Trade-off Clustering Approach for Multivariate Multi-Step Ahead Time-Series Forecasting

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Abstract: Time-Series forecasting has gained a lot of steam in recent years. With the advent of Big Data, a considerable amount of data is more available across multiple fields, thus providing an opportunity for processing historical business-oriented data in an attempt to predict trends, identify changes and inform strategic decision-making. The abundance of time-series data has prompted the development of state-of-the-art machine learning algorithms, such as neural networks, capable of forecasting both univariate and multivariate time-series data. Various time-series forecasting approaches can be implemented when leveraging the potential of deep neural networks. Determining the upsides and downsides of each approach when presented with univariate or multivariate time-series data, thus becomes a crucial matter. This evaluation focuses on three forecasting approaches: a single model forecasting approach (SMFA), a global model forecasting model (GMFA) and a cluster-based forecasting approach (CBFA). The study highlights the fact that the decision pertaining to the finest forecasting approach often is a question of trade-off between accuracy, execution time and dataset size. In this study, we also compare the performance of 6 deep learning architectures when dealing with both univariate and multivariate time-series datasets for multi-step ahead time-series forecasting, across 6 benchmark datasets.

1 INTRODUCTION

Large volume of data are daily generated and stored in capacious databases, in hopes of being exploited later on (Oussous et al., 2018). These data can be stored in different formats and structures. A particular type of data are time-series data. Time-series is a set of sequential data collected through repeated measurements over time. When a time-series describes a single variable, it is referred to as univariate time-series. For example, in weather forecasting, past recorded temperature values are used to predict future temperatures. On the other hand, when it involves multiple variables, it is referred to as multivariate time-series. An example of a multivariate time-series forecasting is the forecasting of the future price of Bitcoin based on historical times series of the price itself, as well as other variables such as volume and date-derived features. The plethora of time-series data in recent years has enriched the field of Big Data and prompted the development of machine learning techniques capable of dealing with the complexity associated with such data, whether it be for forecasting, classification or clustering purposes. Various statistical models have been proposed over the years, exclusively designed for univariate time-series forecasting (Box, 1970). The main downside with most classical time-series models is that they tend to perform poorly on nonlinear data and are generally more suited for univariate time-series forecasting.

The limitations associated with statistical techniques have motivated the development of machine learning algorithms, such as, support vector regression (SVR), decesion trees, XGBoost, AdaBoost and deep neural network models, among others. Among all cited algorithms, deep neural networks have managed to draw significant attention.

These models are able to find temporal structures, model seasonality and temporal dependencies in sequential data. They have gained quite a reputation these last years and have been implemented across multiple fields for resolving numerous problems such as natural language processing ,image detection and recognition, stock exchange forecasting, electricity load forecasting etc.

When dealing with neural networks for time-

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series forecasting, multiple forecasting approaches present themselves. Instead of using a separate neural network model to individually forecast each time-series of a particular dataset or even implementing a global model for parallel forecasting, a clustering approach could also be envisaged for this purpose (Bandara et al., 2020)-(Tadayon and Iwashita, 2020). This approach consists of implementing time-series clustering techniques in order to group homogeneous time-series into subgroups, with the intention of using as many neural network models for forecasting as there are subgroups. The clustering approach was proposed as a means to overcome global models' accuracy decrease when presented with multiple heterogeneous time-series as input.

In this paper, we propose a comparative study of the three multivariate time-series forecasting approaches on 6 benchmark time-series datasets. The first approach, denoted as Separate Model Forecasting Approach (SMFA), involves individually forecasting each time-series of a dataset with a separate deep learning model. The second strategy referred to as a Global Model Forecasting Approach (GMFA), where cross-series information sharing is exploited by using a unique and global model to process in parallel, all time series at once. The third strategy is dubbed as Cluster-Based Forecasting Approach (CBFA), which consists of grouping together similar time-series by implementing clustering algorithms, prior to the forecasting phase. To our knowledge, there has not been any comparative study of these three approaches in one single study, with the implementation of multiple state-of-art time-series deep neural networks. In addition a hybrid neural network model's performance (CNN-GRU) is evaluated and compared to that of individual deep learning models (MLP, RNN, LSTM, GRU, CNN) with respect to the Weighted Average Percentage Error Metric (WAPE) and in terms of execution time.

This paper is organized as follows: Section 2 mentions the related work associated with local, global and cluster-based forecasting approaches for univariate and multivariate time-series. Section 3 specifies the proposed forecasting approaches implemented for this evaluation. Section 4 details the requirements needed prior to forecasting approaches performance evaluation and the results of the clustering algorithms' tuning is also analyzed. Section 5 presents and discusses results of our forecasting approaches' performance evaluation, whereas Section 6 draws conclusions on the results of our evaluation and points out what future work should entail.

2 RELATED WORK

In this section, we present the related work pertaining to three main approaches implemented when dealing with time-series forecasting, as well as the research carried out on deep learning architectures for time-series predictions.

Local Based Technique for Time-Series Forecasting. When aiming to forecast multiple time-series in a dataset, one's traditional approach would be to individually model each time-series present in the dataset. Such approach is dubbed a local approach and exploits univariate time-series datasets. In such regressive cases, a time-series' future values only depend on its past observations. There has been a lot a research done on using deep learning models to regressively forecasts univariate time-series. In (Chandra et al., 2021), a performance evaluation of multiple deep learning models such as long short term memory (LSTM), recurrent Neural networks (RNNs), convolutional neural networks (CNNs) and bidirectional LSTM (BiLSTM), is conducted. These models are implemented on univariate time-series and a multi-step ahead forecasting scheme is carried out on benchmark datasets. The study concluded that bidirectional networks and encoder-decoder LSTM outcompeted their rivals in terms of accuracy for both simulated and real-world time series problems. In (Papacharalampous et al., 2018), a univariate time-series forecasting study is presented. In this study, temperature and precipitation are predicted using both machine learning (ML) and statistical methods. Problems associated with univariate time-series forecasting such as, lagged variable selection, hyperparameter selection and performance comparison between machine learning and classical algorithms are explored and dealt with.

Global Based Techniques for Time-Series Forecasting. A unique universal function approximator can also be used for multivariate time-series forecasting. In such scenarios, a unique deep learning model takes multiple time-series as input at once, processes them in parallel and outputs predictions for each time-series of a dataset. In (Montero-Manso and Hyndman, 2021), the local and global principles are studied and both statistical and deep learning models are implemented on benchmark datasets. According to this study, as the length of a series increases so does the complexity of local models, which is not the case with global models. The authors showed that global models with an increased complexity outperformed local state-of-the-art models on most datasets, with way fewer parameters. Nonetheless, they argued that the benefits of one principle over the other depends on the context. Their findings underline the necessity of further research in the field of time-series forecasting. In (Sen et al., 2019), a hybrid model is proposed, capable of thinking globally but acting locally. The model achieves such a feat by leveraging its convolution layers, which capture both local and global time-series properties in a dataset. The proposed model outperformed its contenders on 4 benchmark datasets. In (Wan et al., 2019), a novel multivariate temporal convolutional network is proposed for multivariate time-series forecasting and compared to existing widely used models for such tasks, such as LSTMs, CNNs and multivariate attention-based models.

Clustering-Based Techniques for Time-Series Forecasting. When dealing with multiple time-series forecasting problems, a number of approaches have been put forward over the years in an effort to ameliorate time-series forecasting accuracy. One of this approach entails a clustering paradigm, whose advantages have been detailed in (Bandara et al., 2020), (Pavlidis et al., 2006), (Asadi and Regan, 2020) , (Cherif et al., 2011) and (Martínez-Rego et al., 2011). In (Bandara et al., 2020) a clustering approach was evaluated on two different datasets: CIF2015 and NN5. On the CIF2015 dataset, the proposed clustering model outperformed the other models with respect to the specific evaluation metrics used in the competition. On the NN5 dataset, a model based on the clustering method was the best performing contender in terms of the average rankings, over the evaluated error measures. A similar clustering method was put forward in (Tadayon and Iwashita, 2020), where the clustering approach results indicated overall forecasting improvements in terms of accuracy and execution time. In (Pavlidis et al., 2006), the clustering approach was implemented on a financial dataset so as to address noise and non-stationarity. The experimental results were promising for one-step-ahead forecasting, while multi-step ahead forecasting being a more difficult task. In (Sfetsos and Siriopoulos, 2004), a clustering method was implemented for pattern recognition on separate datasets.

In this study (Yatish and Swamy, 2020), clusters were generated by a data analysis oriented cluster methodology that formed groups with similar linear relationships of their most common property. Thereafter, a pattern recognition scheme was employed for forecasting. The proposed scheme showed an improvement in terms of error over conventional forecasting algorithms. In (Stoean et al., 2020), a similar approach was implemented, where self-organizing maps, a shape-similarity clustering model was used to group similar medical data of patients and prior to implementing a CNN-LSTM model for classification.

Deep Learning Architectures. When it comes to time-series forecasting, one has multiple avenues for achieving it. Traditionally, statistical methods such as ARIMA were the default choice. But the shortcomings of such statistical approaches lead to the development of neural network architectures. Initially, Feed Forward Neural Networks (FFNN) were proposed for time-series forecasting. Nonetheless, these were not tailor-made architectures for time-series processing as they did not take into account the sequentiality associated with time-series data. Later on, sequential processing oriented architectures were proposed for time-series data, most notably, recurrent neural networks and its variants such as Elman Recurrent Networks (ERNNs), Long Short-Term Memory (LSTM) and Rated Recurrent Units (GRU), tailor-made for processing sequential data.

In recent years, convolutional neural networks (CNNs) which were primarily earmarked for image and audio processing have also earned quite a reputation in the field of time series forecasting, as they are quite adept at extracting spatial and temporal information in sequential data and are computationally cheaper than recurrent neural networks.

Hybrid models based on a combination of statistical and deep learning models have also recently emerged. In (Zhang et al., 2019) results showed that the merging of the two models significantly resulted in reduction in the overall forecasting error, with the hybrid model being able to capture concurrently both linear and nonlinear patterns in the dataset. Hybrid models based solely on combination of machine learning models have also been widely studied and democratized. In (Pan et al., 2020), (Yu et al., 2021) and (Sajjad et al., 2020), a hybrid CNN-GRU model is utilized for resolving various tasks such as, water level prediction, license plate recognition, oil soil moisture prediction and short-term residential load forecasting respectively. Despite the success of supervised learning, in particular that of recurrent architectures in the field of time-series forecasting, other machine learning branches have also proposed various models for time-series forecasting, such as, state spate models in (Franceschi et al., 2020), representation learning based models in (Rangapuram et al., 2018) and natural language processing attention-based models dubbed transformers in (Grigsby et al., 2021).

3 PROPOSED FORECASTING APPROACHES

In this section, we present in detail three forecasting approaches:

1. Separate Model Forecasting Approach - SMFA (section 3.1)
2. Global Model Forecasting Approach - GMFA (section 3.2)
3. Cluster-Based Forecasting Approach - CBFA (section 3.3)

These approaches propose a multi-step ahead time-series prediction scheme, by implementing a Multi Input Multi Output strategy (MIMO). The purpose of this conducted study is to determine the appropriate way of processing multivariate time-series for forecasting when exploiting various deep learning neural network architectures and identifying the most important factors related to each approach in order to obtain optimal results.

3.1 Separate Model Forecasting Approach (SMFA)

SMFA is depicted in figure 1 and is implemented in (Wang and Jiang, 2015). It involves individually processing each time-series of a dataset with a separate deep learning model. In this scenario, the forecasting results of a particular time-series are solely based on the historical data of that particular series. This is a autoregressive process in which a time series is explained by its past values rather than that of other time-series variables.

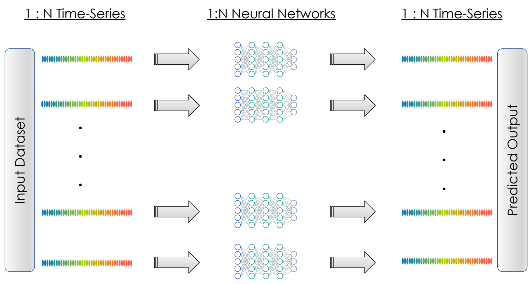


Figure 1: Separate Model Forecasting Approach (SMFA).

3.2 Global Model Time-Series Forecasting Approach (GMFA)

GMFA is presented in figure 2 and is implemented in (Karunasinghe and Liong, 2006). In this approach, cross-series information sharing is being exploited, by using a unique and global model to process in parallel, all time-series at once. In this context, cross-series information sharing becomes an essential and decisive factor. Indeed, the predictions of a particular time-series are influenced not only by its historical data but also by those of other time-series contained in the same dataset.

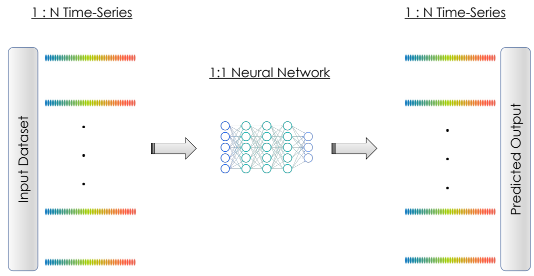


Figure 2: Global Model Forecasting Approach (GMFA).

3.3 Cluster-Based Time-Series Forecasting Approach (CBFA)

CBFA approach is presented in figure 3. This approach is based on two phases:

1. Clustering phase: In this phase, time-series are processed in order to determine similarity in such a way as to partition the dataset into homogeneous groups, called clusters (Aghabozorgi et al., 2015).
2. Forecasting phase: During this phase, a separate deep neural network model is implemented for each cluster previously identified in the clustering phase.

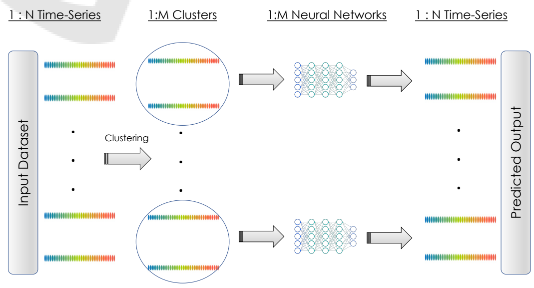


Figure 3: Cluster-based Model Forecasting Approach (CBFA).

Time-series clustering techniques have been extensively resorted to (Tadayon and Iwashita, 2020) as tools for resolving plenty of challenges such as motif discovery, clustering, anomaly detection, classification, sub-sequence matching, etc., across multiple fields, such as, engineering, finance, health care, business (Liao, 2005).

In the following, we present three main clustering algorithms that have been referenced in the literature and will be exploited for the CBFA approach:

1. The Self-Organising-Map (SOM) algorithm is a particular type of neural networks, which uses unsupervised learning to perform dimensionality reduction (Kohonen, 1982) (Aghabozorgi et al., 2015). It does so by reducing a multidimensional input space into a two-dimensional map. It can also be used for clustering time-series features. Instead of optimization algorithms, such as gradient descent, the SOM algorithm relies on competitive learning during the learning process. It is considered as a model-based clustering approach as it uses the trained weights to determine the appropriate clusters (Aghabozorgi et al., 2015)(Rani and Sikka, 2012). The SOM algorithm's dimensions (x and y integer values), that is, the number of input neurons must be specified prior to implementation. We determined the x and y parameters needed for the SOM algorithm by using a method employed by practitioners in Equation 1. Later on, these two parameters will be modified with the aim of generating multiple clusters (section 4.5).

$$x = y = round((\text{ Number of series in dataset })^{\frac{1}{4}}) \tag{1}$$

2. The Ordering points to identify the clustering structure (OPTICS) is a density-based clustering algorithm, capable of effectively detecting clusters in data of varying density (Ankerst et al., 1999). It determines neighboring points by linearly arranging them in order, in a manner that the closest points in space become neighbors. It identifies core samples of high density, generates clusters from them and it is well suited for large datasets. The algorithm requires the number of samples in a neighborhood for a point to be considered as a core point (min_sample) to be specified before implementation. This parameter will be varied at a later stage, for the purpose of producing various clusters (section 4.5).

3. K-Means is an unsupervised learning algorithm, intended for unlabeled data, which involves grouping similar data points within a dataset into k clusters. This is usually achieved by a proximity measure, such as the Euclidean distance. Each cluster is represented by a prototype and is iteratively updated by calculating the mean of each cluster after points have been assigned (Syakur et al., 2018). Unfortunately, in order to do so effectively, the number of clusters is required beforehand, which is usually unknown when it comes to untagged data. Different techniques including the elbow method are often used to address this conundrum.

4 FORECASTING APPROACHES PERFORMANCE EVALUATION REQUIREMENTS

In this study, six publicly available datasets were used to compare the three forecasting approaches (section 4.1). These approaches were evaluated based on WAPE and execution time metrics (section 4.2). To do so, the hardware requirements needed to carry out this evaluation study are presented in section 4.3 and the neural networks models' configuration are presented in section 4.4. In addition, we have foregone further experimentation to determine the optimal clusters for each dataset (section 4.5) for each clustering algorithms: SOM (section 1), OPTICS (section 2) and K-Means (section 3).

4.1 Datasets

In this section, we briefly present 6 publicly available datasets [1] used for our study in table 1: *ExhangeRate* datasets, *NN5*, *SolarEnergy*, *Traffic-metr-la*, *WikiWebTraffic* and *Traffic-perms-bay* datasets. These datasets, originate from different areas, vary from small to large datasets, with a number of time-series ranging from 8 to 997 and with the series' length ranging from 735 to 52105 samples. These datasets have been used in forecasting competitions and other time series forecasting reviews such as (Lara-Benítez et al., 2021) and (Hewamalage et al., 2021).

Table 1: Six different datasets used in the evaluation of forecasting approaches' performance.

Datasets	N of Time-Series	Length	Source
ExchangeRate	8	7588	Exchange rate data
NN5	111	735	Financial transaction data
SolarEnergy	137	22744	Solar production records
Traffic-metr-la	207	34260	Traffic speed data
WikiWebTraffic	997	550	Wikipedia traffic flow
Traffic-perms-bay	325	52104	Traffic network data

4.2 Evaluation Metrics

To evaluate our three forecasting approaches, we use the WAPE metric (section 4.2.1) to assess the accuracy of predictions as well as completion time (section

[1] Datasets are available at the reviewers' request

4.2.2) to evaluate execution time, which considered a crucial factor in multiple practical applications. The Mean Absolute Error (MAE) metric was also used to evaluate accuracy but was excluded from the study due to its results being similar to that of the WAPE metric.

4.2.1 Weighted Average Percentage Error Metric (WAPE)

The WAPE metric, Equation 2, is a well-known error-scaling metric when dealing with time series forecasting. It is suited for low volume data and allows comparable evaluation across time series of inconsistent scales (Lara-Benítez et al., 2021).

$$WAPE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{\sum_{i=1}^{n} |y_i|} \quad (2)$$

where n and i represents the number of observations and the current observation respectively, y_i represents the actual value of the series and $\hat{y}_i$ represents the predicted value.

4.2.2 Execution Time

The execution time is considered a crucial evaluation metric. It is used for evaluating the forecasting approaches' completion time as well as the execution time associated with each neural network model. It also provides variable indications for both forecasting approaches and neural models' performance. Hence, in the evaluation result section (5.2.2), we will present:

1. Execution time per forecasting approach: It corresponds to the completion time across all implemented neural networks models for each forecasting approach and for each dataset.
2. Execution time per neural network model: It corresponds to the completion time of each specific neural network model across all forecasting approaches and for each dataset.

4.3 Hardware Requirements

The evaluation of the three forecasting approaches, across six different neural networks models and six different datasets, required an adapted hardware for the experimentation. Hence, for the hardware specifications, we used our laboratory distributed memory system [2]. It is made up of 2320 computing cores, 20 GPUs, corresponding to a computing power of 225 teraFLOPS, and 19.4 TB of memory and a visualization node (1 GPU). The platform also benefits from 3D scanners, humanoid robots and adapted software.

[2]More details regarding our laboratory system and a link to its website are available at the reviewers' request.

4.4 Deep Neural Networks' Parameters

Deep learning models' parameters that were shared across 6 deep leaning models for this evaluation are depicted in Table 2. As for the parameters associated to each model, they are displayed in Table 3.

Table 2: Deep Learning Models' Shared Parameters.

Parameters	Values
Normalisation (ED)	Minmax
Optimizer	Adam
Batch size	32
N of epochs	100
Learning Rate	0.01
Past History	30 timesteps
Forecast Horizon	20
Forecasting scheme	Multi-Input Multi-Output (MIMO)

Table 3: Deep Learning Models' Hyperparameters.

Models	Parameters	Values
MLP	Hidden Layers	[8, 16, 32, 16, 8]
RNN	Layers	3
	Units	32,32
	Return sequence	False, True
LSTM	Layers	2
	Units	32,32
	Return sequence	False, True
GRU	Layers	2
	Units	32,32
	Return sequence	False, True
CNN	Layers	2
	Filters	32,32
	Pool size	2, 2
CNN-LSTM	Layers	1 - 2
	Filters - Units	64 - 200,100
	Pool size - Return sequence	None - False, True

4.5 Towards Optimal Clusters Generation

Prior to evaluating the clustering approaches' performance (CBFA), the goal is to process the time-series in each dataset and group them into homogeneous clusters. To do so, three different clustering algorithms are used: K-Means, OPTICS and SOM. However, the clustering algorithms' results tend to vary when their hyperparameters are tampered with. Hence, we proceed in two steps:

1. Clusters generation phase : During this phase, we implement clustering algorithms on each dataset to generate clusters. We then vary the parameters of those clustering algorithms, which results in the

formation of various clusters for each dataset. The results associated to each clustering algorithm are presented in Table 4.

2. Clusters selection phase: Following the clustering generation phase, we determine the best clusters for each dataset. We do so, by selecting the clusters with the lowest average WAPE error across 6 neural networks models mentioned in 3 for each dataset. As a result, we determine the appropriate clusters formations (or in another word, the appropriate parameters for each clustering algorithm) for each dataset. The results are exhibited in Figure 4.

The procedure and details associated with the clusters generation phase for the SOM and OPTICS algorithms are presented in figure below. As for the K-Means algorithm a different technique is implemented for identifying the appropriate clusters :

- With the goal of determining the optimal clusters for the SOM algorithm, we tamper with the dimension parameters (x and y) mentioned in equation 1. We present five variations of these parameters. Each variation results in a different clusters formation. For example, SOM_4 is the result of determining x and y parameters with equation 1, and then increasing by 2. The lowest number of clusters proposed varying the SOM algorithm is equal to 1 and the highest number of clusters is 49 clusters.
- As for the OPTICS algorithm, we vary the minimum sample (min_sample) parameter in section 2. We vary this parameter 4 times, with each modification resulting in a new cluster formation. For example, $OPTICS_4$ is the result of changing the minimum sample parameter to equal 5. The lowest number of clusters proposed varying the OPTICS algorithm is equal to 1 and the highest number of clusters is 600 clusters.
- As for the K-Means algorithm, we opt for a different technique in determining optimal clusters for each dataset. Indeed, we instead implement the elbow method for determining the optimal number of clusters needed as input to the algorithm. The elbow technique is a way of heuristically approximating the optimal number of clusters in a dataset, for the K-Means algorithm (Marutho et al., 2018). It consists of generating clusters for a range of values of K while using a cost function to estimate each cluster's error. When plotted on a graph, it takes the shape of a curved arm. The resulting curve, resembling an elbow, dictates the idyllic number of clusters. The number of cluster corresponding to the point of inflection on the curve is then considered the optimal number of clusters needed.(Liu and Deng, 2020). Its selection is more often than not a trade-off between the possible number of clusters and the cost function's estimated error for each cluster.

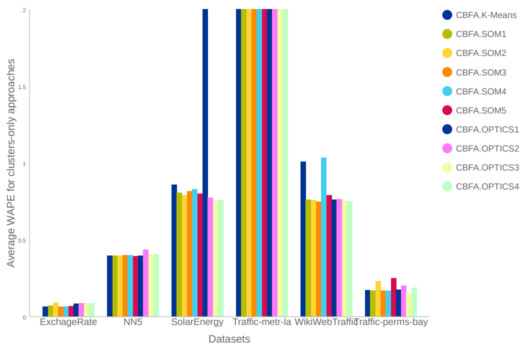


Figure 4: CBFA Clusters' Average WAPE Error.

5 FORECASTING APPROACHES PERFORMANCE EVALUATION RESULTS

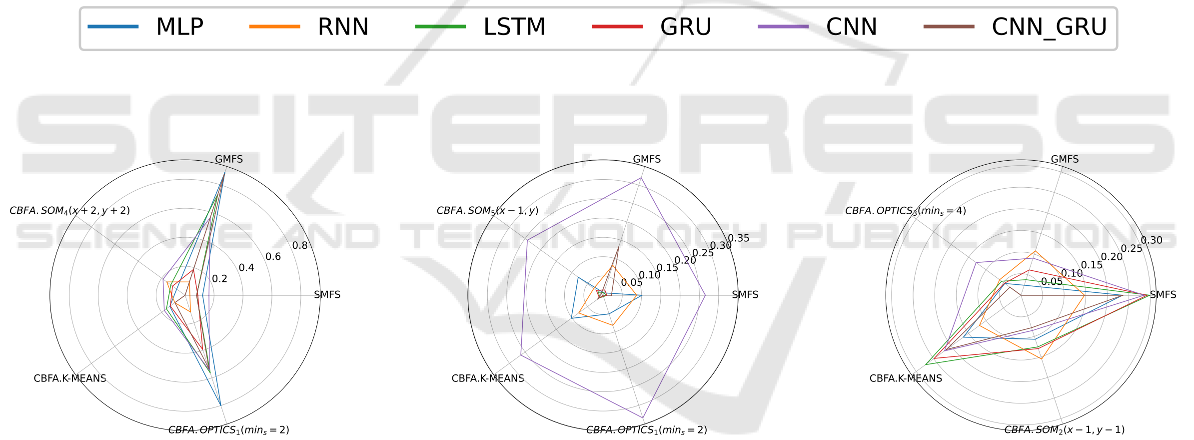
In this section, the experimental results of our evaluation study are displayed. We proceed to evaluate our 3 forecasting approaches. The first approach being the individual model approach (SMFA) section3.1, the second being the global model approach (GMFA) detailed in section 3.2 and the third one being the clustering approach section 3.3, proposed by CBFA.SOM, CBFA.OPTICS and CBFA.K-Means algorithms, whose most suitable clusters for each dataset was determined in section 4.5. The accuracy of both forecasting approaches and neural networks models are displayed in section 5.1. In addition, the completion time for both forecasting approaches and neural networks models are showed in 5.2. The 200 last points of each dataset were used as the training set.

The radar plots in 5, display the normalized results described in 5.1, allowing for the comparison of both forecasting approaches and models' performance. For each plot, the smallest value for the WAPE metric, corresponding to the best approach, is positioned at the center of the radar plot. They present the average results obtained over the 10 predictions that were carried out by each model for each approach.

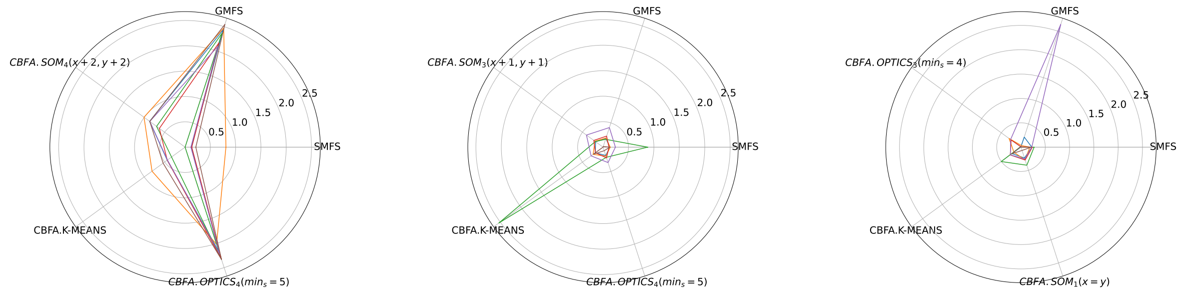
The distribution of the results over the 10 predictions is displayed in figure 6. This representation allows for a visualization of the average results obtained per approach and per dataset. The mean value of the

Table 4: Cluster Generation Results.

Clustering Algorithms	ExchangeRate	NN5	SolarEnergy	Traffic-metr-la	WikiWebTraffic	Traffic-perms-bay
K-means	4	80	80	80	600	150
Execution Time (seconds)	0.11	0.66	3.43	7.06	6.04	8.57
OPTICS$_1$ (min_sample=2)	1	10	21	21	59	72
Execution Time (seconds)	0.22	0.09	6.82	24.29	9.05	8.14
OPTICS$_2$ (min_sample=3)	1	5	5	18	16	20
Execution Time (seconds)	0.01	0.07	0.69	2.23	1.08	7.52
OPTICS$_3$ (min_sample=4)	1	3	3	14	3	4
Execution Time (seconds)	0.01	0.07	0.68	2.37	1.01	7.58
OPTICS$_4$ (min_sample=5)	1	2	1	7	1	3
Execution Time (seconds)	0.02	0.06	0.68	2.51	1.15	7.51
SOM$_1$ (x = y)	4	16	16	16	35	25
Execution Time (seconds)	93.87	57.44	645.66	1060.82	74.91	6097.14
SOM$_2$ (x-1,y-1)	1	9	9	9	25	16
Execution Time (seconds)	33.74	35.87	439.81	57.99	859.35	2866.27
SOM$_3$ (x+1,y+1)	7	25	25	25	49	36
Execution Time (seconds)	180.71	67.05	1675.99	87.82	2945.29	8478.53
SOM$_4$ (x+2,y+2)	8	36	36	36	64	49
Execution Time (seconds)	301.03	85.86	2719.38	115.82	5529.85	11625.32
SOM$_5$ (x-1,y)	2	12	12	12	30	20
Execution Time (seconds)	40.87	40.24	740.79	124.74	1184.59	3820.11



(a) ExchangeRate. (b) NN5. (c) SolarEnergy.



(d) Traffic-metr-la. (e) WikiWebTraffic. (f) Traffic-perms-bay.

Figure 5: Forecasting Approaches' Evaluation Results.

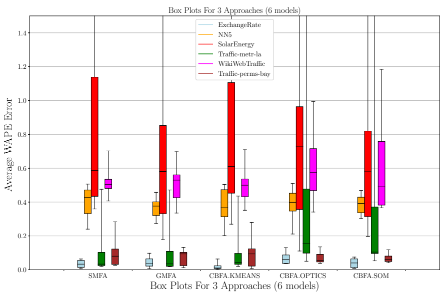


Figure 6: Results' Distribution For 3 Approaches.

WAPE metric is represented by the horizontal bar in the box plots, the standard deviation by the length of the boxes, while the minimum and maximum values are associated with the ends of the segments. This figure highlights the effectiveness of the different approaches, in particular those of the Exchange Rate, Traffic-metr-la and Traffic-perms-bay datasets, while showing the variability of the results obtained from one prediction to another, particularly significant for the Solar Energy dataset.

5.1 Average WAPE Results

For estimating a forecasting approach's performance displayed by spider plots in figure 5, a WAPE error metric is computed for 6 different neural network models, i.e., MLP, RNN, LSTM, GRU, CNN, CNN-GRU, for that particular approach. The overall error for each forecasting approach is calculated by averaging the the WAPE errors across all neural network models for each time-series and each dataset.

Table 5 condenses the results of the radar plots depicted in figure 5, by emphasizing this time around the 2 most advantageous approaches for every dataset with respect to the WAPE error metric. For the ExchangeRate dataset, the individual approach (SMFA) outperforms other approaches, whereas a variation of the SOM algorithm (CBFA.SOM$_4$) produces the second-best results. For the NN5 dataset, a clustering approach (CBFA.SOM$_5$) is the most effective approach, followed by another clustering approach CBFA.OPTICS$_1$. As for the solarEnergy dataset, the most notable approach is the unique approach (GMFA), which is trailed by a clustering approach (CBFA.OPTICS$_3$). For the Traffic-metr-la dataset, the individual approach (SMFA) achieves the best results, with a clustering approach (CBFA.K-Means) falling behind it. As for the WekiWebTraffic dataset,the unique approach (GMFA) claims first spot while a clustering approach (CBFA.OPTICS$_3$) settles for second place. At last, as for the Traffic-perms-bay dataset, a clustering approach (CBFA.OPTICS$_3$) outperforms other approaches and the unique approach (GMFA) achieved the second-best results.

In general, the clustering forecasting approaches (CBFA) perform best on 2 out of 6 datasets (NN5, Traffic-perms-bay) and maintain second place on 5 out of 6 datasets (ExchangeRate, NN5, SolarEnergy, Traffic-metr-la and WikiWebTraffic). In other words, the clustering approaches are either the first and the second-best approach at every instance, in terms of accuracy. The second-best performing approach tend to be the SMFA, outdoing other approaches on 2 out of the 6 datasets (ExchangeRate and Traffic-metr-la) approach followed by the GMFA approach (SolarEnergy and WikiWebTraffic). Amongst all clustering approaches, those proposed by the OPTICS (CBFA.OPTICS) clustering algorithm tend to lead to better results, followed by those generated by the SOM and K-Means algorithms respectively.

Table 5: Forecasting Approaches' Average WAPE Error.

Datasets	1st approach	2nd approach
ExchangeRate	SMFA	CBFA.SOM$_4$
NN5	CBFA.SOM$_5$	CBFA.OPTICS$_1$
SolarEnergy	GMFA	CBFA.OPTICS$_3$
Traffic-metr-la	SMFA	CBFA.K-Means
WikiWebTraffic	GMFA	CBFA.SOM$_3$
Traffic-perms-bay	CBFA.OPTICS$_3$	SMFA

5.1.1 Neural Networks' Average WAPE Results

Each neural network produces 10 predictions, which each prediction being of a horizon of 20 samples and being evaluated by the WAPE metric. In order to estimate the overall forecasting performance of a model on a dataset, the average error across all 10 predictions is computed.

Table 6 summarizes the results portrayed in radar chart depicted in figure 5, by highlighting the two leading neural networks architectures, in terms of average WAPE error for each dataset. The RNN model achieves best results on the ExchangeRate dataset. On the NN5 dataset, the LSTM model beats the other models and on the Traffic-metr-la dataset, its the GRU model the comes out on top. Finally, CNN-GRU model outperforms its competitors on the SolarEnergy, WikiWebTraffic and Traffic-perms-bay datasets.

Overall, the CNN-GRU model performs best on the 3 largest out 6 datasets (SolarEnergy, WikiWebTraffic and Traffic-perm-bay), with respect to the average WAPE error metric, which suggest that the model is more suitable for larger datasets. The model with the highest average WAPE error consistently remains the CNN model. Moreover, the findings show that the CNN model tend to be the worst in at least

3 out of 6 datasets (NN5, SolarEnergy and Traffic-perms-bay). Furthermore, the spider figures showed in 5 go to show the sporadic nature of the LSTM model illustrated on the WikiWebTraffic dataset. Indeed, although the LSTM model occasionally outshines its adversaries, e.g., on the NN5 dataset, it can substantially become the worst model by a wide margin e.g., on the WikiWebTraffic dataset, with a WAPE error 3 times higher (2,44) than the highest observed CNN-GRU WAPE error (0,77) for the WikiWebTraffic dataset.

Table 6: Neural Network Models' Average WAPE Error.

Datasets	1st Model	2nd Model
ExchangeRate	RNN	GRU
NN5	LSTM	GRU
SolarEnergy	CNN-GRU	MLP
Traffic-metr-la	GRU	CNN
WikiWebTraffic	CNN-GRU	MLP
Traffic-perms-bay	CNN-GRU	MLP

5.1.2 Forecasting Approaches and Models' Lowest WAPE Results

The results obtained for each dataset are described in the radar figures 5 . The table 7 summarizes the results portrayed in radar charts 5, by highlighting the two leading forecasting approaches and models, in terms of lowest WAPE error for each dataset. As a whole, the clustering approaches tend to produce the finest results by ranking first on 3 out of 6 datasets (ExchangeRate, NN5, WikiWebTraffic). The SMFA approach trails the clustering approaches by ranking second-best on 3 out of 6 datasets (ExchangeRate, Traffic-metr-la et WikiWebTraffic).The MU approach also achieves good results by ranking first on 2 out of 6 datasets (SolarEnergy and Traffic-perms-bay). As far as the neural networks models are concerned, the results clearly show that the CNN-GRU model outperforms its rivals by ranking first on 5 out of 6 datasets (ExchangeRate, NN5, SolarEnergy, WikiWebTraffic, Traffic-perms-bay). The podium is completed by the LSTM and GRU neural network models. Once again, the clustering approaches proposed by the OPTICS algorithm produce good results on two datasets (NN5, and WikiWebTraffic).

Table 7: Neural Network Models' Lowest WAPE Error.

Datasets	1st Model/Approach	2nd Model/Approach
ExchangeRate	CNN-GRU-(CBFA.SOM$_4$)	RNN (SMFA)
NN5	CNN-GRU (CBFA.OPTICS$_1$)	GRU (SMFA.OPTICS$_1$)
SolarEnergy	CNN-GRU (MU)	MLP (MU)
Traffic-metr-la	LSTM (SMFA)	CNN (SMFA)
WikiWebTraffic	CNN-GRU (CBFA.OPTICS$_1$)	GRU (SMFA)
Traffic-perms-bay	CNN-GRU (MU)	LSTM (MU)

5.2 Completion Time

5.2.1 Forecasting Approaches' Completion Time Results

Figure 7 shows the execution time (in hours) per forecasting approach presented for our 6 datasets. The total execution time of an approach is estimated by summing up the completion time for all 6 neural network models of that approach. As we can observe, among all approaches , the global model forecasting approach (GMFA) dominates its rivals by achieving substantially better results than its opponents, across all datasets probably due to parallel processing taking place, making it undoubtedly the dominant choice when completion time is the most crucial factor. For example, for the ExchangeRate dataset, the GMFA approach's execution time is 0.06 hrs (3.6 minutes), making it the faster approach for that dataset while the slowest one is the SMFA approach with an execution time of 0.55 hrs (32.4 minutes) Another illustrating example is on the Traffic-perms-bay dataset, where the GMFA is almost 185 times faster (0.79 hrs) than the SMFA approach (145.94 hrs). Amongst the clustering approaches, the CBFA. The CBFA.K-Means approach tends to be the most time-consuming on 4 of the 6 datasets and the CBFA.OPTICS approach appears to be the least time-consuming clustering approach. Unsurprisingly, the worst approach in terms of execution across all datasets is the SMFA approach, finishing last at every instance. This is due to the fact that this approach individually processes each time-series in a dataset.

5.2.2 Neural Networks' Completion Time Results

Figure 8 displays the completion time (in hours) per neural network model for our 6 datasets. The completion time for each model is estimated by summing up the completion time for each model across all approaches. The results show that CNN-GRU is the most time-intensive model across all datasets and conversely MLP has been the least costly neural network model time-wise across all datasets. For example, on the Traffic-metr-la dataset, the MLP model (2.07 hours) is 16 times faster than the CNN-GRU

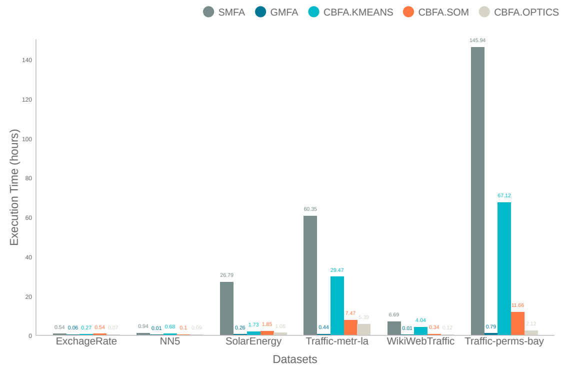


Figure 7: Forecasting Approaches' Average Completion Time.

model (34.08 hours). The podium is respectively completed by CNN, RNN, LSTM and GRU neural network models. The findings is quite consistent across all 6 datasets.

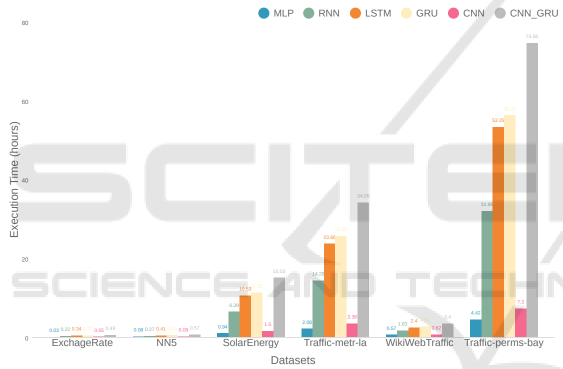


Figure 8: Deep Neural Networks' Average Execution Time.

6 CONCLUSION

In this paper, we have conducted a comparative evaluation of 3 time-series forecasting approaches, that is, the single model forecasting approach (SMFA), the global model forecasting approach (GMFA) and the cluster-based forecasting approach (CBFA). To our knowledge, there has not been any comparative evaluation of these three approaches with the implementation of multiple state-of-art time-series deep neural networks.

When it comes to determining the best forecasting approach, there is a trade-off to be made between the three forecasting approaches. The single model forecasting approach (SMFA) achieves good results in terms of accuracy but is the most time-consuming approach. The global model forecasting approach (GMFA) is the least accurate approach but by far the most time-saving one. The cluster approach appears to be a good compromise between SMFA and GMFA, as it produces good results with respect to the WAPE metric and is not as time-consuming as the SMFA approach. The same goes with choosing a neural network model, the neural network model with the best completion time is the MLP model but the most accurate one is the (CNN-GRU) model which happens to be the most time-consuming one. Identifying the appropriate approach and/or model should depend on the application context, the tasks at hand, the requirements and constraints in terms of accuracy and completion time.

In future work, we intend to enhance our work by implementing and comparing more recent state-of-the-art forecasting models, such as, deep state space models, representation learning models and attention-based transformers for time-series forecasting. Another extension of our work would be to consider dataset with various time-series lengths instead of only equal-length time-series. Another interesting work would be to propose novel time-series forecasting approaches and compare them to current ones.

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