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RESEARCH ARTICLE

An Architecture to Improve Energy-Related Time-Series Model Validity Based on the Novel rMAPE Performance Metric

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ABSTRACT In this paper, an architecture based on computational intelligence for time series modeling is proposed to guarantee the automatic adjustability of trained models no matter the dynamic behavior of the modeled phenomena. Time series are widely used to plan and execute operational and strategic tasks related to the need of forecasting phenomena. Several conventional and non-conventional techniques have been studied for time series modeling. However, the model performance and metrics are affected by non-stationary behaviors. In addition, determining effectively when a model fails can be problematic because the Mean Absolute Percentage Error (MAPE) metric does not necessarily reveal changes in the model predicted curve. Therefore, a novel metric to assess the performance is proposed; and then, an effective maintenance routine for the time-series model is properly devised. Thus, an auditor is created to identify when a model must be updated before losing forecast performance. Hence, using the defined rMAPE performance metric, the auditor output trustworthy detects if the updating process does not achieve better performance, and if replacing a time-series model is required. It is important to note that the devised scheme counts with several assemblies in a local knowledge base. The intelligent system allows building time-series models automatically considering exogenous variables such as weather, calendar, and statistical transformations that can lead to the number of models required for a particular application. The proposed approach has been experimentally tested for power consumption and energy price via simulation. The forecasting results showed an improvement in the MAPE of up to 23% in the tests performed.

INDEX TERMS Forecasting, intelligent systems, time series modeling.

I. INTRODUCTION

Time series modeling is a helpful tool to establish operative and strategic approaches in several economic sectors like marketing, energy, telecommunications, etc. For example, energy demand forecasting can provide valuable information to the different electricity-market actors (regulators and utilities) to ease taking actions such as load balancing in electrical circuits. However, if the target phenomena have a non-stationary behavior, the time-series model can lose reliability due to static parameters; therefore, the performance of such a model drops below a desired level, making it useless. For example, in the case of power consumption and energy price, it can be identified that the time series have non-stationary characteristics that impose the integration of multiple statistical techniques looking to maintain the modeling dynamics. For this purpose, several authors have proposed different conventional and unconventional statistical modeling strategies, such as the Autoregressive Integrated Mobile Average (ARIMA) models [1], [2], [3]; however, this technique has some limitations such as low adaptability, limited forecast scope, and complex model-parameter setting.

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Since exogenous variables (weather, the type of day, types of users, etc.) [4], [5], [6] can further affect power-consumption and energy-price modeling, the literature has suggested that integrating multiple statistical techniques with computational intelligence techniques [7], [8], [9], [10], [11], [12], [13] can be used to maintain the model validity. Thus, power consumption and energy price time-series modeling has been complemented using techniques such as Support Vector Machines (SVM) [14], Fuzzy Logic (FL) [15], [16], Markov Chains (MV) [17] and Artificial Neural Networks (ANN) [2], [18], [19]. Some authors have proposed grouping techniques to create sub-profiles that add different forecasts together to obtain more accurate results [20], [21]. However, it still is common that state-of-the-art models keep losing their reliability, therefore, requiring retraining [22], [23], [24], [25], [26]. SVM, ANN, Regression Tree Ensembles (RTE), and some combinations with classification techniques such as K-means, Self-Organizing Maps (SOMs), and decision trees are commonly used to pursue high adaptability in time-series modeling.

A performance metric is required to identify when a model should be retrained or replaced, anticipating performance detriment. In the case of model replacement, an indicator that evaluates which of the available modeling techniques could be used to recover the expected performance is also helpful. Therefore, a comprehensive evaluation strategy is necessary to automatically support the adaptation and maintenance of various time-series modeling techniques.

In a previous work, the authors analyze commonly used techniques in performance comparison of time series modeling for different applications [27]. However, the deficiencies of using the performance metrics separately in the forecasting process were evident. As a result, a performance metric capable of evaluating the capabilities of forecasting performance using he deviation in the shape and magnitude of the forecast should be defined.

Hence, this paper describes an architecture that allows updating or replacing the structure and parameters of a given time-series model before the performance decreases given a minimum level. To devise such an architecture, first, it is required to propose a novel forecasting performance metric based on computational intelligence that, with a high level of certainty, can alert and indicate when retraining or replacing should be carried out. The metric takes advantage of the relation between correlation and MAPE to get information about the reliability of the time series-forecasting. The devised procedure also includes a series of models conforming a knowledge base available for model replacement, if needed. The proposed approach has been tailored to the energy sector to adapt to changing behavior due to the trend, seasonality, and stochastic nature of energy generators.

The proposed approach is presented in Section II, while Section III describes the architecture implementation. Section IV presents the results of the experiments and the associated analysis. Finally, Sections IV and V present a discussion of the results from which conclusions are drawn.

II. PROPOSED ARCHITECTURE SCHEME

The time-series modeling process requires the characterization and selection of significant variables to describe the phenomenon of interest. Once the variables have been selected, it is necessary to define which statistical technique fits the time-series features. Now, the scheme displayed in Figure 1 is devised since the models are expected to deteriorate their performance over time. Each of the proposed stages is described in the following subsections: *A.* Time-series Data, *B.* Model Assembly, *C.* Training Process, *D.* Auditor, and *E.* Selection Criterion.

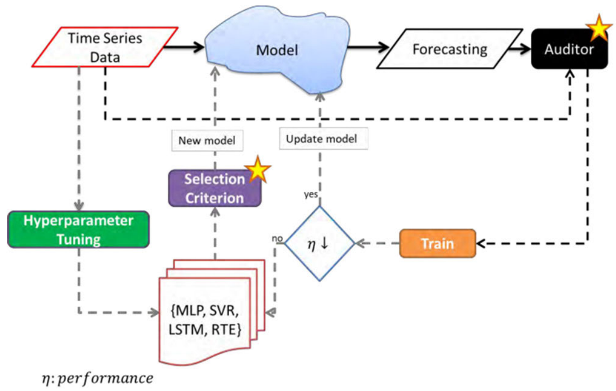

FIGURE 1. Proposed architecture for time-series modeling.

A. TIME-SERIES DATA

The use of time series requires data characterization to identify statistical properties that guide the selection of a proper model. Defining stationarity[1] is critical since not all statistical modeling techniques are suitable if a non-stationary process is at hand. If the statistical properties change, such as mean and variance, transformation-related adjustments must be implemented, such as differentiation and logarithmic operations. A defined trend and variance (i.e., homoscedasticity) is a desired property in the modeling process because a stable model behavior can be guaranteed.

Once the time series is obtained, the extraction of its characteristics explains the associated phenomenon. The Time-Series Data block executes the following tasks:

1) INTERDEPENDENCE OF THE TIME SERIES (PREVIOUSLY TRANSFORMED TO STATIONARY TIME SERIES)

It includes the evaluation of the historical information required to describe the behavior of the phenomenon. For this case, it is important to determine the amount of historical data needed to forecast future behavior. Total and partial autocorrelation analysis is employed at this stage.

[1] Stationarity in the time series (weak sense) is a desired property since it guarantees that the statistical properties do not change among periods. Thus, the mean and variance are constant regardless of position of the random variable within the stochastic process.

2) IDENTIFICATION OF EXOGENOUS VARIABLES
It is necessary to identify which variables minimize the uncertainty to ease the description of the phenomenon of interest. Usually, a correlation matrix is proposed to identify variables that provide significant information on the time-series behavior.

3) REDUCTION OF THE CONSIDERED VARIABLES
It can be found that not all the identified variables lead to a better description of the time series but increase its complexity during modeling. Therefore, the proposed procedure incorporates principal-component and factorial analysis for reducing and grouping the variables.

4) IDENTIFICATION OF SIMILARITIES WITHIN THE TIME-SERIES DATA
The needed number of models depends on the relation between the observed variability and the complexity of the time-series data. Data similarity is evaluated through the Tukey-Kramer test to identify the requirement of multiple models.

5) EVIDENCE OF PERIODICITY WITHIN THE TIME SERIES
The seasonality of the data provides information about forecasts. Periodicity in the time series leads to considering historical information related to data with similar conditions.

6) PATTERN IDENTIFICATION IN THE TIME SERIES
It is possible to detect a diversity of behaviors that can be grouped into small groups in the same time series. Grouping time-series subsets with similar characteristics allows the calculation of aggregated series that provides information about the most representative patterns. Data classification is carried out through decision trees. Once the data are grouped, each aggregated series is calculated by adding the curves that belong to the same subset.

B. MODEL ASSEMBLY
The existing energy-related time-series modeling methods rely on statistical and computational intelligence techniques such as SVM, FL, MV, ANN, RTE, K-means, SOMs, among others. The proposed approach is based on combining both approaches to provide improved robustness that enhances model functionality. It performs an hyperparameter optimization for a Bayesian algorithm with a Support Vector Regression (SVR), a Long Short-Term Memory (LSTM) neural network and RTE. A Multilayer Perceptron (MLP) is trained to generalize the forecasting models. Thus, the devised scheme comprising three stages provides stable forecasting with low variability. This approach is adjusted for energy associated phenomena (i.e., load balancing, price, etc.). Thus, the devised scheme comprising three stages provides stable forecasting with low variability. This approach is adjusted for energy associated phenomena (i.e., load balancing, price, etc.). Thus, the first stage consists of the implementation of an intelligent clustering technique to obtain the shape of a typical load curve for time series data with hourly granularity (weekdays, weekends, and holidays). The second stage presents the base curve (i.e., the reference curve) for each day that will be forecasted. This base curve is done by implementing statistical techniques that use historical data of time series and the typical curves obtained in the first stage. Finally, the third stage allows correcting the base curves considering external variables (e.g., weather conditions). The authors explain the stages in [28].

C. TRAINING PROCESS
Two strategies for training and optimizing time-series modeling are considered. The idea is to find the optimal hyperparameters for Bayesian optimization [29]; and then, experimentally iterate to identify the most significant parameters according to the guidelines explained by the authors in [30]. A more detailed explanation of the two-step training process is developed next.

1) TRAINING OPTIMIZATION–HYPERPARAMETERS–(SVR, LSTM, AND RTE)
The use of machine-learning-based models proves to be suitable and adjustable due to the multiple parameter definition and their interaction with an objective function associated with the model precision. The backpropagation algorithm is implemented to obtain the gradient of an objective function for each model parameter. The training process is based on making the right decisions that allow the functions of the multidimensional space to be suitably integrated with an evaluation metric that guarantees optimal learning. Once the functions and the learning algorithm have been established according to experience in the problem, defining a starting point or initial values of the model parameters becomes crucial. This parameter initialization is known as hyperparameters optimization.

2) TRAINING OPTIMIZATION–MLP (MULTILAYER PERCEPTRON)
The objective of this task is to find the highest level of generalization of the forecasting models. The employed metric is based on finding the critical factors for the training and configuration of a neural network in terms of error, that is the MAPE.

D. AUDITOR
Time-series modeling requires a set of guidelines for analyzing, debugging, and selecting variables for the training model. However, the time-series models that apply to the considered phenomena in this paper lose validity making them useless. A list of facts that could lead to requiring a model update or replacement due to loss of accuracy includes:

- Errors obtained during the training or validation process. The profile building is used in the training stage through the clustering process. Typically, the non-stationary time series varies its statistical properties over time, and this is due to an increase or a change in the consumption patterns, marketing campaigns, etc. The profiles may vary from those obtained during the training process.

- Variations in the probability distribution functions because of the training process. This variable works as an indicator of the data frequency and its typical behavior in normal conditions.

- A deviation from the training error trend to the forecasting.

- The number of periods outside of the confidence interval of the training error.

Some strategies can be employed to measure and reduce the effect of the previous elements, for example:

- Employing the Dynamic Time Warping (DTW) algorithm to measure the similarity between the time series.

- Getting information on the time-series dynamics by determining the variation between the training and the implementation stages.

- Comparing the growth rate of error.

- Analyzing the number of periods outside the confidence interval during the implementation stage.

Thus, a block based on computational-intelligence techniques is added so that continuous performance is monitored, and corrective action can be applied. Such an additional block is called Auditor, and the information of the variables required is shown in Figure 2. The Auditor will provide a logical indicator (0 or 1) indicating the loss of validity of the time-series models and a corrective action must be then applied. From the Auditor point of view, the suggestion is to retrain the system. Section III-D will explain the computational intelligence technique selected for the Auditor.

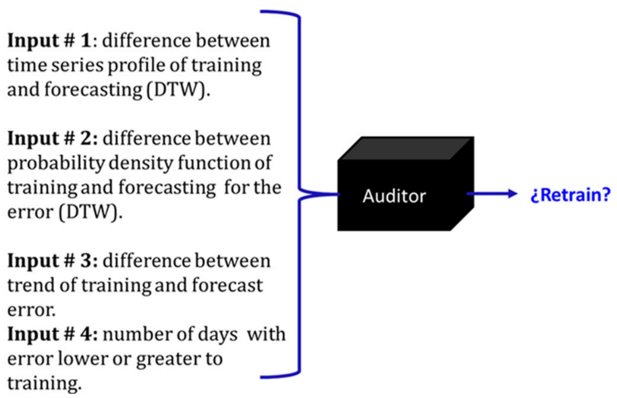

FIGURE 2. Proposed intelligent system for the Auditor.

E. SELECTION CRITERION

From Figure 1, it is possible that retraining the time-series model does not recover the desired performance, so the output of the Auditor will keep indicating that retraining is required. When this situation occurs, the architecture concludes that the initially selected model no longer represents the phenomena, and replacing the model is the only way to recover performance.

However, it has been analyzed that employing the MAPE as a metric is not trustful to decide when this drastic decision must be taken. The MAPE could still indicate adequate performance when a model has lost validity since the MAPE fails to provide reliable information due to the shape and deviation of the time series. Hence, this work defines a novel performance metric called rMAPE, whose definition overcomes where the MAPE falls short.

The rMAPE is symbolized with η (see Figure 1) and is defined as:

$$rMAPE = \frac{MAPE}{r_{xy}}, \tag{1}$$

where

$$MAPE = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| x100, \tag{2}$$

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - \left(\sum x_i\right)^2}\sqrt{n\sum y_i^2 - \left(\sum y_i\right)^2}}, \tag{3}$$

r_{xy} : Sample statistic of Pearson's correlation coefficient.
$MAPE$: Mean Absolute Percentage Error,
x_i : actual data time series,
y_i : time series forecasting,
n : number of time series data.

The metric now ranges in the $-\infty \leq rMAPE < \infty$ interval, and the values for this new performance metric can be understood as described next. Figure 3 shows case examples and compares both metrics.

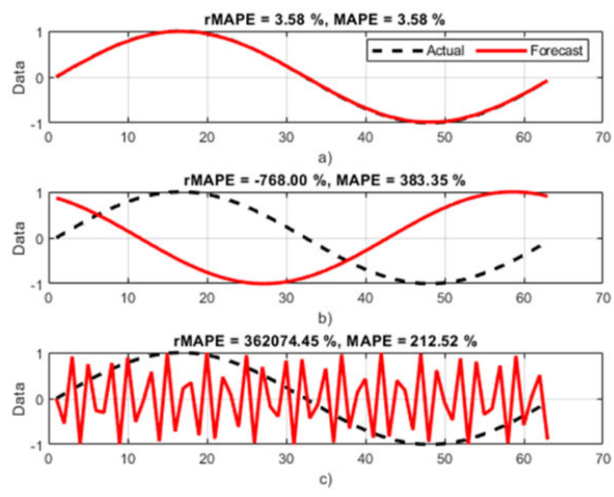

FIGURE 3. Different cases showing the convenience of using rMAPE as a performance metric over the MAPE.

If the rMAPE is close to zero (0); then, it can be concluded that the MAPE is small but also that the correlation (r_{xy}) is close to one (1) (see Figure 3a). Therefore, the forecasted time series is closer to the actual magnitude and shape. If the rMAPE tends to infinite; then, the correlation (r_{xy}) is close to zero (0) no matter the MAPE behavior, which indicates that the forecasted time series is closer to the actual magnitude, but its shape does not fit properly (see Figure 3b and 3c). Figure 3 shows examples of the different rMAPE values and the associated MAPE values to exemplify how the MAPE can fail in providing a trustful decision for the intelligent system. Thus, with the rMAPE it is possible to evaluate the capabilities of forecasting performance.

The use of rMAPE does not avoid the comparison with other works since, by transitivity, when using the rMAPE and looking for such a metric to be low, the MAPE is also low. That transitivity property does not apply from MAPE to rMAPE, as shown in Figure 3. Thus, in this work, the intelligent-system decisions are based on the rMAPE, but the MAPE performance will be listed for fairness when comparisons are provided.

Figure 3 shows three comparison scenarios between the rMAPE and MAPE metrics. The rMAPE exhibits greater sensitivity and can capture when the predicted curve departs from the actual curve, and MAPE may not detect this situation. The rMAPE expands its range from $-\infty$ and $+\infty$ as reporting any departure from the actual curve, even when the MAPE remains stable under curve shape difference.

III. PROPOSED ARCHITECTURE-BASED TOOL

A computational tool is developed to handle the time series while considering the different exogenous variables to analyze, debug, select, and assemble more suitable models.

The tool allows for handling weather information, the taxonomic variable of the day, and calendar type. The time-series data are requested before building the model, and the time-series data are hourly.

A. DATA ANALYSIS

Figure 4 shows the flowchart used by computational tool for data analysis. Although the model-building process is automatic with minimal human intervention, the user must upload the corresponding time-series. The tool can list several added time series. Since the devised procedure handles exogenous variables, a set of models are built for every type of day and different weather seasons of the year for each time series. The user can validate the assembled models,

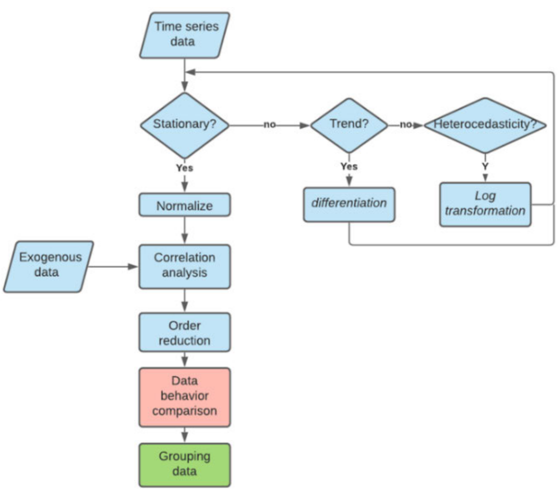

FIGURE 4. The flow chart and steps for data analysis.

the weather-correlated variables, and lags associated with the non-stationary time-series transformation (Autoregressive process).

The user must indicate the start date and the end date to forecast the data for the selected time series. Once the forecast is indicated. The tool displays the historical and forecasted data curves so that the accuracy of the used models can be compared. Once the models are implemented, the Auditor carries out the continuous monitoring of the model performance; in case that retraining is detected, the Retrain will be enabled. Thus, the user could carry out the retraining tasks for each model.

The graphical analysis techniques provide the user tools to understand the grouping of the different models, the detection of stationary patterns, the identification of the amount of prior data (lag) to generate the autoregressive process, and the selection of the exogenous variables to explain the behavior of the time series.

It is important for the user to establish which curves do not represent a typical behavior as a preliminary step for retraining and the characterization of the time-series data. Besides, it can help to avoid the addition of values that do not correspond with reality or add noise to the modeling process.

B. MODEL BLOCK IMPLEMENTATION

A complete description of the implementation of the atypical-curve identification, base-curve generation, and base-curve intelligent correction can be found in [28]. Figure 5 shows a summary of each required stage of the forecasting models.

C. ASSEMBLED MODEL TRAINING PROCESS

1) SVM, LSTM, AND RTE TRAINING

An optimization process based on Bayesian theory is proposed to train SVM, LSTM, and RTE models. Bayesian optimization carries out the global optimization for multimodal functions, such as models based on computational intelligence systems. A Bayesian hyper model represents the data behavior and the qualitative information through the distribution of probabilities. Figure 6 shows the flow chart that describes each stage of the process.

Table 1 shows the factors to be considered during the training and validation processes.

An experimental design is set to evaluate and select the model with the best performance to train a feedforward neural network. The factors that influence adaptability and generalization in the training process, validation, and selection of neural networks are identified according to recommendations given by authors in [30]. Figure 7 shows the proposed training and selection stages for the best model base on neural networks.

Next, the Bayesian optimization process algorithm is defined as:

- Step 1: Include a prior about a phenomenon before any evidence is presented. Since there is no knowledge

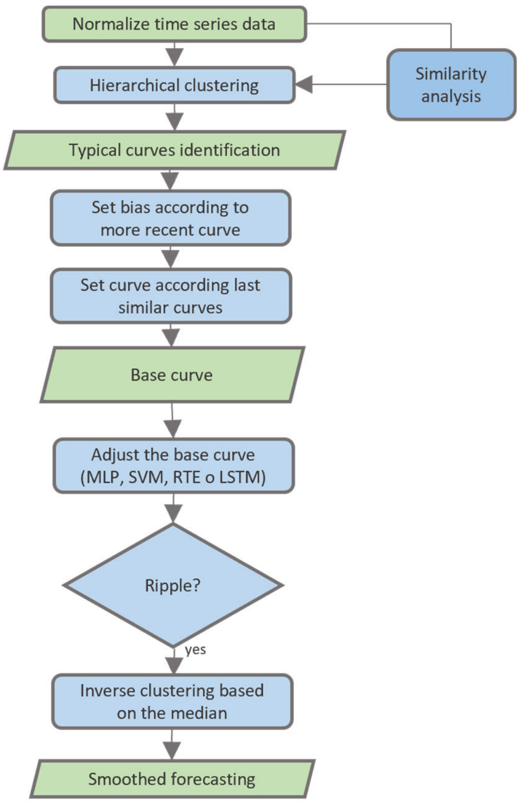

FIGURE 5. **Implementation of modeling stages for the time series.**

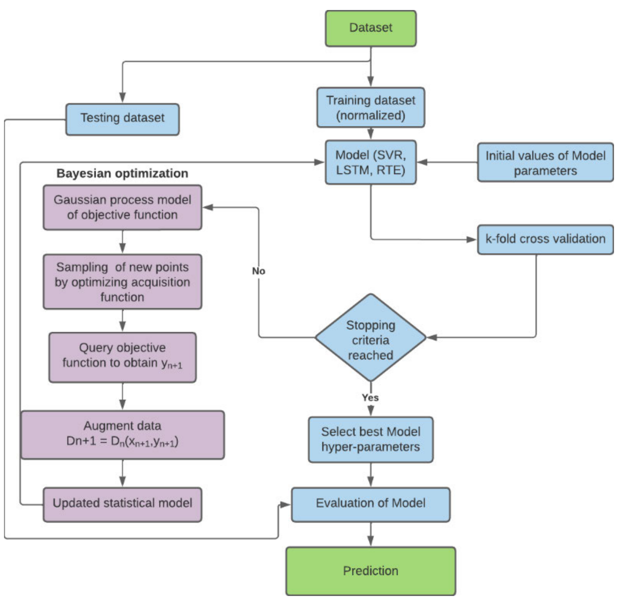

FIGURE 6. **Training process of SVR, LSTM and RTE models.**

about a parameter, the prior is treated as a random variable (e.g., Gaussian multivariable function).

- Step 2: Combine the prior distribution with some given observations to get a posterior distribution (MAP, i.e., Maximum A Posteriori) on the target (the estimation where it has the actual function).

TABLE 1. **Initial machine learning (ML) models and their hyperparameters settings.**

ML Model	Hyperparameters	Value
LSTM	HiddenLayerSize learning rate	[1, 50] [1e-3, 1]
SVR	C	linspace(0.01, 5, 20)4
	gamma	range(0.01, 0.5, 0.05)
	kernel	{linear, poly, rbf}
RTE	max_depth	range(8,15)

All models were trained using statistics and the machine learning toolbox of MATLAB.

- Step 3: Use the posterior distribution to evaluate the next configuration according to an acquisition function. It is possible to test the next configuration with the majority of the information.

- Step 4: Evaluate the selected configuration from the previous step.

Steps 2-4 must be iterated until the values converge [30].

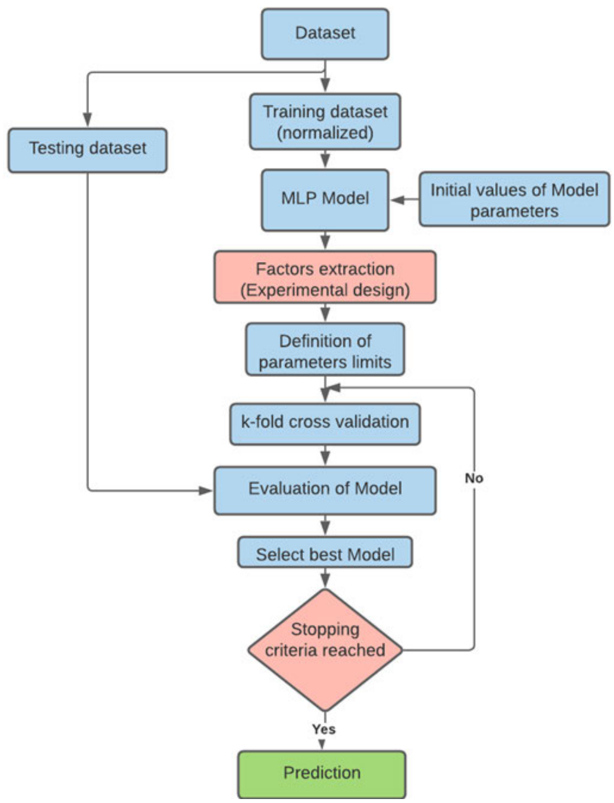

FIGURE 7. **Training and selection stages for the best model base on neural networks.**

D. AUDITOR CORE PROCESS

Once the variables to be considered are characterized by the Auditor, expert knowledge is used to build a supervised model using Random Forest (RF) due to the capability to improve the predictive accuracy and control over-fitting. A graphical description of the Auditor process is shown in Figure 8. This figure shows the Auditor behavior in three stages: 1) continuously monitoring the model performance, 2) detecting performance detriment, and 3) providing recommendations to guarantee performance stability. According to the description of the Auditor, the recommendation can be to continue monitoring with or without retraining the model.

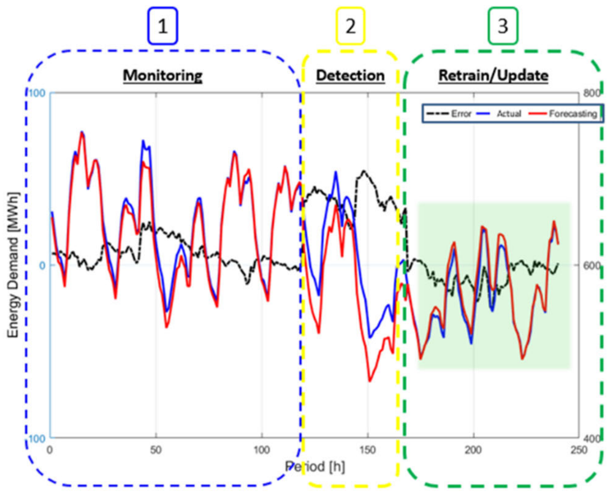

FIGURE 8. Auditor core process.

E. SELECTION CRITERION

It is necessary to train and evaluate the performance of each model by using the rMAPE metric to carry out the implementation of this stage. For each case, a model with the lowest value will be selected to characterize the data from each subgroup. Figure 9 shows a comparison between rMAPE and MAPE where it is highlighted how rMAPE penalizes a shape deviation of the forecasting data. This example shows how the proposed performance metric is more sensible a variation in a shape during the model selection.

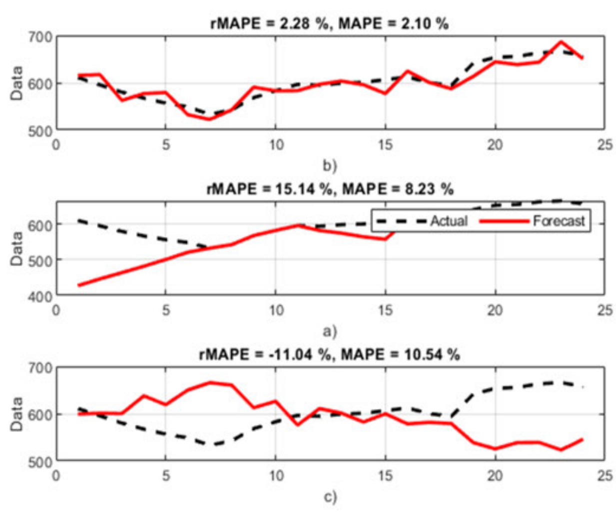

FIGURE 9. rMAPE vs MAPE.

Figure 9 (a) and (c) show an improved rMAPE sensitivity compared to the MAPE. It can be noticed how the rMAPE can quantify variations in the shape of the predicted and current curves.

IV. EXPERIMENTAL TESTING AND RESULTS

A. DATA DESCRIPTION

In this section, the comparison of the proposed approach with other methods is carried out to demonstrate the superiority in time-series forecasting for power consumption and energy market. The performance contribution of each stage for the forecasting is summarized, and Table 2 shows the dataset summary used for the evaluation.

TABLE 2. Datasets chosen to evaluate the proposed procedure.

No.	Datasets	Number of instances	Number of attributes
1	Electrical demand in a building.	2542	107
2	Energy demand in electrical market # 1.	730	107
3	Energy demand in electrical market # 2.	730	107
4	Electricity hourly-ahead market price.	365	107

1) ENERGY DEMAND

Data of several energy-demand-related time series are used for performance assessment.

Case #1. Energy demand in a building. Hourly data related to energy demand in a building are used in training, validation, and testing for a total data equal to 2,542 days / 24 hours per day. Data zeroes and outliers are cleaned because they add noise to the assembled model. Dataset has non-stationarity properties and weather seasons to modify the times-series behavior over time. The authors thank the E-LAND project for providing the data (see Figure 10) [31].

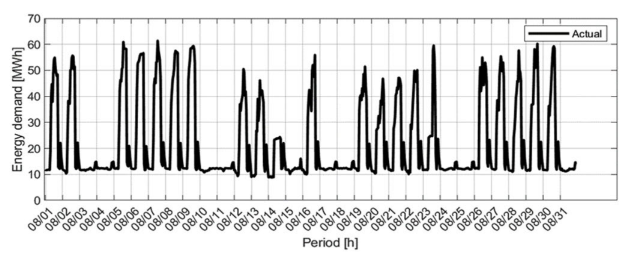

FIGURE 10. The energy demand of a building in the E-LAND Project.

Case #2. Energy demand in electrical markets. Energy demand data are normalized when assembling the forecasting models for each commercialization market (see Figure 11 and Figure 12). Historical energy demand data of two energy commercialization markets in Colombia are used to analyze the energy demand (Market 1: State of Atlántico and Market 2: State of Antioquia). Dataset has non-stationarity properties to modify the times-series behavior over time.

In addition, the time series has changing characteristics in shape and trend due to energy consumption behavior. Weather data are consulted through the website www.accuweather.com.

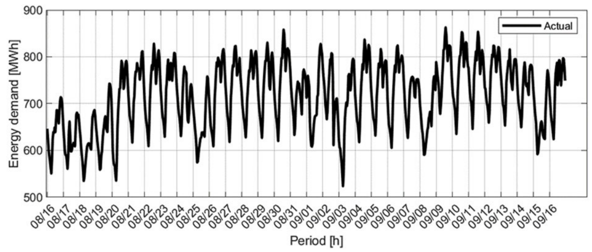

FIGURE 11. The energy demand of Electrical Market # 1.

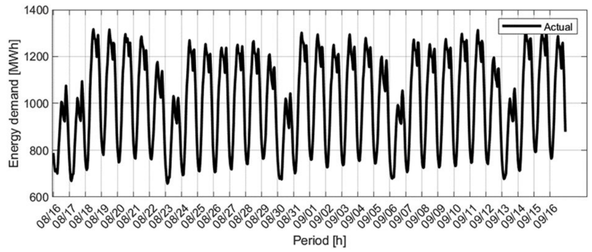

FIGURE 12. The energy demand of Electrical Market # 2.

2) ENERGY MARKET

For this case, the Hourly Energy Price (HOEP) is the basis for regulated rates charged to residential and small business customers. The HOEP is charged to Local Distribution Companies (LDCs) in the Independent-Electricity-System-Operator (IESO) administered market and paid to self-scheduling generators. Customers that use more than 250,000 kWh/year pay the HOEP (see Figure 13). The HOEP values are reported as $/MWh.

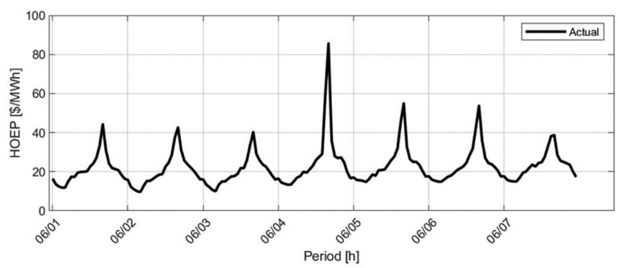

FIGURE 13. Hourly energy price.

The models are trained on hourly data of an electricity market. Data detailed above are provided by [32].

Data is normalized to avoid differences in data magnitudes that can affect the consistency of data distribution. The normalization process is performed through Equation 4 for each variable considered for the time-series forecasting. Data normalized according to

$$X_{normalized} = \frac{X - min(X)}{max\,(X)\; - min(X)}, \tag{4}$$

where

$X_{normalized}$: normalized time series,
X : original time series,
max(X) : maximum value of time series,
min(X) : minimum value of time series.

B. EXPERIMENTAL DESIGN

The following experimental design for the forecasting is carried out by evaluating the rMAPE metric and the distribution of the selected models. At the same time, it is evaluated if there is a difference in the performance obtained by each one of the available forecasting models.

For each time series, 70% of the data are taken for training, 15% for validation, and 15% for testing. The model performance is validated using one of the rolling windows with a step k that depends on the number of models for each subset. The data separation in small subsets has been proposed for the validation process to avoid data overlapping during the training procedure. Hence, the models are unaware of all the validation data. Once the training process for the model is complete, the testing data are used to evaluate the model performance. The training data selection takes place randomly and follows a uniform distribution.

Therefore, the following characteristics define the experiment design:

Response Variable:
1) Time-series data.
Independent Variable:
2) Time-series models:
1. ANN.
2. SVR.
3. LSTM.
4. RTE.
3) Time-series data. Electric demand and electrical market time series.

Experimental design results are complemented with plots that summarize the results obtained by each response variable. The results describe the performance of each available model and the suitability of each technique to be considered.

Two graphical comparisons are implemented to carry out the statistical analysis of the proposed procedure: 1) Accumulated average, and 2) Tukey-Kramer multi-comparison means test. The analysis allows the identification of the error trend in a variable time window. Besides, the inclusion of the multi-comparison test in the analysis brings information about the performance of each model.

1) EXPERIMENTAL METRICS

Although this paper uses rMAPE to ensure low MAPE values and highly correlated models, the results presented will use MAPE so that fair comparisons can be made with other available state-of-the-art works.

C. EXPERIMENTAL RESULTS

1) ENERGY DEMAND

Case #1: A testing analysis is performed on time-series data resulting in a MAPE equal to 14.49%. Figure 14 shows a time series forecasting.

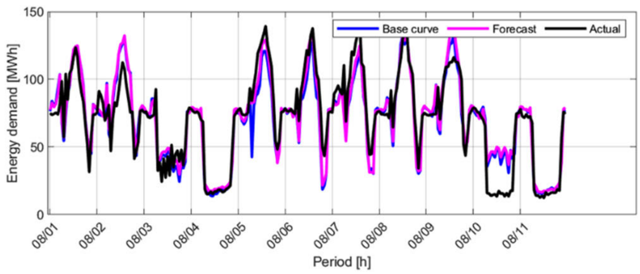

FIGURE 14. Base curve, intelligent correction, and actual data of time series of building.

Case #2: Forecasting data published on the official Colombian Energy Market Regulation Agency, XM, website [33]. These data are taken as a reference to compare the results obtained from the proposed architecture.

Figure 15 shows the forecasting of the energy demand commercialization for the Electrical Market #1.

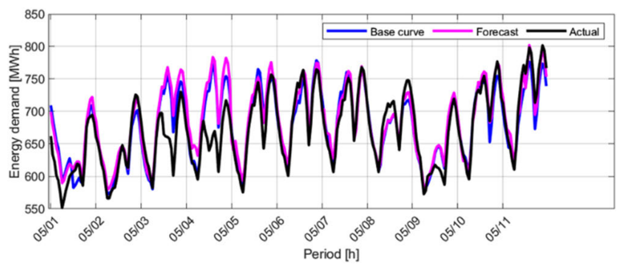

FIGURE 15. Base curve, intelligent correction, and actual data of time series for Electrical Market #1.

Figure 16 shows the forecasting of the energy demand commercialization for Electrical Market #2.

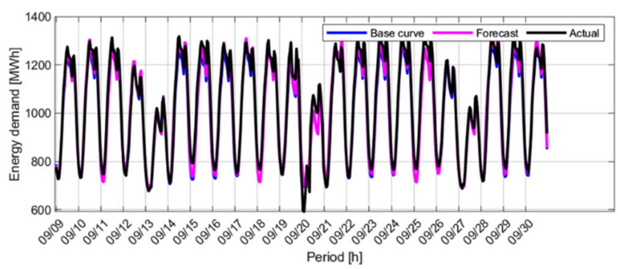

FIGURE 16. Base curve, intelligent correction, and actual data of time series for Electrical Market #2.

Figures 17 – 18 show the performance (MAPE) of this Proposed Architecture (PA) for the forecasting process of Commercialization Markets 1 and 2.

Figure 19 shows the individual performance of each one of the modeling techniques and the results from the PA for the time series of the Electrical Market 2 for a forecasting window (7 days forward).

2) ENERGY MARKET

The data to be used for this experiment are described in Section IV-A1. Reference [34] is used as a comparison since

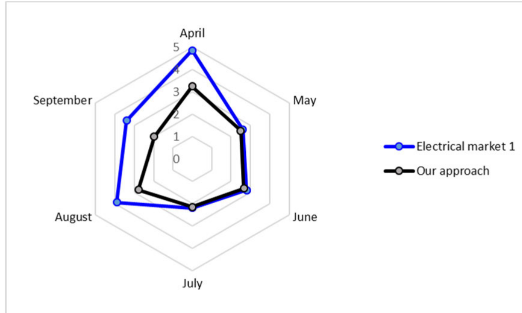

FIGURE 17. Performance comparison among the model used by the electrical market 1 operator and the PA model.

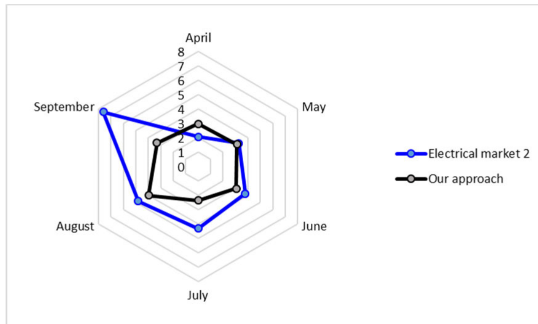

FIGURE 18. Performance comparison among the model used by the electrical market 2 operator and the PA model.

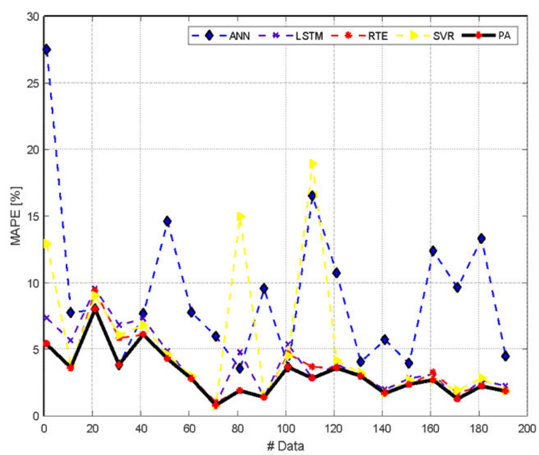

FIGURE 19. Cumulative average MAPE for seven days ahead forecasting.

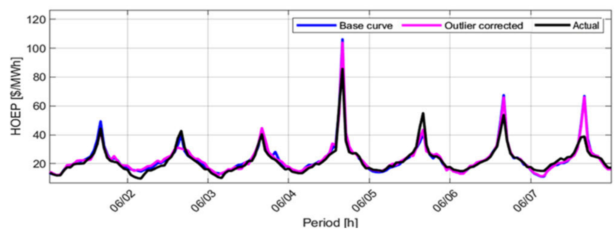

FIGURE 20. Base curve, intelligent correction, and real data of time series of the energy market.

an ANN has been used to compute the forecasted price in the electricity market. The results shown in Figure 20 correspond to six months of data selected to carry out the tests. The performance (MAPE) achieved by the test period is 14.22%.

Table 3 shows a comparative analysis of the obtained results by the proposal and the authors work reported in [34].

TABLE 3. **Performance comparison (MAPE) of the proposed architecture.**

Date	PA	[33]
June	**11.7**	13.66
July	**11.72**	21
August	25.2	**21.25**
September	**11.74**	20.35
October	**11.18**	566.35
November	**12.93**	18.34
December	**14.83**	16.14
Total	**14.22**	96.72

It is possible to adjust the average MAPE from Reference [34] without the month of October to carry out a comparison without extreme data, which clearly shows a very large data error. Thus, the new MAPE would be equal to 18.07% showing a better performance by the PA.

V. DISCUSSION AND CONCLUSION

The results and analysis carried out during this paper have highlighted the characteristics of the devised architecture considering the response variables discussed in Section IV-A. The main objective is to propose a procedure that will allow ensemble models to fit themselves into the characteristics of different time series (the lowest MAPE) without affecting their performance over time. For the forecasting of the energy demand in a building, the achieved performance index (MAPE) is suitable for the goals of the work.

The building of consumption profiles proved to be a proper step towards forecasting time series. However, a preliminary base curve does not incorporate the effect of external variables such as weather conditions. Therefore, an intelligent correction (SVR, ANN, LSTM, and RTE) is necessary. Such correction technique can be adjusted for each period independently; however, it is possible to induce a ripple in the output curve. Therefore, the intelligent correction agent is complemented with smoothing and outlier suppressing mechanisms to guarantee the best performance. LSTM and RTE showed a better performance than SVR and ANN. In addition, adding several computational intelligence techniques within the knowledge base allow the consideration of multiple alternatives for other cases where the techniques may show a better performance.

In the forecasting process for the energy demand of Electrical Markets 1 and 2, the performance achieved by the proposed approach is superior for both markets in comparison to the models implemented by Reference [33].

Different modeling techniques allow evaluating alternatives for the same time series and the different profiles obtained in the profiling stage. The results show that the inclusion of more than one modeling technique helps in the process of characterization of the time series. The proposed architecture provides the possibility to build hybrid models in those cases where a unique technique does not guarantee better performance.

The performance of each one of the modeling techniques included on the knowledge base for 7 days show better performance (accumulated average) for the LSTM and RTE. ANN presents a poorer performance than SVR.

Implementing the Auditor module and the retraining process help in the maintenance process of the models, minimizing the decreasing rate in the performance of the assembly forecasting models. Once the Auditor identifies the need for retraining, the system can evaluate the performance of each of the available modeling techniques in the knowledge base for the window of the time series under study. As a result, the architecture guarantees the automatic adjustability of trained models no matter the dynamic behavior of the modeled phenomena using rMAPE metric. The forecasting results showed an improvement in the MAPE of up to 23% in the tests performed with the proposed metric via simulation.

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