

Mission Critical Hybrid MMPF+GARA Forecasting of ESDD and Electrical Load using Field Electric Measurements

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Abstract: - Surface contamination is one of the main causes of flashover on outdoor insulators, since deposits accumulated on the insulator surface reduce its resistance and can lead to failure. Monitoring techniques based on parameters such as the Equivalent Salt Deposit Density (ESDD) are widely used to estimate this contamination level and warn operators before a flashover occurs, yet reliable forecasting of ESDD remains a challenging task due to its nonlinear and noisy behavior. Forecasting in power systems must be accurate, reliable, and fast when applied on a short-term or online basis, particularly in mission-critical operating environments, since it plays a significant role in decision-making and in overcoming economic and operational problems. Traditional methods have proven effective under linear or stationary assumptions, but recent challenges are nonlinear, high-dimensional, and noisier, requiring more complex approaches. To address this complexity, a hybrid method combining the Multi-Model Partitioning Filter (MMPF) with a Genetic Algorithm for Resource Allocation (GARA) is presented. The method refines the initial probabilities (weights) provided by the MMPF through an iterative, fitness-driven search for optimal weight values. The proposed approach is compared against a previously presented method that combines MMPF with Support Vector Machines (SVM), using real ESDD and electricity load measurements.

Key-Words: - Equivalent Salt Deposit Density (ESDD), Multi-Model Partitioning Filter (MMPF), Genetic Algorithm for Resource Allocation (GARA), Adaptive Forecasting, Electricity Load Prediction, Field Data Analysis, Mean Absolute Percentage Error (MAPE), Mission-Critical Systems.

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1 Introduction

Forecasting plays an important role in modern power systems, supporting several mission-critical tasks such as predictive maintenance, energy planning, and system reliability assurance. The ability to assess the system's behavior can significantly reduce operational costs and prevent failures.

Accurate forecasts are often based on historical measurements to enable optimal scheduling and

dispatch. Prediction accuracy is critical, and considering the case where the available data is typically nonlinear, noisy, and time-dependent, the proposed forecasting methods must be both adaptive and robust.

Recent research has moved from conventional deterministic models to hybrid and ensemble approaches. One adaptive approach is the Multi-Model Partitioning Filter (MMPF), which combines the outputs of several Kalman Filters (typically ten),

calculating dynamically updated performance-based weights. MMPF has been successfully applied in diverse applications, including mission-critical ones, leveraging its ability to track model accuracy over time and to produce reliable ensemble outputs even in the presence of uncertainty [1], [2], [3], [4], [5], [6], [7], [8], [9], [10].

Despite its good performance, MMPF's procedure may overlook hidden patterns or nonlinearities. To overcome this limitation, this study proposes a hybrid extension in which the model weighting process is further refined using a Genetic Algorithm for Resource Allocation (GARA). The aim is to enhance prediction accuracy by searching for an improved set of model weights starting from the MMPF-based initialization.

The performance of the proposed MMPF+GARA approach is evaluated and compared against a previously established configuration that combines MMPF with a Support Vector Machine (SVM) as a post-processor, successfully applied in short-term wind speed forecasting presented in [8]. The comparative analysis focuses on the predictive performance of the two approaches under real-world scenarios. The first one is the prediction of the equivalent salt deposit density of medium voltage insulators, a problem where the algorithm can be used offline. The second application is the electric load forecasting of the Hellenic Grid.

2 Method Presentation

2.1 MMPF+EKF

The structure of the MMPF with Extended Kalman Filters applied in this work follows the architecture analytically described and validated in [1], [5], [7], [8]. As illustrated in Figure 1, each MMPF implements a bank of Extended Kalman Filters (EKF), typically ten, depending on the application and model complexity.

A notable advantage of the MMPF configuration is that each EKF or KF is executed separately, enabling full parallelization of the filter bank, drastically reducing computational time, especially in real-time applications or when high-dimensional state spaces are involved [11].

Each Extended Kalman Filter (EKF) in the MMPF bank assumes a discrete-time non-linear system defined by:

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \quad (1)$$

$$z_k = h(x_k) + v_k \quad (2)$$

where x_k is the state vector, z_k is the measurement, and w_k, v_k represent the process and measurement noise with covariances Q and R , respectively.

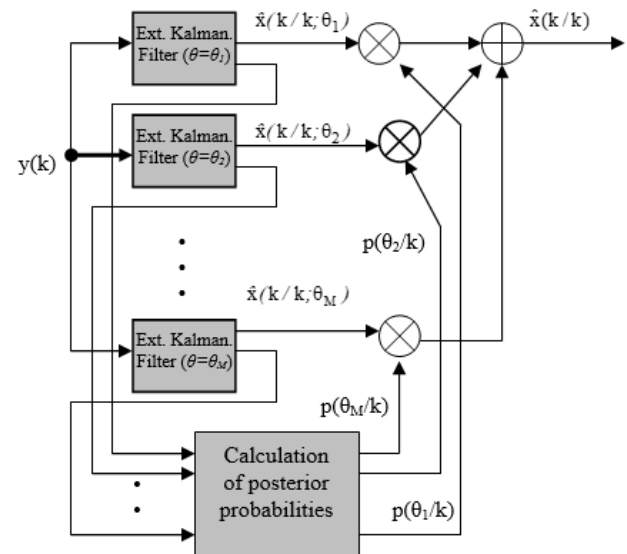


Fig. 1: MMPF+EKF block diagram. Each EKF implements an ARMA model.

Source: created by the authors.

2.2 MMPF+SVM

This hybrid method is analytically presented in [8]. The output of this hybrid model is the sum of the linear output $\tilde{L}(k)$ produced by the MMPF and the non-linear one $\tilde{NL}(k)$ calculated by the SVM. Actually, the SVM models the residuals of the MMPF and gives a refined prediction. Figure 2 depicts this architecture.

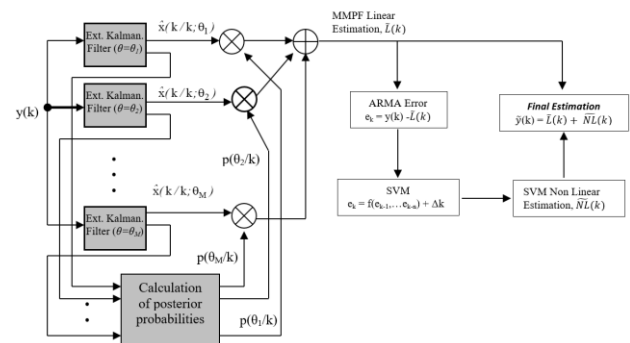


Fig. 2: MMPF+SVM block diagram.

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2.3 MMPF+GARA

This is the new proposed approach, as depicted in Figure 3.

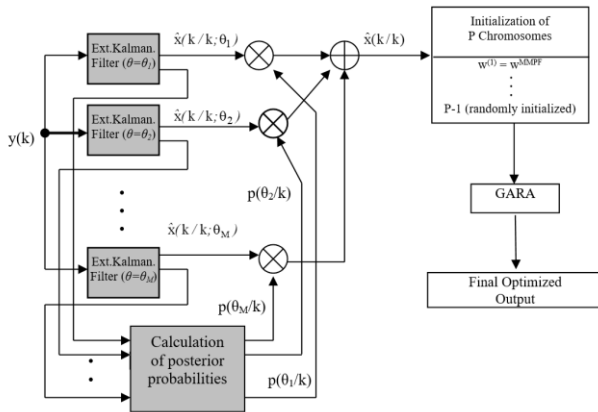


Fig. 3: MMPF+GARA block diagram.

Source: created by the authors.

Unlike the MMPF+SVM architecture summarized in the previous section, the present approach applies GARA that operates directly on the probabilistic model weights generated by the MMPF and searches for an improved feasible weight vector. Thus, MMPF+SVM is included as an established benchmark rather than as a contribution of the present work.

The MMPF output $\hat{x}(k/k)$, from now on $\hat{x}_{MMPF}$, serves as the reference solution, and the corresponding weight vector w^{MMPF} is used as the center of the search space in the next stage.

The term w^{MMPF} refers to a probabilistic weight vector containing the individual probabilities $p(\theta_1/k) \dots p(\theta_M/k)$, assigned by the Multi-Model Partitioning Filter (MMPF) to each candidate model, given the current data. At this point, we should bear in mind that $\sum_{m=1}^M p(\theta_m/k) = 1$.

The probability (weight) $p_i(k)$ for the i -th model at time k is updated recursively using the likelihood of the current measurement:

$$p(\theta_i|Z^k) = \frac{L(\theta_i; z_k) \cdot p(\theta_i|Z^{k-1})}{\sum_{j=1}^M L(\theta_j; z_k) \cdot p(\theta_j|Z^{k-1})} \quad (3)$$

where $L(\theta_i; z_k)$ represents the likelihood function of the i -th filter and is computed from the innovation $\tilde{y}_i(k)$ and its covariance $S_i(k)$:

$$L(\theta_i; z_k) = \frac{1}{\sqrt{(2\pi)^m |S_i(k)|}} \exp\left(-\frac{1}{2} \tilde{y}_i(k)^T S_i(k)^{-1} \tilde{y}_i(k)\right) \quad (4)$$

This shows that models with smaller residuals (closer to actual field measurements) naturally gain more weight. In order to refine the forecast and overcome any data non-linearities, GARA is used to search for an improved weight vector in the local vicinity of the MMPF solution.

2.3.1 Chromosome Initialization

Each chromosome in the GARA population represents a candidate vector of model weights:

$$w^{(j)} = [w_1^{(j)}, w_2^{(j)}, \dots, w_M^{(j)}], \text{ with } \sum_{i=1}^M (w_i^{(j)}) = 1, \quad (5)$$

where $w_i^{(j)} \in [0,1]$.

The number of chromosomes in the population is denoted by P . The initialization process is designed to explore a local neighborhood around the MMPF solution, while maintaining diversity.

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

$$w^1 = w^{MMPF} = [p(\theta_1/k) \dots p(\theta_M/k)] \quad (6)$$

The remaining $P-1$ chromosomes are initialized by applying small random perturbations around w^{MMPF} . Specifically, a uniformly sampled deviation $\delta_i \sim \text{Uniform}(-\delta, \delta)$ is added as follows:

$$w_i^{(j)} = w_i^{MMPF} \pm \delta_i \text{ for } j = 2, \dots, P \quad (7)$$

After every iteration, the vector is re-normalized so that $\sum w_i = 1$.

At this point, it should be noted that the value of δ is important for the overall estimation. A value that is too small leads to chromosomes very close or identical to the ones produced by the MMPF, limiting the exploration. On the other hand, if the value is too large, the population diverges significantly from the MMPF values, behaving like a random initialization. In this work, the value of δ chosen was $\delta = 0.05$, corresponding to a $\pm 5\%$ deviation around each MMPF weight. This localized initialization strategy leverages the statistically informed solution of the MMPF, while maintaining sufficient diversity in the initial population to facilitate effective search by the genetic algorithm.

2.3.2 Fitness Evaluation

The fitness of each chromosome is based on the prediction error produced by the corresponding weights. Given a candidate vector $w^{(j)}$, the forecast is calculated as: $\hat{x}^{(j)} = \sum_{i=1}^M w_i^{(j)} \cdot \hat{x}_i$ (8)

The Root Mean Square Error (RMSE) between the predicted and the actual value x_k is computed as: $\text{Fitness}^{(j)} = -\text{RMSE}(\hat{x}^{(j)}, x_k)$

$$\text{Fitness}^{(j)} = -\sqrt{\frac{1}{n} \sum_{t=1}^n (z_t - \sum_{i=1}^M w_i^{(j)} \cdot \hat{x}_i)^2} \quad (9)$$

where z_t is the actual measurement and $\hat{x}_i$ is the estimate from the i -th EKF.

This formulation ensures that chromosomes producing lower prediction errors are assigned higher fitness values. The use of the *negative RMSE* was chosen over its reciprocal because it avoids

numerical instability in case of a value of zero or very close to zero. This enables smooth, continuous fitness that facilitates convergence.

2.3.3 Selection Procedure

Parent selection is implemented using the roulette wheel method, based on the fitness values. Since the fitness values are negative, a linear transformation is applied to ensure non-negative selection probabilities:

$$f'_j = f_{\max} - \text{Fitness}^{(j)} \quad (10)$$

$$\text{where } f_{\max} = \text{Fitness}^{(j)} \quad (11)$$

$$\text{Also, } P_j = \frac{f'_j}{\sum_{i=1}^P f'_i} \quad (12)$$

The probabilities P_j define the likelihood of each chromosome being selected for crossover.

2.3.4 Crossover Operator

Selected parent chromosomes are recombined using an arithmetic crossover scheme. Given two parent vectors $w^{(p1)}$ and $w^{(p2)}$, an offspring is generated as follows:

$$w^{\text{offspring}} = \alpha \cdot w^{(p1)} + (1-\alpha) \cdot w^{(p2)} \quad (13)$$

where $\alpha \sim \text{Uniform}(0,1)$.

After the crossover, the offspring vector is normalized to maintain valid probabilistic constraints such as

$$\sum_{i=1}^M w_i^{\text{offspring}} = 1, \text{ where } w_i^{\text{offspring}} \in [0,1].$$

2.3.5 Mutation Operator

To maintain diversity and prevent premature convergence, a mutation operator is applied to each gene w_i in the offspring chromosome with a fixed probability $P_m = 0.05$. Each mutated gene is perturbed by a small random noise $\epsilon \sim \text{Uniform}(-\eta, \eta)$, where $\eta = 0.05$.

After mutation, the chromosome is re-normalized to ensure feasibility. The values of η and P_m are aligned with the perturbation range δ used during initialization, ensuring consistency in the scale of variation throughout the search process.

2.3.6 Final Forecast

The chromosome with the highest fitness is selected as $w^{\text{best}} = \text{argmax}_{(j)} \text{Fitness}^{(j)}$. (14)

The final GARA-optimized forecast is given by $\hat{y}_{\text{GARA}} = \sum_{i=1}^M w_i^{\text{best}} \cdot \hat{x}_i$ (15)

This output represents the refined prediction, starting from the statistically derived MMPF weights and enhanced through evolutionary search.

The condition to terminate the evolutionary refinement is when the relative improvement of the best RMSE satisfies Eq. (16) for 10 consecutive generations:

$$\frac{|RMSE_{\text{best}}^{(g)} - RMSE_{\text{best}}^{(g-1)}|}{RMSE_{\text{best}}^{(g-1)}} \leq 10^{-4}. \quad (16)$$

Although this threshold is quite demanding, it is computationally acceptable because the optimization is performed off-line. At the same time, it ensures that the search is continued until further improvements in the forecasting error become negligible.

2.3.7 Mathematical Interpretation of the Local Optimization

The proposed GARA stage in this work can be interpreted as a constrained local optimization of the MMPF model probabilities. In Eqs. (3)–(4), the MMPF recursively assigns larger posterior weights to models whose innovations are closer to the measurements. In that sense, w^{MMPF} is not an arbitrary starting point but a statistically informed solution derived from the available observations. So, the GARA search is centered on this solution rather than being initialized over the entire admissible domain. According to Eqs. (5)–(7), every candidate solution is constrained to the probability simplex, $w_i^{(j)} \in [0,1]$ and $\sum_{i=1}^M (w_i^{(j)}) = 1$, while δ the perturbation parameter determines the extent of the local neighborhood around. The fitness definition in Eqs. (8)–(9) makes the optimization objective explicit. By maximizing the fitness, the forecasting RMSE is minimized. Selection and crossover in Eqs. (10)–(13) enhance improved feasible combinations of model weights, whereas mutation provides a mechanism for exploring neighboring solutions and reducing premature stagnation. After each operation, normalization returns the candidate vector to the feasible probability simplex. Finally, Eqs. (14)–(16) select the highest-fitness feasible vector and use it to obtain the refined forecast. The purpose of the local search is therefore not to replace the probabilistic information supplied by the MMPF, but to refine it within a controlled neighborhood. This formulation reduces the search domain compared with an unrestricted initialization and preserves the physical and probabilistic interpretation of the MMPF weights.

This formulation preserves the probabilistic basis of MMPF while introducing a controlled

evolutionary refinement of its model weights. Its contribution lies in this constrained interaction between probabilistic model weighting and local optimization, rather than in the independent use of either method.

3 Results

3.1 ESDD Prediction

The Equivalent Salt Deposit Density (ESDD) is used as the key indicator of insulator contamination and serves as the main criterion for planning maintenance actions, particularly the cleaning or washing of medium-voltage insulators. ESDD remains one of the leading causes of surface flashovers on insulators, often leading to power outages and service disruptions in distribution networks. To improve the prediction of ESDD and support proactive maintenance strategies, the two strategies presented are being compared [12], [13], [14].

This research is grounded in operational data collected from the Hellenic Electricity Distribution Network Operator S.A. from 2020 to 2024. This dataset enabled accurate modeling and training of both prediction techniques, and it formed the basis for validating the predicted ESDD values against actual field measurements. Although traditional ESDD measurements are costly and time-consuming, they remain the most widely used standard for diagnosing pollution severity.

The results of this paper show that both techniques successfully predicted ESDD values with high accuracy when tested against real measured data. These findings underline the practical value of using actual field data in model development.

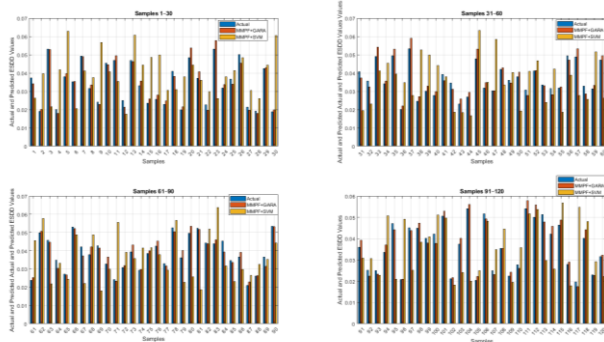


Fig. 4: ESDD actual and predicted values.
Source: created by the authors.

Figure 4 shows that both methods successfully estimated the ESDD values. The available dataset covers a period of four consecutive years, offering a thorough view of ESDD variations under real

environmental and operating conditions. The data from the first three years are used for the training and modeling of the proposed methods, while the fourth year is utilized for evaluation. The prediction task involves estimating the average ESDD value across the samples for the fourth year. To assess the accuracy of the predictions, the Mean Absolute Percentage Error (MAPE) is employed because it expresses the prediction error as a percentage relative to the actual measured values, allowing for a scale-independent comparison and easy interpretability. The MAPE is calculated as:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{A_i - P_i}{A_i} \right| \quad (17)$$

where A_i is the actual value, P_i is the predicted value, and n is the total number of samples. In our case, the MAPE for MMPF+GARA was 3.2% and for MMPF+SVM was 4.1%. The outcomes are close, but the proposed method performs slightly better in terms of MAPE. The prediction error covers the complete testing set.

3.2 Electric Load Prediction

In this study, the electricity demand load was categorized into two distinct behavioral patterns: weekdays (normal working days) and weekends, acknowledging the inherent differences in consumption across the week [15], [16], [17], [18]. Unlike traditional approaches that require prior modeling assumptions or the removal of seasonal components, the proposed algorithms were trained and validated directly on the raw data, without any seasonal preprocessing. This approach allows the models to capture the underlying periodicity in the data and evaluate performance in a more realistic and operationally relevant setting. The study was based on real data for the year 2024 provided by the Independent Power Transmission Operator.

Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12 depict the performance of the proposed method, MMPF+GARA, in comparison with MMPF+SVM.

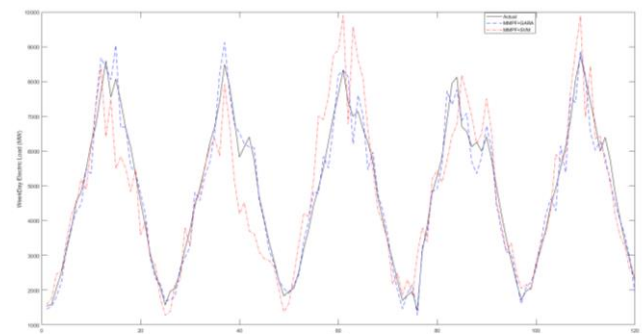


Fig. 5: Actual and Predicted Values for Weekdays (Monday-Friday). Both methods utilize 10 EKF's.
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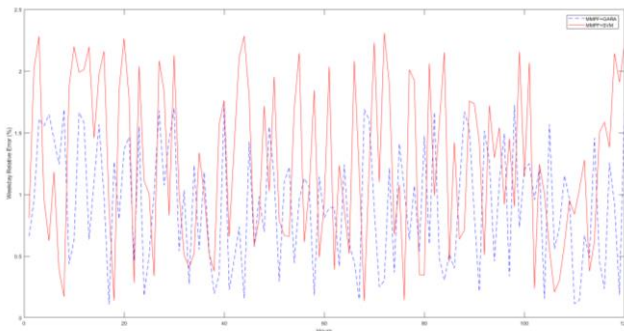


Fig. 6: Weekday Prediction Errors. Both methods utilize 10 EKF's.

Source: created by the authors.

For electrical-load forecasting, performance is evaluated through the absolute prediction. Figure 5 and Figure 6 show that both methods effectively predict the weekday electricity load. However, the MMPF+GARA approach presents lower prediction error, with values ranging from 0.201% to 1.876% (Figure 6). At this stage, a variation of the method was also tested. A comparison was conducted between MMPF+GARA using 8 Extended Kalman Filters (EKFs) and MMPF+SVM using 10 EKFs. The results show that MMPF+GARA, although utilizing fewer EKFs, achieved performance comparable to MMPF+SVM. This finding is particularly important, as using fewer filters means reduced computational load and shorter execution time, which are critical factors for short-term prediction applications.

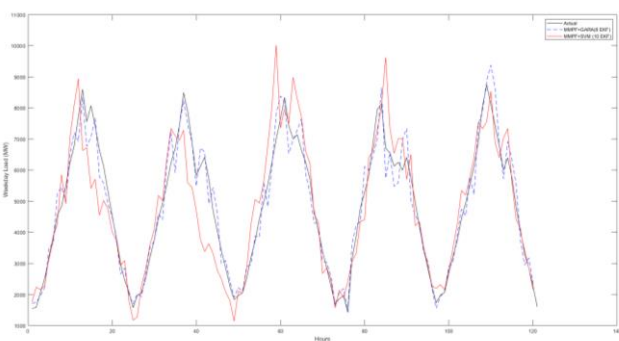


Fig. 7: Actual and Predicted Values for Weekdays (Monday-Friday). MMPF+GARA implements 8 EKF's, while MMPF+SVM 10 EKF's.

Source: created by the authors.

The same procedure was applied to estimate the electric load during the weekend (Saturday-Sunday). As in the previous case, the MMPF+GARA method demonstrated superior performance compared to MMPF+SVM when both techniques were implemented using 10 Extended Kalman Filters (EKFs). Additionally, even when

MMPF+GARA implemented 8 EKFs, it still matched the performance of MMPF+SVM using 10 EKFs. This further reinforces the advantage of MMPF+GARA in terms of computational burden.

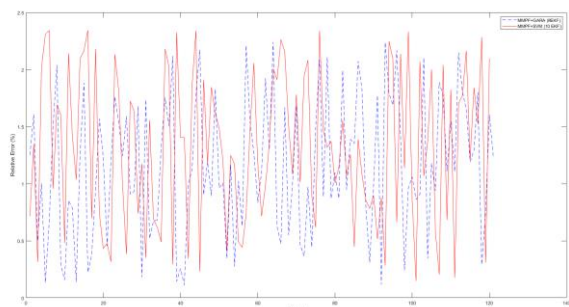


Fig. 8: Weekday Prediction Error. MMPF+GARA implements 8 EKF's, while MMPF+SVM 10 EKF's.

Source: created by the authors.

The results highlight the versatility of AI-based approaches, which are increasingly applied not only in power systems but also in domains such as e-commerce and wireless sensor networks [16].

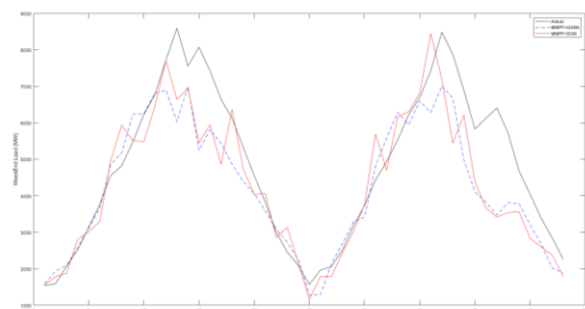


Fig. 9: Actual and Predicted Values for Weekend (Saturday-Sunday). Both methods utilize 10 EKF's.

Source: created by the authors.

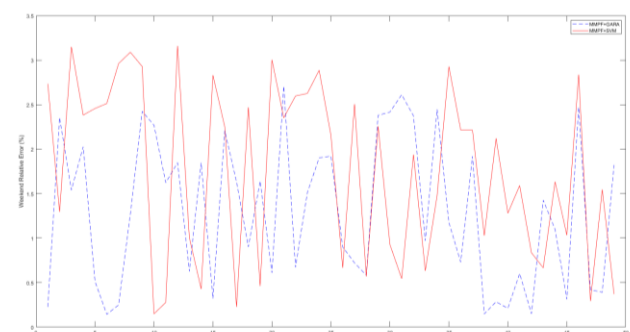


Fig. 10: Weekend Prediction Errors. Both methods utilize 10 EKF's.

Source: created by the authors.

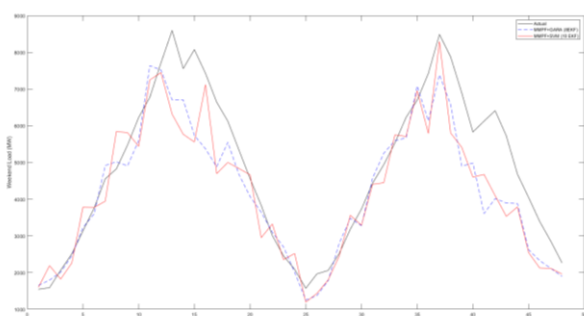


Fig. 11: Actual and Predicted Values for Weekend (Saturday - Sunday). MMPF+GARA implements 8 EKF's, while MMPF+SVM 10 EKF's.

Source: created by the authors.

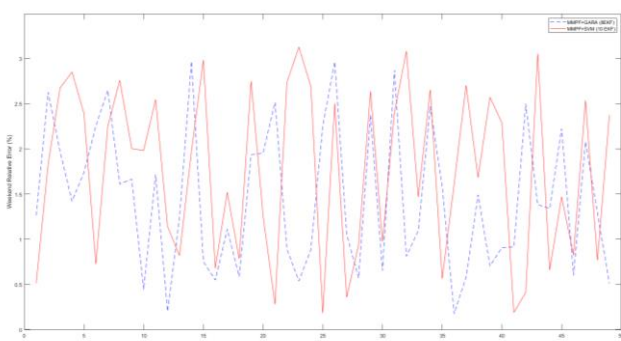


Fig. 12: Weekend Prediction Error. MMPF+GARA implements 8 EKF's, while MMPF+SVM 10 EKF's.

Source: created by the authors.

4 Conclusion

This study presented and evaluated a new hybrid forecasting method that combines the Multi-Model Partitioning Filter (MMPF) with a Genetic Algorithm for Resource Allocation (GARA). The task was to enhance the predictive performance while reducing the computational complexity. The proposed MMPF+GARA approach was assessed against an established MMPF+SVM configuration using real data for two applications, namely the prediction of the Equivalent Salt Deposit Density (ESDD) of medium-voltage insulators and the short-term forecasting of electricity demand. In both cases, the proposed method achieved comparable or superior prediction accuracy, as measured by the Mean Absolute Percentage Error (MAPE). Additionally, demonstrated the ability to perform equally well using fewer Extended Kalman Filters (EKFs). This reduction in computational load is very important for real-time or short-term forecasting scenarios, where speed and efficiency are critical. The results demonstrate that the proposed framework provides a robust forecasting

solution, making it suitable for mission-critical power systems. Future research could also explore deep learning approaches, such as Bidirectional LSTM networks [19], [20], [21], [22] which have shown promising results in short-term electricity load forecasting.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Conflict of Interest

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