Adaptive Hybrid Electric Load Forecasting for Critical and Strategic Power Systems

STYLIANOS PAPPAS, NIKOS MASTORAKIS
Department of Electrical Engineering and Computer Science
Hellenic Naval Academy
Terma Chatzikyriakou, 18539, Piraeus
GREECE

Abstract: Accurate and computationally efficient forecasting is essential for the undisturbed operation of power systems. Traditional methods cannot detect the nonlinear behaviour of modern electrical grids, affected by various factors such as seasonal variations, peak-hour demand fluctuations the increasing penetration of renewable energy sources, etc. To overcome these limitations, an adaptive hybrid method is proposed, combining the Multi Model Partitioning Filter (MMPF) with Nonlinear Autoregressive Exogenous (NARX) models and a Genetic Algorithm for Resource Allocation (GARA).
The MMPF structure remains unchanged, implementing NARX submodels to detect the non-linear data characteristics. Additionally, the GARA optimizes the MMPF overall weights through an evolutionary, procedure. The new method is evaluated using real data from the Hellenic grid and compared against two established methods, MMPF–SVM and MMPF–GA. The results indicate that the proposed method achieves better forecasting accuracy and reduced computational burden, making it suitable for applications including autonomous or mission-critical energy networks.

Key-Words: - Electric load forecasting, Multi Model Partitioning Filter, Nonlinear Autoregressive Exogenous models, adaptive hybrid modelling, Genetic Algorithm for Resource Allocation, Support Vector Machines.

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1 Introduction

Electric load forecasting is important for the reliable and economic operation of modern power systems. Accurate forecasting helps energy providers and system administrators to improve generation scheduling, resource allocation, manage reserves, and help the system's stability under varying operating conditions. Traditional statistical methods, implementing ARIMA or other methods, have been shown to perform well under the assumption that the data is linear. The increasing penetration of renewable energy sources and the impact of consumer behaviour lead to frequent load fluctuations, introducing nonlinear characteristics, reducing the accuracy of the above-mentioned methods, [1].

To overcome the nonlinearities, Artificial Intelligence (AI) and Machine Learning (ML) approaches have been widely implemented lately, offering the ability to resolve the obstacles posed by the nonlinear characteristics and time-dependent patterns, [2], [3]. Finally, hybrid techniques have been shown to outperform individual methods, especially when applied to large and noisy datasets, [4], [5].

MMPF has been applied successfully in the past to adaptive electric load forecasting, using real data, [6]. Variations of this approach are its combination with Support Vector Machines (SVM) and Genetic Algorithms (GA). Both methods led to significant improvements in prediction accuracy, [7], [8], [9], [10].

In this study, a hybrid forecasting method based on MMPF is proposed. The new model combines Nonlinear Autoregressive Exogenous (NARX) submodels instead of EKF, allowing nonlinear characteristics to be effectively captured. The Genetic Algorithm for Resource Allocation (GARA) adaptively refines each NARX's weight, providing accuracy and reduced computational complexity.

The proposed model is validated using real data from the Hellenic power system and compared against two established methods, MMPF-SVM and MMPF-GA. The results indicate better accuracy for electric load forecasting, which is the problem at hand. Although the present study focuses on grid-level electric load forecasting, similar challenges arise in isolated or mission-critical energy systems, such as naval, defense, or islanded microgrids, where forecasting reliability directly influences operational stability.

2 Problem Formulation

The electric load forecasting problem is reformulated based on the extension of the MMPF as introduced in previous works, [9], [10], [11]. In its classical form, the MMPF divides the estimation space into a set of parallel submodels, each one representing different characteristics of the system under study. Each submodel produces an independent estimate in terms of a probability of the output, while the overall prediction is obtained as a weighted combination of these individual forecasts.

In the proposed method, the MMPF implements Nonlinear Autoregressive Exogenous (NARX) models, instead of KF or EKF. Each submodel acts as a nonlinear predictor trained to model the electric load, incorporating exogenous variables that describe external influences, such as time and weekly effects.

2.1 MMPF with EKF

The structure of the MMPF with EKF, Figure 1, follows the architecture presented analytically in, [8]. Each MMPF consists of a parallel bank of EKFs, usually ten, but depending on application complexity, more may be used, which are executed independently at every iteration. Posterior probabilities are assigned to all models, and as the process evolves, the probability of the most accurate model approaches one, while the rest tend to zero. The final estimate is obtained as a weighted combination of all submodel outputs. This configuration enables parallel execution, significantly reducing computational time in real-time or high-dimensional tasks.

The optimal Minimum Mean Square Error (MMSE) estimate is given by:

$$\hat{x}(k/k) = \sum_{i=1}^{M} \hat{x}(k/k;\theta)\, p(\theta/k) d\theta \tag{1}$$

The probabilities are calculated online in a recursive manner as follows:

$$p(\theta/k) = \frac{L(k/k;\theta)}{\sum_{i=1}^{M} L(k/k;\theta)\, p(\theta/k-1) d\theta}\, p(\theta/k-1) \tag{2}$$

where,

$$\begin{aligned} L(k/k;\theta) &= \left|P_Z(k/k-1;\theta)\right|^{1/2} \cdot \\ &\exp\left\{-1/2 \left\| \tilde{z}(k/k-1;\theta) \right\| \cdot P_Z^{-1}(k/k-1;\theta)\right\} \end{aligned} \tag{3}$$

and P_Z^{-1} is calculated by the EKF equations.

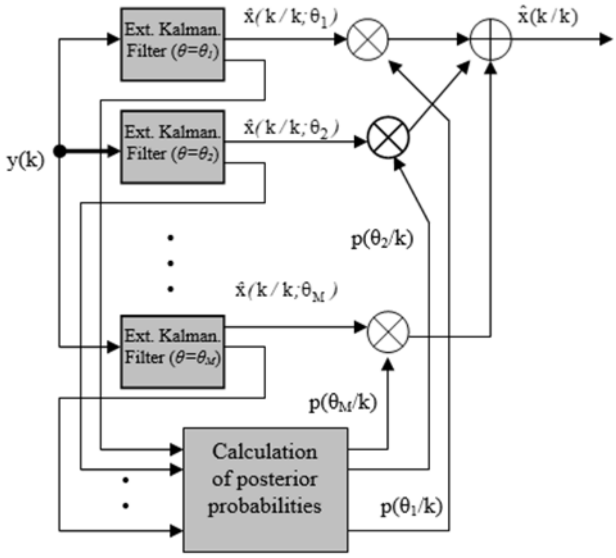

Fig. 1: Block diagram of MMPF+EKF. Every EKF implements an ARMA model.
Source: created by the authors.

2.2 MMPF with SVM

This approach is analytically described in [12]. The overall estimation of this hybrid model is obtained by summing the linear component. $\tilde{L}$(k) given by the MMPF and the non-linear one $\widetilde{NL}$(k), computed by the SVM. In this configuration, the SVM models the residuals of the MMPF to enhance the final prediction accuracy. The structure is illustrated in Figure 2.

$$e_k = y(k) - \tilde{L}(k) \tag{4}$$

is the MMPF estimation error at any time interval *k*.

The residual equation, as modelled by SVM, is given by

$$e_k = f(e_{k-1}, \dots e_{k-n}) + \Delta k \tag{5}$$

where f is nonlinear, and Δk is a random error. The final output is given by:

$$\tilde{y}(k) = \tilde{L}(k) + \widetilde{NL}(k) \tag{6}$$

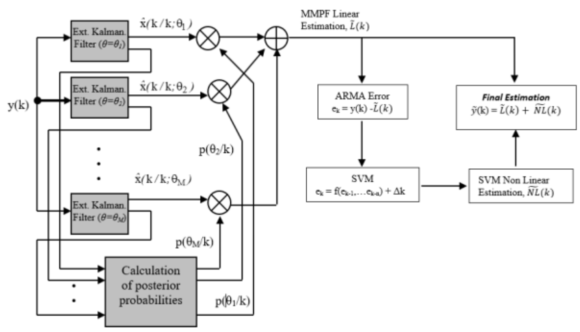

Fig. 2: Hybrid MMPF+SVM block diagram.
Source: created by the authors.

2.3 MMPF with GA

This method (see Figure 3) provides improved performance in estimation and optimization tasks, as analytically detailed in [9]. The MMPF computes the posterior probabilities according to (2), which are then used as the corresponding fitness values (*FV*) for the genetic algorithm. The next generation is produced through the standard GA operations of selection, mutation, and crossover. The total number of generations is manually specified, and the final population represents the updated set of candidate MMPF models. The GA component of the method was implemented using the Matlab® Genetic Algorithm Toolbox. Some relevant recent studies demonstrating the effectiveness of Genetic Algorithms in hybrid forecasting problems can be found in [13], [14], [15], [16], [17], [18], [19], [20], [21], [22].

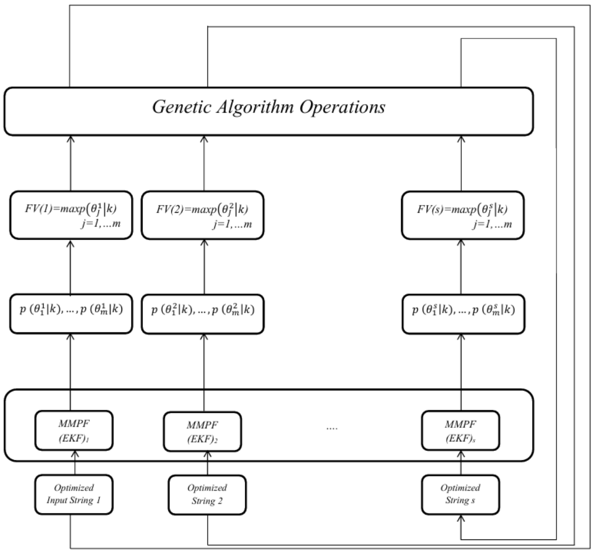

Fig. 3 (created by the authors): Hybrid MMPF+GA block diagram.
Source: created by the authors.

3 MMPF-NARX-GARA

3.1 MMPF with NARX-based submodels

In the proposed method, the ARMA models implemented in every EKF in 2.1, 2.2, and 2.3 are replaced by Nonlinear Autoregressive Exogenous (NARX) models, which act as nonlinear predictors within the MMPF structure (see Figure 4). Recent studies implanting NARX models in nonlinear forecasting problems can be found at [23], [24], [25], [26], [27], [28], [29], [30].

NARX submodels trained in parallel to approximate The nonlinear relationship between the present and past values of the electric load, using both autoregressive and exogenous variables.

The general form of each NARX submodel is expressed as:

$$\tilde{y}_i(k) = F_i\,(y(k-1), y(k-2),\ldots, y(k-p), u(k-1), \ldots\, u(k-q)) \quad (7)$$

where $F_i\,(\cdot)$ represents the nonlinear vector of the i^{th} submodel, p and q are the autoregressive and exogenous input vector orders, respectively. The predicted electric load at time instant k, by the MMPF-NARX, is denoted by $\tilde{y}_i(k)$.

In this case study case the exogenous input vector $u(k)$ is defined as:

$$u(k) = \left[\sin\left(\frac{2\pi D_{hour}}{24}\right), \cos\left(\frac{2\pi D_{hour}}{24}\right), D_{week}(k), \sin\left(\frac{2\pi D_{month}}{24}\right), \cos\left(\frac{2\pi D_{month}}{24}\right), \bar{y}_{(k-6,k)}\right] \quad (8)$$

where:

- $D_{hour}\,(k)$= is the current hour of the day (1–24)
- $D_{month}\,(k)$= represents the month of the year (1-12)

both expressed in a unit circle. This encoding prevents discontinuities (i.e., from 23:00 to 0:00, or from the 12th month to the 1st). It effectively models the diurnal pattern of energy consumption. This approach is included in forecasting algorithms and machine learning models as presented in [31], [32], [33], [34], [35].

- $D_{week}\,(k)$= is the day of the week (1–7)
- $\bar{y}_{(k-6,k)}$ is the moving average of the load, over the past six hours, defined as: $\frac{1}{6}\sum_{j=k-6}^{k-1} y(j)$

Each NARX submodel minimizes its own mean-squared error:

$$J_i = \frac{1}{M}\sum_{k=1}^{M}\left(y(k) - \tilde{y}_i(k)\right)^2 \quad (9)$$

3.2 Adaptive Genetic Resource Allocation (GARA)

Each chromosome represents a candidate weight vector:

$$\boldsymbol{W} = [w_1\;, w_2\;,\ldots\, w_M], \quad (10)$$

with $\sum_{i=1}^{M} w_i\;)$= 1, and $w_i\;\in [0,1]$

The first chromosome is initialized directly using the vector of posterior probabilities estimated by the MMPF:

$$w^1 = w^{MMPF\text{-}NARX} = [p(\theta_1/k)\;\ldots.\; p(\theta_M/k)] \quad (11)$$

with $\sum_{i=1}^{M} w_i\;)$= 1, and $w_i\;\in [0,1]$.

The fitness function measuring the forecasting accuracy is given by:

$$f(\boldsymbol{W}) = \frac{1}{N}\sum_{k=1}^{N}\left|y(k) - \sum_{i=1}^{M} w_i\tilde{y}_i(k)\right|^2 \quad (12)$$

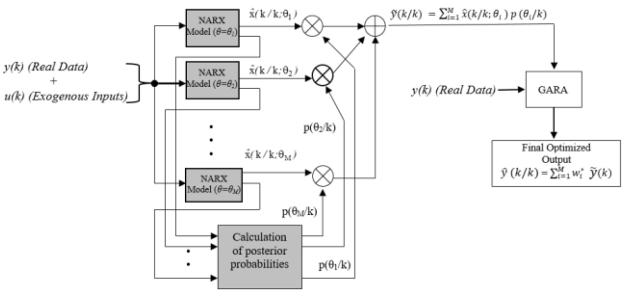

Fig. 4: The structure of the proposed MMPF-NARX-GARA method.
Source: created by the authors.

The Genetic Algorithm evolves the population through its typical procedures of selection, crossover, and mutation until convergence. The mutation rate is defined as

$$\mu_t = \mu_0 \left(1 - \frac{t}{t_{max}}\right) + \varepsilon \quad (13)$$

where,

- μ_t = is the mutation rate at generation t
- μ_0 = is the initial mutation rate
- t_{max} = maximum number of generations
- ε is the residual mutation term, ensuring minimal diversity near convergence

In this study, μ_0 was selected as 0.1, providing a moderate mutation (10%) that prevents early convergence and keeps a balanced level of exploration. Since the GARA optimizes adaptively the weights assigned to each NARX submodel's output, t_{max} was decided to be equal to 40. Finally, ε was set to 0.003 to introduce a small stochastic disturbance for maintaining diversity near convergence and preventing stagnation when fitness plateaus, without affecting stability, [36], [37], [38].

The optimal weight vector is given by:

$$\boldsymbol{W}^* = argmin\, f(\boldsymbol{W}) \quad (14)$$

and the final optimized forecast is expressed by

$$\hat{y}\,(k/k) = \sum_{i=1}^{M} w_i^* \,\tilde{y}_i(k) \quad (15)$$

where, w_i^* represents the optimal weight assigned to the i^th NARX submodel.

4 Results

The dataset covers the period from January 2020 to December 2025. The data is used sequentially to preserve temporal dependencies. Approximately 60% of the data was used for training the MMPF–NARX submodels, 20% for validation, and the remaining 20% for testing and prediction. The prediction window was set to two months, representing a medium-term load forecasting scenario to examine for the first time the proposed hybrid method. To assess the accuracy of the predictions, the Mean Absolute Percentage Error (MAPE) is calculated, [39], [40].

The MAPE is defined as

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left|\frac{A_i - P_i}{A_i}\right| \quad (16)$$

where A_i is the actual value, P_i is the predicted value, and n is the total number of samples.

At this point, it should be mentioned that the proposed MMPF–NARX–GARA method implements seven submodels, while MMPF–SVM and MMPF–GA ten submodels to achieve comparable accuracy. The reduced number of NARX submodels didn't affect the method's performance. On the contrary, the adaptive weight optimization performed by the GARA component improved its precision.

The reduction in the number of submodels is important in reducing the computational burden. Additionally, it is promising for future assessment on short-term or real-time applications.

The forecasting results for all the methods under consideration along with their associated absolute errors are depicted in Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, and Figure 10.

The proposed method (red line in Figure 6, Figure 8, and Figure 10) has the smallest absolute error throughout the entire testing period. Additionally, the Mean Absolute Percentage Error (MAPE) of each method for every forecasting interval is presented in Table 1.

Table 1: Mean Absolute Percentage Error (MAPE) of Each Forecasting Method Across Different Periods.

Method	**January–February**	**April–May**	**August–September**
MMPF–NARX–GARA	2.1%	2.2%	2.1%
MMPF–SVM	2.4%	2.6%	2.5%
MMPF–GA	2.8%	2.9%	2.9%

Source: created by the authors.

The proposed MMPF–NARX–GARA method has the lowest Mean Absolute Percentage Error (MAPE) across all forecasting periods (Table 1). The improvement in accuracy ranges from 0.3% to 0.8% compared to the MMPF–SVM and MMPF–GA methods. This demonstrates the superior forecasting capability and adaptability of the proposed hybrid structure.

It is also important to note that the proposed method employs only seven submodels, while MMPF–SVM and MMPF–GA use ten.

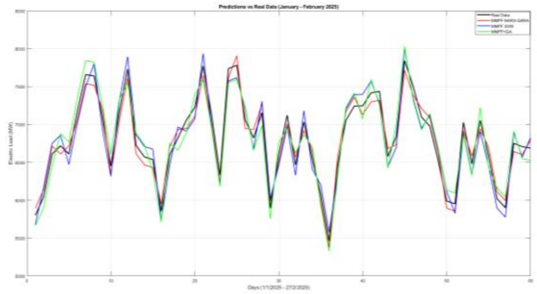

Fig. 5: Hellenic power market daily system load from January 1st, 2025, to February 27th, 2025, compared with MMPF-NARX GARA, MMPF-SVM, and MMPF-GA, for day-ahead forecast.
Source: created by the authors.

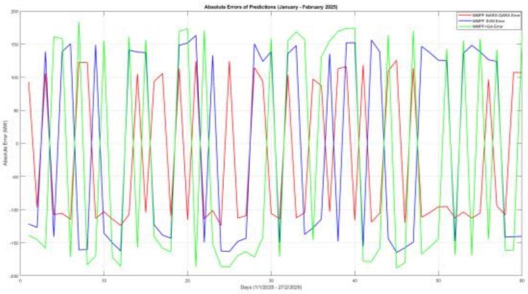

Fig. 6: Absolute Prediction Errors for all methods, January 1st 2025 to February 27th 2025.
Source: created by the authors.

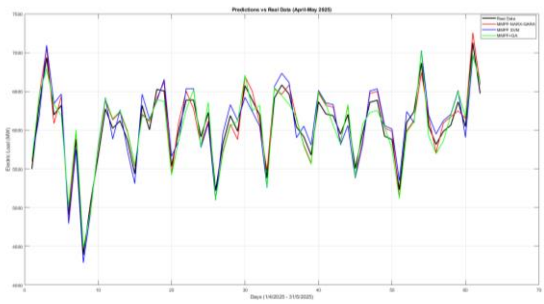

Fig. 7: Hellenic power market daily system load from April 1st, 2025, to May 30th, 2025, compared with MMPF-NARX GARA, MMPF-SVM, and MMPF-GA, for day-ahead forecast. Source: created by the authors.

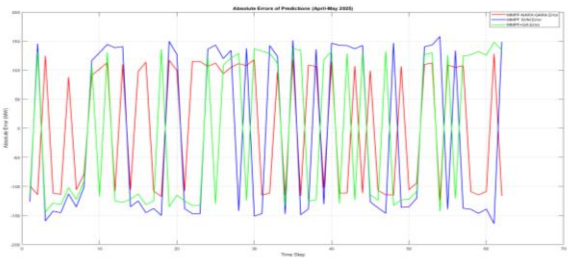

Fig. 8: Absolute Prediction Errors for all methods, April 1st 2025 to May 30th 2025.
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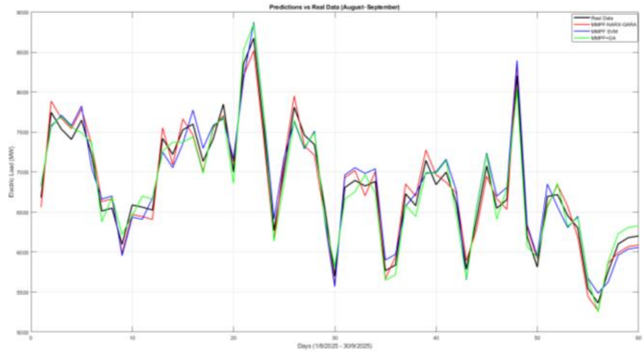

Fig. 9: Hellenic power market daily system load from August 1st, 2025, to September 30th, 2025, compared with MMPF-NARX GARA, MMPF-SVM, and MMPF-GA, for day-ahead forecast. *Source: created by the authors.*

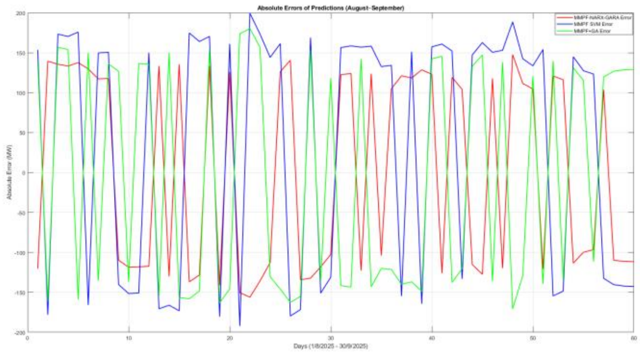

Fig. 10: Absolute Prediction Errors for all methods, August 1st 2025 to September 30th 2025.
Source: created by the authors.

5 Conclusion

In this study, a new adaptive hybrid forecasting approach, MMPF–NARX–GARA, was developed and applied to real data from the Hellenic power system. The method combines the Multi-Model Partitioning Filter (MMPF) with Nonlinear Autoregressive Exogenous (NARX) submodels, while the Genetic Algorithm for Resource Allocation (GARA) adaptively adjusts the weights of the submodels. This method enhances the nonlinear prediction capability of the MMPF and achieves improved adaptability with reduced computational effort.

The method was tested over real grid data covering the years 2020–2025, under a medium-term forecasting horizon of two months. Comparative evaluation with two established hybrid methods, MMPF–SVM and MMPF–GA, showed that the proposed MMPF–NARX–GARA achieved lower forecasting errors in all examined periods, with MAPE values ranging between 2.1% and 2.2%, compared to 2.4%–2.9% for the other methods.

Although the proposed method implemented seven submodels, three fewer than the other methods, it demonstrated higher accuracy with lower computational burden.

While the research is based on the commercial Hellenic power system, the method's structure makes it suitable for applications including autonomous or mission-critical energy networks. The novelty of the proposed model is the integration of NARX models, ensuring theoretical continuity and improved adaptability of the classical MMPF architecture.

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Stylianos Pappas developed the methodology, performed the simulations, data analysis, and manuscript preparation.
Nikos Mastorakis supervised the research, contributed to the conceptual design of the study, reviewed the results, and participated in the final editing of the manuscript.

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