVM-CSA	MAPE: 1.959. MSE: 6308
97	2012	ARIMA-SVM	MAPE: 3.85
98	2013	FOA + GRNN	MAPE: 0.132, 0.541, 2.964, 2.107, 0.001
99	2013	SVR-DEKF-RBFNN	MAPE: 0.72
100	2013	WNN	MAPE: 0.09-0.49
101	2014	WGMIPSO	MAPE: 0.45, 0.7237, 0.6826, 1.82
102	2014	SVR-MFA	MAPE: 1.6909
103	2014	PSO + BPNN + GA-BPNN	MAPE: 0.335
104	2014	Pattern + Context Analysis	MAPE: 3.23- 4.34
105	2014	DWT + ANN	MAPE: 0.6.
	2014	DWT + SVM	MAPE: 0.02
106	2014	SVR + MFA	MAPE: 1.85, 6.13, 6.15
107	2015	Wavelet + BNN	MAPE: 0.4383
108	2015	GMDH + DWT	MAPE: 0.959
	2015	ANN + DWT	MAPE: 1.252
109	2015	WT-ELM-MABC	MAPE: 0.55-1.87
110	2015	GABPNN	MAPE: 1.02

Ref. №	Year	Model Name	Performance
111	2015	2xANN	MAPE: 0.85
33	2016	ANFIS	MAE: 1,475; MAPE: 2.299; RMSE: 1,571
35	2016	DNN + RBM	MAPE: 3.2-8.84. RMSRE: 4.1-10.62
112	2016	HFM	MAPE: 10.25
113	2016	HW+NN	MAPE: 5.64, 8.34
114	2016	ELM	MAPE: 0.54
115	2017	SDPSO + ELM	MAPE: 2.182. MAE(MW): 22.93
116	2017	LSTM-RNN	MAPE: 2.13-2.57
117	2017	LSTM-RNN	MAPE: 0.0535, RMSE: 0.0702
118	2018	ANN + Fuzzy Logic	MAPE: 3.9, 4.8
	2018	ANFIS	MAPE: 4.91, 6.39
119	2018	NARX-NN + SVR	MAPE: 8-15
120	2018	AS-GCLSSVM	MAPE: 0.5596
43	2019	iForest + LSTM	MAPE: 0.66-0.92
	2019	iForest + BP	MAPE: 1.49-2.50
121	2019	MI + ANN + mEDE	MAPE: 1.24
	2019	MI + ANN	MAPE: 3.81
122	2019	FA-SVM	MAPE: 1.56-1.79
123	2019	HP (Hybrid parallel topology)	MAPE: 1.14-1.31
124	2019	ANN-IEAMCGM-R	MAPE: 3.18, 3.89, 3.55, 7.3
17	2020	ISO-TS-RBF-RFNN	MAPE: 6.82
	2020	SO-TS-RBF-RFNN	MAPE: 7.62
	2020	GA-LSTM	MAPE: 6.92
44	2020	GRU + CNN	MAPE: 2.8839. RMSE: 1203.23
48	2020	GA-LSTM	MAPE: 0.027
125	2021	CNN + GRU	MAPE: 3.73

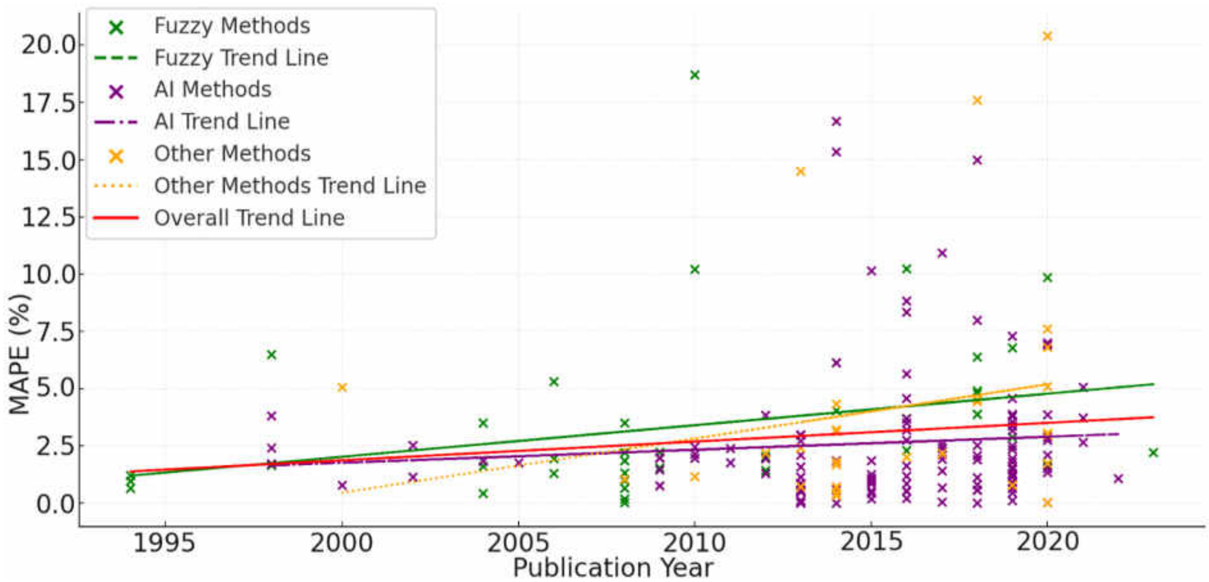

Fig. 8. MAPE Trends over Years for different Hybrid Methods.

Hybrid methods incorporating Fuzzy Logic have proven especially effective in handling uncertainty and ambiguity in load data. Models like ACO + GA Fuzzy achieved a MAPE of 3.9, demonstrating the adaptability of fuzzy systems when enhanced with optimization techniques like Genetic Algorithms (GA) and Ant Colony Optimization (ACO). Similarly, ANN + NFIS

(2.30) integrated neural networks with Neuro-Fuzzy Inference Systems to capture non-linear dependencies, achieving highly competitive performance with MAPE values as low as 0.000396. These approaches illustrate the strength of hybrid fuzzy systems in managing complex dependencies while maintaining interpretability. Hybrid models involving Artificial Intelligence have pushed the boundaries of load forecasting.

By integrating multiple AI techniques, these hybrids address specific limitations of standalone systems. For example, CNN + LSTM enhances short-term load forecasting by combining convolutional networks for spatial analysis with LSTMs for temporal patterns, though it reported a higher MAPE of 10.16 in certain contexts. Probabilistic AI hybrids, such as SARSA + DBN, combine reinforcement learning with probabilistic modeling to achieve robust performance, with RMSE values as low as 0.02. Hybrid methods also incorporate diverse combinations beyond AI and Fuzzy Logic. Wavelet Transform + Neural Networks + Regression demonstrated superior multi-horizon forecasting, achieving MAPEs of 0.27 for 1-hour predictions and 1.42 for 24-hour predictions. Models like EMD + DL Ensembles integrate signal processing with deep learning ensembles to achieve MAPEs of 3.00, highlighting their effectiveness in capturing both temporal and frequency-domain patterns. The dataset reveals a continuous increase in publications on hybrid methods, reflecting their growing importance in load forecasting research. Early hybrid models, such as Kalman + Structural Time-Series, laid the groundwork for integrating statistical and probabilistic approaches.

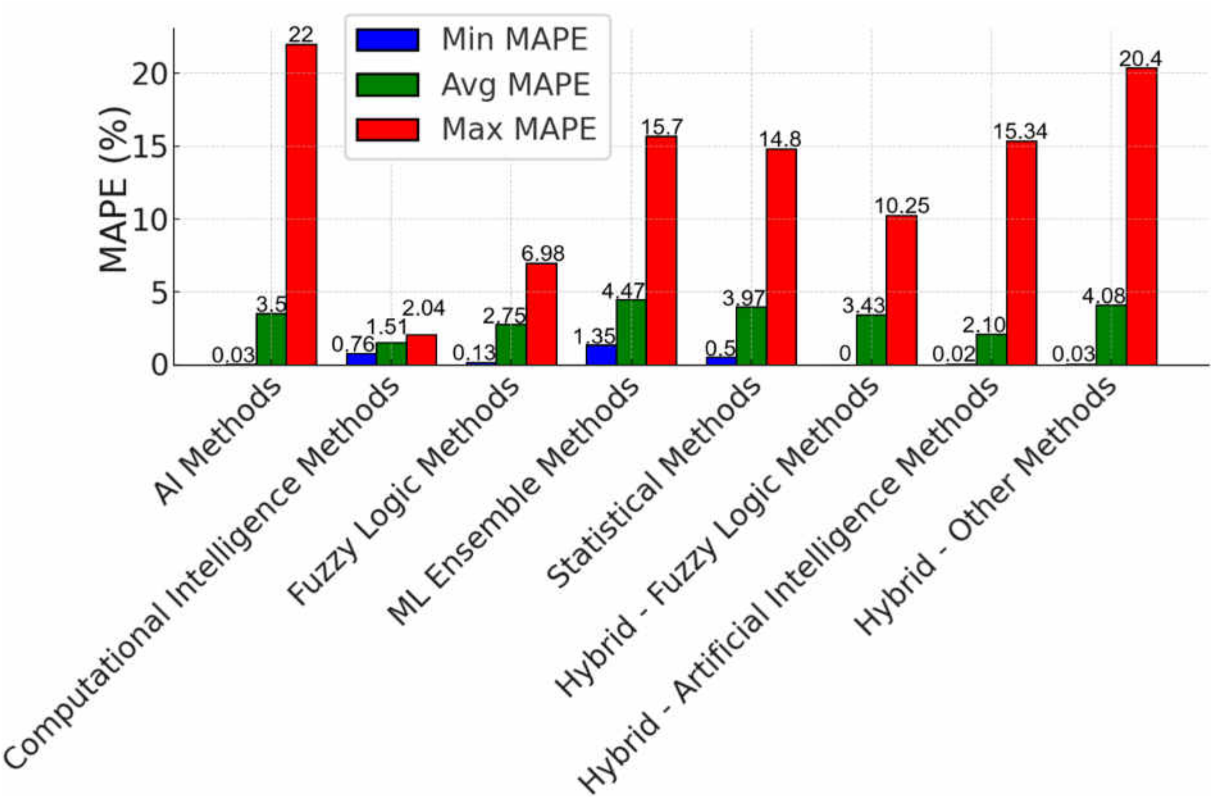

Fig. 9. MAPE performance for different model's type.

Over time, hybrid methods have become increasingly complex, incorporating advanced AI, fuzzy systems, and signal processing techniques. This growth trend is accompanied by a steady improvement in accuracy, with MAPEs declining significantly over the years.

While early hybrids reported MAPEs of 10–15, recent models often achieve MAPEs below 5, with some reporting values as low as 1–2. Hybrid methods have become the backbone of modern load forecasting research, offering unmatched flexibility, adaptability, and accuracy.

By integrating the strengths of diverse methodologies, these models address the non-linear, seasonal, and uncertain characteristics of load data effectively. The continuous growth in hybrid methods publications and their proven ability to outperform traditional and standalone models ensure their pivotal role in the future of energy forecasting.

SUMMARY AND CONCLUSIONS

The analysis underscores the exceptional potential of hybrid methods in load forecasting, which have consistently outperformed standalone techniques across all key metrics. AI methods demonstrate considerable potential, with an average MAPE of 3.93, highlighting their ability to achieve precise predictions under optimal conditions. However, their high maximum MAPE of 23.5 suggests occasional challenges in handling certain datasets or modeling scenarios. In contrast, Fuzzy Logic Methods stand out for their consistent performance, achieving a minimum MAPE as low as 0.13 and maintaining average MAPEs below 3, showcasing their robustness in managing uncertainty and vagueness in data.

Hybrid approaches that integrate Fuzzy Logic and Artificial Intelligence exhibit exceptional performance, with Hybrid Fuzzy Logic Methods achieving a minimum MAPE of 0.000396 and Hybrid AI Methods reaching as low as 0.03.

The continuous decline in MAPE values over the years reflects the transformative impact of hybrid models, with modern approaches frequently achieving MAPEs below 5 and approaching near-perfect predictions in some cases. This progress highlights the increasing adoption of hybrid techniques and their pivotal role in overcoming the limitations of traditional methods.

Future research should prioritize further development and optimization of hybrid approaches. Enhancing integration strategies between methodologies, refining feature selection processes, and leveraging advanced computational tools can unlock even greater forecasting potential. By focusing on hybrid systems, researchers can drive breakthroughs that not only achieve superior accuracy but also ensure the reliability and adaptability required for the evolving demands of modern power grids.

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