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Literature Review for Large-Scale Aggregate Load Forecasting Using Large Volumes of Smart Meter Data[#]

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ABSTRACT

Large-scale short-term aggregate load forecasting involves predicting energy consumption across geographic areas or large sets of users. This practice is crucial in power systems, particularly for energy suppliers. The widespread installation of smart metering technology has facilitated the collection of extensive data on user load profiles. By incorporating such granular data, large-scale load forecasting becomes more accurate and reliable, capturing the variability and trends across consumer segments. However, transforming smart-meter data into effective load forecasting models faces significant challenges. For instance, smart-meter data presents issues related to its high volume, variety, and fine-grained temporal resolution. Consequently, different techniques can be considered to mitigate these issues before applying forecasting models to the data. This paper conducts a two-step literature review to provide insight into the data, forecasting approaches, and model evaluation used in large-scale, short-term aggregate load forecasting from smart-meter data. We propose classifying the different forecasting approaches into integrated, residential-based, and cluster-based strategies. We additionally draw insight into the effect of data volume on forecasting models, performance comparison between forecasting approaches, and the tendency of model complexity in this research domain.

Keywords: load forecasting, big data, artificial intelligence, large-scale, large volume, energy supplier, smart grid.

NOMENCLATURE

Abbreviations	
AT	Attention Mechanism
CER	Commission for Energy Regulation
DL	Deep Learning
DTW	Dynamic Time Wrapping
GNN	Graph Neural Network
GPU	Graphical Processing Unit
ENTSO-E	European Network of Transmission System Operators for Electricity
LP	Load Profile
LR	Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
K-NN	K-Nearest Neighbors
MLP	Multi-Layer Perceptron
NRMSE	Normalized Root Mean Square Error
NYISO	New York Independent System Operator
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
STLF	Short-term Load Forecasting
SVM	Support Vector Machine
TB	Tree-Based

1. INTRODUCTION

In the context of energy transformation, the digitalization process facilitates the collection and processing of vast amounts of data [1]. This advancement enables more accurate consumption predictions and management of energy systems [2], contributing to smarter, more resilient, and more sustainable energy systems [3, 4]. For instance, the roll-out of smart meters has allowed for more granular and detailed data [5]. These data can benefit many energy stakeholders, given that smart meters, located at endpoints, can be aggregated in various ways based on specific criteria or shared characteristics [6]. For example, meters situated in a particular geographical area (such as a neighborhood), connected to a certain feeder, transformer, substation, or the entire distribution system, or those belonging to a specific energy provider can be grouped to inform the forecasting system at that level [7].

These new sources of data exhibit characteristics such

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as heterogeneous energy usage patterns and temporal granularity across large volumes of multiple load profiles. Consequently, this requires a rethink of data-processing techniques and model selection to effectively incorporate these properties into forecasting models. For instance, traditional forecasting approaches often rely on non-granular data aggregation and do not consider variability. Meanwhile, new approaches can consider clustering to address, for example, variability in load profiles. With clustering, user load profiles are grouped by similarity, allowing models to train under a lower variability scenario, improving overall performance [8].

Although the available literature is extensive and literature reviews exist, the relationship between large volumes of smart-meter data and the forecasting approaches on these data is often overlooked. For example, the authors in [9] presented a literature review focused on load forecasting, avoiding data volume's impact on developing a forecasting system. Meanwhile, authors in [10] examined load forecasting models within the context of big data analysis. However, they emphasize the models themselves rather than the approaches or workflows of the forecasting process. Additionally, their focus is more on multivariate forecasting models that use exogenous variables, such as weather data, rather than smart-meter data at the household level. Thus, a potential research gap in applying short-term aggregate load forecasting to the increasing availability of user data, along with the lack of a comprehensive review of the existing literature, motivates this study to explore large-scale aggregate load forecasting using smart-meter data.

We structure the remainder of this paper as follows: In Section 2, we introduce our research approach to conduct our literature review. In Section 3, we present the primary results on large-scale aggregate load forecasting using vast data volumes from the perspectives of data, forecasting approaches, and model evaluation. Specifically, we categorize different approaches for forecasting aggregate load based on user-side data. In Section 4, we draw some insight into these findings. Finally, in Section 5, we summarize the findings and suggest directions for further research.

2. LITERATURE REVIEW METHODOLOGY

We consider the principles outlined by [11], [12], and [13] to design our two-step literature review process, illustrated in Fig. 1.

The first step is a scope review [14] that provides the first insight into load forecasting using a large volume of data. We identified two research domains from it: load forecasting from a single system load profile using additional exogenous variables and load forecasting from multiple user load profiles. The research object of the former case is system load profiles, as seen for European Network of Transmission System Operators for Electricity (ENSTO-E) [15], New York Independent System Operator (NYISO) [16], which gives the forecast at the system level. In contrast, the latter case focuses on employing and manipulating multiple smart-meter load profiles to make short-term forecasts at either the residential or aggregate level. Drawing from this insight and aligning with our research question, we limited our literature review to aggregate (or large-scale) forecasting systems using multiple user load profiles.

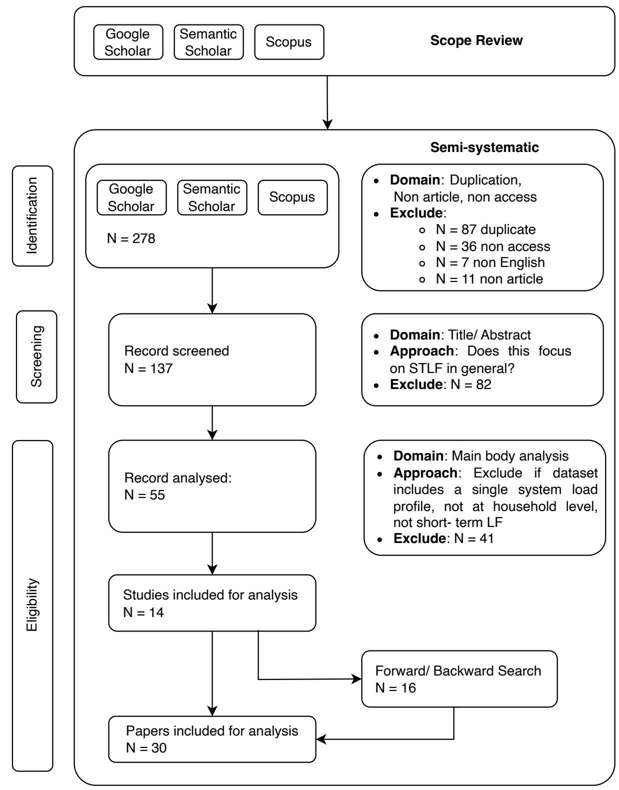

Fig. 1 Two-step literature review process.

The second step is a semi-systematic literature review, consisting of three different phases: 1) *identification*, 2) *screening*, and 3) *eligibility*. In the *identification* phase, we used the search string ((*"large scale"* OR *"Big Data"*) AND (*"load forecasting"*)) between 2010 and 2024 to filter paper titles in three databases: Google Scholar, Semantic Scholar, and Scopus using Publish or Perish 8 [17]. We then used the same search string tailored with (*"smart-meter data"* OR *"user-level data"* OR *"residential data"* OR *"household data"*) in the keyword filter. From our *identification* phase, we collected 278 studies. After removing duplicates, book chapters, lectures, non-English studies, non-access [1] study, 137 studies remain. In the *screening* phase, we excluded the studies whose title and abstract specifically mention *medium-* or *long-term* load forecasting. We also excluded articles targeting load forecasting in specific areas such as charge stations, transportation, and industrial customers. With it, we narrowed our database down to 55 studies. In *eligibility* phase, we again filter the current database to focus on large-scale short-term aggregate load forecasting using smart meter data by evaluating the models and data for training. This process left us with 14 studies. Later, we applied a forward search (that is, studies citing the original work) using Litmaps [18] and a backward search (that is, studies cited in the original work) by analyzing the references, which yielded an additional 16 studies. In the end, we initiated the study with a total of 30 studies.

3. LITERATURE REVIEW

We structure our findings as follows: in Section 3.1, we provide an overview of the datasets in the analyzed studies; meanwhile, in Section 3.2, we categorize the various forecasting approaches identified in the literature; and finally, in Section 3.3, we present a summary of the model evaluation appearing in the analyzed studies.

3.1 Big Data management

We analyzed the included studies based on the dataset's characteristics and the Big Data solution for storage and processing.

3.1.1 Datasets

The datasets used in load forecasting in the large-scale context vary according to the use case and intention. In order to provide a holistic overview of the datasets, we used Big Data's 5V as Big Data is often characterized on those terms [5]. These are:

Volume: refers to the massive amount of data generated from various sources such as smart meters and weather stations [19]. Traditional toolkits for modeling might struggle to handle the sheer volume of data collected from smart meters [20]. In the scope of this review, the dataset can contain up to terabytes of data [21], order of hundred thousand houses [22] or millions of records [23].

Velocity: denotes the speed at which new data are generated and the pace at which data move from one point to the next, which is crucial for short-term load forecasting. Within our included and analyzed studies, velocity usually ranges from 15 minutes [7, 24], 30 minutes [25, 26] and one hour [21] to daily [22], aligning with the needs for short-term load forecasting.

Variety: denotes the various types of data collected, including structured data (e.g., time-series load data [21, 27]), semi-structured data (e.g., weather data [8, 19]), and unstructured data (e.g., user survey, questionnaire [28]). These exogenous features are important in load forecasting. For example, the effect of meteorological data on the predictive power of load forecasting systems is well-studied in [29, 30]. The composition of user types also contributes to the variety of the datasets. For example, the dataset covers the mix of rural areas and urban areas [31, 32] and focuses on a mixture of both residential customers and business [23, 33], adding one more layer of difficulty in discovering the electricity usage pattern.

Veracity: denotes the quality of the data, which can vary greatly. This can include the accuracy of the data, the trustworthiness of the data source, and how relevant the data are to the problem. The datasets we analyzed usually use public datasets such as the Irish Smart meter data trial [31], Low Carbon London [32], Pecan Street dataset [34]; or private datasets provided by energy suppliers such as in [7, 33] and, lastly, synthetic data (i.e., simulated) from software applications such as EnergyPlus [35, 36]. The public and private datasets still suffer from missing value, and it is usually handled by data imputation techniques [7, 19] or elimination of entire erroneous time series [37].

Value: denotes our ability to transform energy data into value. Insight derived from energy data can improve consumer engagement and efficiency, enhance system reliability, uncover energy consumption patterns, and guide competitive marketing strategies [38]. For instance, "Data-as-an-energy" suggests that big data analytics can yield significant energy savings. "Data-as-an-exchange" means integrating and exchanging energy system data with other sources, which can enhance its overall value. "Data-as-an-empathy" implies that big data analytics can improve energy services, better address user needs, and increase consumer satisfaction [38].

3.1.2 Big Data solution for storage and processing

Many industry-standard solutions exist to store a large volume of user data. In terms of storage, NoSQL databases are designed to handle unstructured and semi-structured data efficiently, allowing flexibility in storing various data types without the rigid schema requirements of traditional relational databases [19, 24]. In [39], the authors provided a performance benchmark of different databases, e.g. Cassandra, Elasticsearch, MongoDB, and HBase, to analyze Smart Grids data and concluded that

[1] The non-excess literature are usually black links in Google Scholar and cannot be found outside.

Cassandra satisfies all the Big Data characteristic requirements and exhibits the highest overall performance in benchmarked operations such as READ, WRITE in a database. Meanwhile, for processing tasks, scalable forecasting systems within the realm of Big Data may require distributed computing-supported solutions such as Spark [20, 40, 41] and Hadoop [21].

3.2 Forecasting Approach

We categorize the studies analyzed into three main approaches [2]: integrated load forecasting, residential-based load forecasting, and cluster-based load forecasting, comprising a total of six distinct branches, as depicted in Fig. 2). These approaches transform multiple load profiles at the user level into an aggregate forecast for an area, neighborhood, city, country, or even balancing groups relevant to energy suppliers.

3.2.1 Integrated load forecasting

The integrated approach applies transformation on all load profiles in the training set before forecasting only at the aggregate level. The most popular and simplest transformation is to sum all available load profiles into an aggregate load profile [20, 21]. Exogenous variables are usually incorporated as input to achieve better performance on a large scale. [20] indicates that at the aggregate level, the correlation between the load profile and the weather data is greater than at the user level. The models tested in this approach include, but are not limited to, Linear Regression (LR), Tree-Based (TB) models [20, 42, 43] and are accelerated by parallel training. In addition, to increase accuracy for load forecasting, similar periods along the temporal axis are grouped for training [21]. The practice of grouping similar periods is similar to clustering (see Section 3.2.3).

In addition to the aggregation step (see Fig. 2), a more complex transformation can be applied. For example, authors in [23] treated each customer as a feature and performed a Hierarchical Principal Component Analysis (PCA) to reduce the dimensionality of the data but keep the temporal axis intact. A model can be fit to the transformed data to forecast energy consumption at the aggregate level.

3.2.2 Residential-based load forecasting

This approach involves training and forecasting individual load profiles and aggregating the forecast result to achieve the aggregate-level prediction. We refer to two distinct approaches from our classification: *Multiple-model* and *Global-model* approach.

[2] In our writing, to be consistent, approach indicates the workflow from data to produce forecast, and method indicates both forecasting model and forecasting approach.

The *Multiple-model* approach requires training a model [27] (or models [21]) for each load profile independently. However, this approach can introduce a high computational cost, as the training time scales linearly with the number of load profiles in the sequential setup. To mitigate this problem, [22] exploited parallel training and shared memory in Graphical Processing Unit (GPU) to build each Multi-Layer Perceptron (MLP) model per load profile for each user, with a total of 160000 users.

On the other hand, the *Global-model* approach aims to produce a general forecast model that is capable of accurately forecasting even at the residential level. The feasibility of this approach lies in the expressiveness of the Deep Learning (DL) models and the increasingly available smart meter data at the residential level for training. A variant of this approach is transfer learning, in which a general model is developed and adapted to different household data [44]. The models used in these regimes are usually complex, such as Recurrent Neural Network (RNN) [45] and transformer models [46]. Another type of DL architecture that simultaneously leverages the information of all load profiles is Graph Neural Network (GNN). These models discover the hidden relations between load profiles themselves and perform load forecasting in every load profile simultaneously. The authors in [47, 48] evaluate the GNN-based models in aggregate Short-term Load Forecasting (STLF) and find positive results.

3.2.3 Cluster-based load forecasting

In this approach, by analyzing customer profiles, similar customers are grouped to improve the performance of load forecasting systems [49]. Consumption demand is highly volatile at the residential level due to customer behavior, but by clustering similar profiles, forecasting models can more easily identify common patterns in training data, leading to more accurate predictions. Two approaches can be taken to leverage the similarity between customers:

On the one hand, the *Cluster-based aggregate* approach first aggregates similar load profiles within a cluster to generate a single load profile. This load time series typically exhibits a smoother trend and adheres to consistent patterns, from which a model can learn [24, 26]. The model can then learn from this load profile and produce a single forecast. The forecast outputs of each cluster are then aggregated to produce a single load forecast [7, 8, 19]. The forecasting models usually used for this approach range from statistical models [50], LR, Support Vector Machine (SVM), MLP to TB models [8, 24, 26].

On the other hand, the *Cluster-based global* approach leverages similar patterns of profiles within the group to

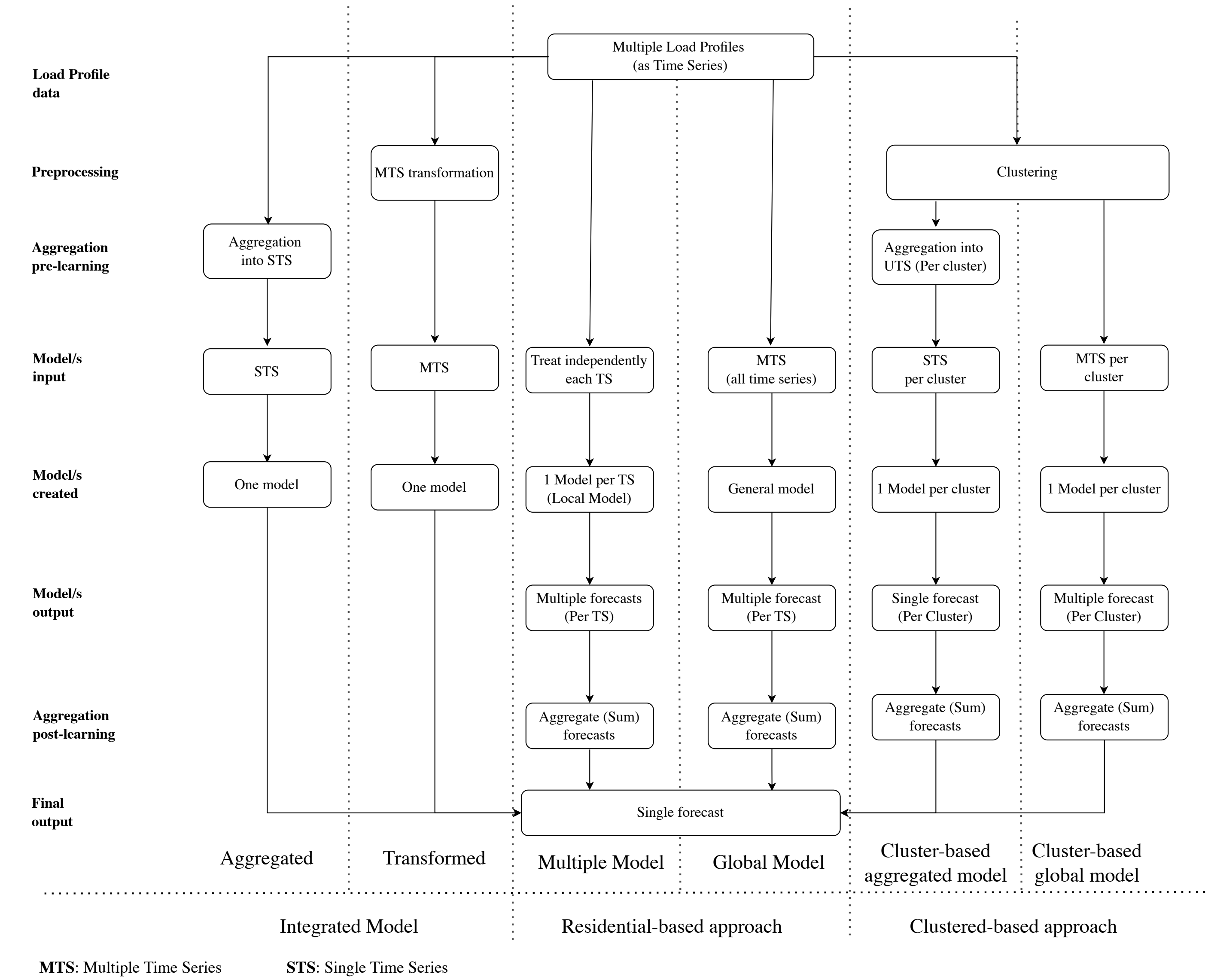

Fig. 2 Overview of forecasting approaches.

produce accurate forecasts at the residential level [45]. This approach is very similar to the global-model approach, with an additional clustering step to reduce heterogeneity within the training dataset. We have not found any study evaluating this load forecasting approach at the aggregate level.

A critical step for *cluster-based* approaches is to identify the similarity between customers. A common approach is to directly compare historical loads in a predefined period [7, 50]. Besides, the quantities engineered from the load profiles, such as *the load ratio, the average daily load* can also classify similar customers [25, 41].

The most popular method for clustering is k-means [51]. In the standard implementation of k-means, the time and space complexity of k-means is linear to the number of points, which implies that it is scalable to the size of the dataset. However, the performance of k-means is prone to outliers and initialization of centroids. This disadvantage can be overcome by k-medoids [52], k-medians [33], DBSCAN [27] and hierarchical clustering [21], but their time complexity and ease of implementation make them less popular than k-means [53].

Most clustering algorithms depend on the notion of distance metrics between two entities, e.g., customer profiles. Euclidean distance is the most prominent metric for measuring the similarity between customers [51]. Alternatively, in terms of comparing historical load, Dynamics Time Wrapping (DTW) is sometimes used to take into account the speed of the two time series [49]. However, this metric takes quadratics time complexity in terms of temporal axis compared to linear time in Euclidean metrics, making it less favored when dealing with extensive recorded periods.

Lastly, to determine the optimal number of clusters, two of the most popular methods are using the Silhouette score [50] and the elbow method [24]. In contrast to these techniques, the optimal number of clusters can also be chosen to minimize validation errors after the forecasting step [7].

3.3 Model evaluation

Model evaluation is an important step in assessing forecasting models' performance. To objectively evaluate the model, practitioners and researchers use error metrics. In the literature, we observed that metrics that are independent of scale and express error as a relative deviation from the actual values are used more frequently. Among the articles analyzed, Mean Absolute Percentage Error (MAPE) is the most common metric for load forecasting, followed by Normalized Root Mean Square Error (NRMSE). However, there are two different definitions of NRMSE in the literature [8, 54], which complicates the performance comparison.

In terms of scale-dependence metrics that produced an error in the power unit, the most frequently used are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). When evaluating at the aggregate level, it is important to take into account the scale of aggregation and the forecast horizon.

In addition, a common practice in model evaluation is to compare the proposed methods with the existing literature. In terms of forecasting models, from our observation, only one of 24 articles includes a simple prediction such as average mean as a baseline model [27]. Most of the time, proposed models are only compared with other models, e.g., SVM, MLP [27, 47, 48] which are well-studied in the literature. However, these models may not be used at an industrial level and do not give further insight into how to compare the proposed method with basic and easy-to-implement models. In contrast, studies proposing forecasting approaches often provide quantitative assessment compared to the aggregated approach, which is usually used from the industrial perspective [8, 20, 26].

Lastly, to ensure compatibility and transparency, common benchmark datasets are also important in model evaluation. This concept is popular in various research domains, such as time series forecasting [55]. In terms of large-scale STLF, the authors in [36] have introduced BuildingsBench [56], a platform to benchmark the STLF models. The dataset comprises both real smart-meter data collected from residential and commercial buildings, as well as simulated smart-meter data representing 900,000 buildings. Such efforts are crucial in facilitating the comparison and improvement of forecasting models in the field.

4. DISCUSSION

Our literature review examines data used in large-scale STLF and categorizes the analyzed studies into six forecasting approaches. In this section, we discuss the performance comparisons between these approaches, the relationship between data volume and forecasting methods, and the trend toward increasing complexity in forecasting models within this research domain.

Performance comparison between different approaches: Researchers have made several attempts to compare the effectiveness of different forecasting approaches. For example, in [27], a performance comparison between the *integrated approach* and the *multiple-model* approach on 69 household data demonstrates that the former performs better around (maximum) 1% in MAPE metrics. On a much larger scale and hence more heterogeneous, authors in [22] built each MLP model per load profile for 160000 user datasets and achieved better performance than the integrated approach of 0. 32% in MAPE. These results demonstrate some potential in STLF from the residential level. The *cluster-based* approach adds some flexibility to the forecasting since the number of clusters can be chosen to maximize the performance of the model. For instance, authors in [8, 26] conducted a thorough evaluation of the number of clusters in the Commission for Energy Regulation (CER) dataset [31] and suggested that an optimal number of clusters could significantly reduce forecast errors. Furthermore, in the *integrated approach*, by transforming the original load profiles via PCA and then training the model with reduced features, the experimental results in [23] suggested that this method could produce superior results compared to the aggregate and cluster-based approaches.

Effect of data volume on forecasting methods: The proliferation of available training data constraints the forecasting methods. Authors in [42] pointed out that the load forecasting system for Big Data should possess a fast parallel computing characteristic. Memory is also a factor to consider. For instance, although K-Nearest Neighbors (K-NN) is a straightforward forecasting model, it is unsuitable for Big Data applications due to its demand for considerable memory to store all data points for prediction [20]. Other methods, such as LR and TB models which support parallel computing, are used widely [42, 43]. These models are also implemented in distributed computing solutions such as MLLib in Spark [41], making them more accessible to practitioners. In terms of forecasting approaches, when entering the regime of Big Data, the most common approach for load forecasting is still to aggregate household load profiles together [20]. In the scope of our review, only a handful of studies, for example, [8, 26], consider varying the number of load profiles in the cluster-based aggregate approach and discover that increasing size of datasets can increase the performance of the proposed method. However, the evidence on the effects of increasing data volume on a proposed model remains fragmentary since most studies report the results with their predefined dataset without changing the size. We believe that this research question deserves to be explored in more in-depth reviews.

Towards more complex methods: Traditionally, large-scale STLF are usually studied using Machine Learning (ML) algorithms, and the aggregated approaches (cluster-based or not) are performed to incorporate all information from smart-meter data. As deep learning models advance in load forecasting, there is a growing focus on zero-shot STLF, where a pre-trained model [28, 57] is tested on a new dataset without further adjustment, and transfer learning [44, 58], where a pre-trained model is fine-tuned for a specific domain. These models can provide a more accurate forecast. In terms of forecasting approach, more and more studies focus on building scalable deep learning methods that can handle large datasets with alternative approaches to traditional ones. For example, by applying spectral clustering to the K-nearest neighbor graph derived from the CER dataset [31], the approach proposed in [59] can handle up to more than 6000 time series collected in one year and a half. At the same time, the work in [22] shows promise in the individual-based approach in handling large datasets through parallel computing and memory management in GPU.

5. CONCLUSION AND OUTLOOK

Our two-step literature review examines various methods and frameworks for short-term aggregate load forecasting on a large volume of smart-meter data. We place emphasis on the data and categorize forecasting approaches into three primary classes: integrated, residential-based, and cluster-based approaches. We also provide insight into the performance comparisons between different approaches. Various remarks on the potential and constraints of the existing methods are discussed. However, we acknowledge that the scale of this study is still limited, and certain areas of load forecasting using a large volume of smart-meter data are not fully covered. For example, the literature on cluster-based approaches is not included in the search string and is found mainly using backward/forward searches. For future research, our aim is to improve the search protocol to cover more studies on large-scale aggregate STLF, develop the forecasting approaches categorization proposed in this study, and provide a more comprehensive quantitative assessment between different forecasting approaches.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

Statement: During the preparation of this work, the author(s) used DeepL [60] and ChatGPT [61] to paraphrase and fix grammatical mistakes. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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