ARQII Publication
APPLICATIONS OF
MODELLING AND SIMULATION
http://arqiipubl.com/ams eISSN 2600-8084 VOL 10, 2026, 28-37

# Hyperparameter Optimization of Multi-Target Support Vector Regression with Sigmoid Particle Swarm Optimization-based Acceleration Coefficients for Electricity Consumption Prediction

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*Submitted 19 November 2025; Revised 18 December 2025; Accepted 28 December 2025; Available online 12 January 2026.*


**Abstract**: The predictive accuracy of Support Vector Regression (SVR) in electricity forecasting is often constrained by hyperparameter tuning. To address the documented poor performance of SVR on the multi-target Tetouan City Power Consumption dataset, an advanced metaheuristic, Particle Swarm Optimization with Sigmoid-Based Acceleration Coefficients (PSO-SBAC), is employed to optimize SVR's regularization constant ($C$) and the RBF kernel coefficient ($\gamma$) hyperparameters. The superior stability of PSO-SBAC was first confirmed on ten mathematical benchmark functions, where it achieved near-perfect success rates, significantly outperforming the less consistent standard PSO on complex multimodal functions. When applied to the forecasting task, the proposed SVR-PSO-SBAC model demonstrated superior generalization capabilities. While the baseline model showed robustness on high-frequency 10-minute data, the proposed SVR-PSO-SBAC achieved the best performance on Zone 1 in the 1-hour interval, recording the lowest test Root Mean Squared Error (RMSE) of 34769.5. Furthermore, the model excelled in handling complex zonal characteristics, achieving a massive 27.4% reduction in error compared to the baseline in Zone 3 (10-minute interval) with an RMSE of 4878.1. The findings resolve a documented performance anomaly, concluding that SVR's perceived limitations are a function of suboptimal tuning, which can be overcome with a robust and adaptive optimization strategy.

Keywords: Electricity energy consumption; Multi-target hyperparameter; Particle swarm optimization; Sigmoid-based acceleration coefficients; Regression.

## 1. INTRODUCTION

Accurate electricity consumption forecasting is a critical task for ensuring the stability and efficiency of modern power grids [1]. Among the various machine learning techniques applied to this domain, Support Vector Regression (SVR) has been recognized as a powerful algorithm for handling complex, non-linear time-series data. However, the predictive accuracy of SVR is fundamentally dependent on the appropriate selection of its hyperparameters, primarily the regularization constant ($C$) and the kernel coefficient ($\gamma$) [2]. The process of identifying an optimal set of these parameters is a significant challenge, as their interactions create a complex search space with no definitive mathematical procedure for their selection, often leading to suboptimal model performance if not addressed rigorously [3-5].

In response to the challenges of hyperparameter tuning, various optimization strategies have been explored. While conventional methods like Grid Search are systematic, they are often computationally prohibitive and struggle with high-dimensional search spaces. Consequently, metaheuristic algorithms have gained prominence as a more efficient alternative. Particle Swarm Optimization (PSO) [6], in particular, has been successfully integrated with SVR in numerous energy forecasting applications [7]. Despite its widespread use, the standard PSO algorithm is not without its limitations, most notably its tendency toward premature convergence, where the swarm may become trapped in a local optimum and fail to adequately explore the entire solution space. This weakness can hinder its ability to find the true optimal hyperparameter configuration required for peak model performance [8-11].

To address the shortcomings of standard PSO, advanced variants incorporating dynamic parameter adaptation have been developed [12]. This study employs one such method: PSO with Sigmoid-Based Acceleration Coefficients (PSO-SBAC). This algorithm introduces a non-linear, dynamic adjustment of the cognitive and social coefficients, which is designed to achieve a superior balance between global exploration in the early stages and local exploitation in the later stages of the search [13]. A compelling case for the necessity of such an advanced optimizer is the documented poor performance of SVR on the multi-target Tetouan city electricity dataset, where conventional tuning methods failed to produce a competitive model. This specific case provides an ideal testbed to investigate the hypothesis that the previously reported failure was not a limitation of the SVR model itself, but rather a consequence of an inadequate optimization strategy [14-16].

Therefore, this paper aims to resolve this documented performance gap by applying the SVR-PSO-SBAC model [13] to the Tetouan forecasting problem. The primary objective is to demonstrate that an advanced, adaptive optimization strategy can unlock the full predictive potential of SVR where conventional methods have failed. To achieve this, the study first validates the superior stability and reliability of the PSO-SBAC algorithm on a suite of ten standard benchmark functions [17]. Subsequently, it applies the validated optimizer to tune the two-dimensional SVR hyperparameter space. The performance of the proposed SVR-PSO-SBAC model is then rigorously compared against a baseline SVR and an SVR tuned with standard PSO, with the goal of establishing a new performance benchmark for this well-known dataset [17, 18]. The main contributions of this study are validating the superior stability of the PSO-SBAC algorithm on ten benchmark functions compared to standard PSO and subsequently applying this adaptive optimizer to resolve the documented underperformance of SVR on the Power Consumption.

## 2. LITERATURE REVIEW

This section reviews the existing body of knowledge in three key areas relevant to this study. First, it examines the application of SVR in energy forecasting and highlights the critical challenge of hyperparameter optimization. Second, it discusses the use of standard PSO as a common solution to this challenge. Finally, it identifies the limitations of standard PSO and introduces advanced adaptive variants, thereby establishing the specific research gap that this paper aims to address.

SVR has been widely recognized as a robust machine learning algorithm for forecasting tasks, particularly in the energy sector due to its effectiveness in modeling complex, non-linear relationships [19], [20]. Its application ranges from predicting consumption in solar-powered homes to broader energy disaggregation systems. However, the efficacy of SVR is not guaranteed and has shown variable performance in energy forecasting studies. The primary reason for this inconsistency is the model's profound sensitivity to its core hyperparameters: the regularization constant ($C$) and the RBF kernel coefficient ($\gamma$) [21-22].

The process of selecting these hyperparameters is non-trivial, as there is no definitive mathematical procedure for determining their optimal values. This creates a significant implementation challenge, where suboptimal choices can lead to poor model generalization and high prediction errors. The study by [2] serves as a critical case in point. When applying an SVR model to the Tetouan city electricity consumption dataset, they found its performance to be substantially inferior to other models like Random Forest, even after employing a conventional Grid-Search optimization. This documented failure highlights a crucial bottleneck: the performance of a potentially powerful SVR model was crippled by the limitations of its tuning strategy. This underscores the need for more intelligent and efficient hyperparameter optimization methods to unlock SVR's full potential.

To overcome the inefficiencies of exhaustive methods like Grid Search, researchers have increasingly turned to metaheuristic algorithms for hyperparameter optimization [23-24]. Among these, PSO has emerged as a popular and effective choice due to its conceptual simplicity and rapid convergence capabilities [25]. The hybridization of PSO with SVR has produced successful models across various energy-related domains. For instance, PSO-SVR hybrids have been effectively used to predict household heat consumption [26], enhance intelligent energy decision-making systems [27], and solve other complex engineering prediction problems [28-29].

These studies collectively demonstrate that a PSO-based search can navigate the complex SVR hyperparameter space more effectively than manual or grid-based methods. By treating hyperparameter selection as a formal optimization problem, PSO can identify superior parameter combinations that lead to significant improvements in the predictive accuracy of SVR models [30, 31]. The literature reveals a clear, multi-layered research gap. While SVR's hyperparameter sensitivity is wellknown, and standard PSO is a common solution, the limitations of standard PSO itself are often overlooked in applied studies [3], [5], [23]. More importantly, while advanced adaptive algorithms like PSO-SBAC have been proposed and validated on theoretical benchmark functions in [13], [17], their application to solve specific, documented, real-world machine learning failures is a novel area of investigation.

Specifically, no previous work has applied an advanced, adaptive PSO variant to resolve the documented poor performance of the SVR model on the Tetouan city electricity consumption dataset originally identified by [2]. This study is the first to bridge this gap. By applying the SVR-PSO-SBAC model to this specific problem, this study not merely tuning a model; this study testing the hypothesis that an advanced optimization strategy is the key to unlocking the true predictive power of SVR where conventional methods have failed.

## 3. METHODOLOGY

The methodological framework of this study is designed as a multi-stage investigation to test the central hypothesis: that the documented poor performance of SVR on the Tetouan electricity dataset is a failure of conventional optimization, which can be resolved by an advanced, adaptive metaheuristic. As illustrated in Figure 1, the framework follows a rigorous three-stage process. Stage 1 involves the a priori validation of the PSO-SBAC and standard PSO algorithms on ten mathematical benchmark functions to establish a baseline of their optimization capabilities.

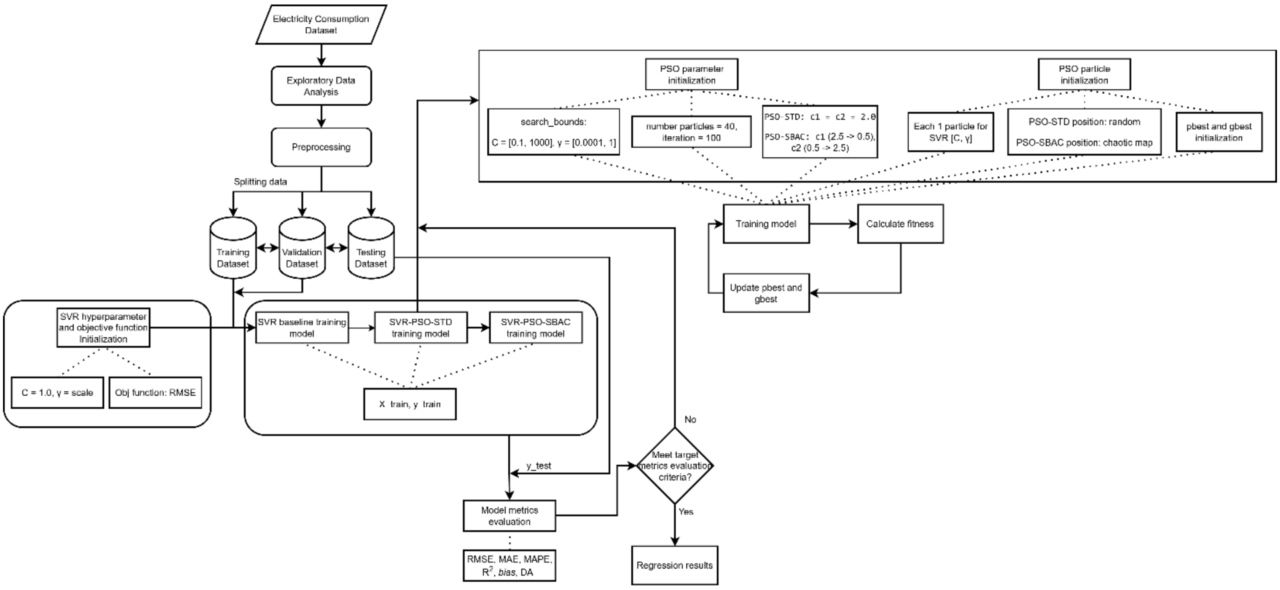


Figure 1. Methodological framework of SVR modelling.

Stage 2 focuses on the primary SVR modeling task, where the validated optimizers are applied to tune the hyperparameters of four distinct SVR models using the pre-processed electricity consumption dataset. Finally, Stage 3 consists of a comprehensive comparative evaluation, where the predictive performance of all four SVR models is measured on the unseen test data using RMSE, MAE, MAPE, $R^2$, *bias,* and DA to determine the most effective approach. This structured process ensures a logical progression from algorithm validation to practical application and conclusive evaluation.

### 3.1 Optimization Algorithm

To confirm the PSO-SBAC algorithm's suitability for the complex fitness landscape of SVR hyperparameter tuning, a preliminary validation was conducted. This step served as a methodological control, verifying the algorithm's capabilities on a search space analogous to the main optimization problem before incurring significant computational cost [32]. A suite of ten benchmark functions (Michalewicz, Schubert, Shekel, Lévy, Colville, Booth, Branin, Dixon & Price, Matyas, and Power sum) was employed to create a composite testbed probing the essential optimizer behaviors required for SVR tuning.

The selection of these functions was deliberate, designed to create a comprehensive testbed that evaluates an optimizer's core capabilities in two distinct domains: exploitation and exploration [33]. As detailed in Table 1, these functions are categorized based on their topology (unimodal or multimodal) to systematically assess these critical performance attributes [34].

Table 1. Justification for benchmark function selection.

| Capability Tested | Category | Benchmark Function | Relevance to SVR Hyperparameter Tuning |
|---|---|---|---|
| Exploitation (Local Search & Precision) | Unimodal | Booth, Matyas, Dixon & Price, Power sum | These functions possess a single global optimum, testing the algorithm's ability to efficiently converge and perform a precise local search within one basin of attraction. This is analogous to finetuning SVR parameters (C and $\gamma$) near an optimal region where small adjustments yield significant performance changes [32], [34]. |
| Exploration (Global Search & Trap Avoidance) | Multimodal | Michalewicz, Schubert, Shekel, Lévy, Colville, Branin | These functions feature numerous local minima, presenting a significant challenge to global search. They test the algorithm's ability to traverse a complex, non-convex landscape and avoid premature convergence. This is critical as the SVR hyperparameter space is known to have multiple suboptimal regions that can easily trap simpler optimization methods [33]. |

The performance of PSO-SBAC was benchmarked against a standard PSO (PSO-STD) across both 10 and 30 independent runs for each function to analyze performance consistency and ensure statistical robustness. This a priori validation provides the necessary empirical justification for selecting PSO-SBAC as the superior tool for the primary SVR optimization task.

### 3.2 SVR Hyperparameter Optimization

The core of this study treats the SVR hyperparameter tuning process as a formal optimization problem, where the goal is to find a vector of parameters that minimizes a complex, data-driven objective function.

#### *3.2.1. Dataset and Preprocessing*

The study utilizes the publicly available Tetouan City Power Consumption dataset, which is the exact dataset used in the benchmark study by [2], sourced from the UCI Machine Learning Repository, enabling a direct and rigorous comparison of

results. The dataset, originally sourced from the Supervisory Control and Data Acquisition (SCADA) system of the regional utility company in Tetouan, Morocco, contains high-resolution recordings throughout the year 2017.
The dataset can be found at https://archive.ics.uci.edu/dataset/849/power+consumption+of+tetouan+city.

Table 2 comprises 52,416 instances recorded at 10-minute intervals. The dataset is structured for a Multi-Target Regression (MTR) task, with three distinct output variables representing the power consumption (in kW) for three different distribution zones. In addition to the target variables, each record includes crucial meteorological features: Temperature, humidity, wind speed, general diffuse flows, and diffuse flows. These environmental factors make it a realistic and challenging testbed, as the model must capture the complex, non-linear interactions between weather and electricity demand. This dataset was deliberately chosen because SVR's performance was previously shown to be anomalously poor, making it the perfect environment to test this study's central hypothesis [2]. To provide context on the environmental conditions impacting power consumption, the nominal ranges of the meteorological parameters in the dataset were analyzed. The ambient temperature ranges from a minimum of 3.25°C to a maximum of 40.01°C, with an average of 18.81°C, indicating a climate with significant seasonal variation. Humidity levels are broad, ranging from 11.34% to 94.8%, averaging 68.26%. Wind speed varies between 0.05 m/s and 6.48 m/s, with a moderate average of 1.96 m/s. Solar radiation metrics also show wide variability, with general diffuse flows ranging from 0.004 to 1163.0 and Diffuse Flows from 0.011 to 936.0, reflecting the dynamic nature of solar irradiance in the region.

Preprocessing included median imputation to handle missing values. The data was then chronologically split into training (56.25%), validation (18.75%), and test (25%) sets. This chronological partitioning is essential to maintain the time-series nature of the data and prevent data leakage. Finally, Min-Max Scaling was applied to normalize all variables to a [0, 1] range, with the scaler being fit only on the training data [2]. Although the DateTime variable is present in the raw dataset to define the temporal sequence, it was excluded from the input feature set for model training. This decision was made to focus the study on regression modeling based on meteorological determinants rather than time-series forecasting based on historical lags.

Table 2. Power consumption dataset.

| Variable | Data Type | Description |
|---|---|---|
| DateTime | Date | Data recording time (format: DD/MM/YYYY HH:MM) |
| Temperature | Continuous | Ambient temperature at a certain time (in °C) |
| Humidity | Continuous | Relative humidity (%) |
| Wind Speed | Continuous | Wind speed (m/s) |
| General Diffuse Flows | Continuous | General diffuse radiation (w/m$^2$) |
| Diffuse Flows | Continuous | Specific diffuse radiation (w/m$^2$) |
| Zone 1 Power Consumption | Continuous | Electric power consumption in Zone 1 (in watts) |
| Zone 2 Power Consumption | Continuous | Electric power consumption in Zone 2 (in watts) |
| Zone 3 Power Consumption | Continuous | Electric power consumption in Zone 3 (in watts) |

### *3.2.2. The SVR-PSO-SBAC Model*

The proposed model integrates the SVR with the PSO-SBAC algorithm. The methodological insight is to frame the SVR's validation error as the "fitness landscape" to be navigated by the swarm.

The optimization process treats the SVR hyperparameters as a decision variable vector $x = [C, \gamma]$. The objective function (Fitness) minimized by the PSO-SBAC algorithm is defined as the Root Mean Squared Error (RMSE) calculated on the validation dataset in Equation (1).

$$J(C,\gamma) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i(C,\gamma))^2} \tag{1}$$

where $y_i$ is the actual target value, and $\hat{y}_i(C,\gamma)$ is the predicted value generated by the SVR model. Mathematically, the prediction $\hat{y}_i$ is dependent on the SVR model structure, which is directly controlled by the regularization parameter $C$ (balancing model complexity and error tolerance) and the RBF kernel coefficient $\gamma$ (defining the feature space mapping). The PSO algorithm searches for the optimal pair $(C^*, \gamma^*)$ that minimizes this $J$ value [35]. This research expands upon previous work by defining a two-dimensional continuous search space for these key hyperparameters: regularization constant ($C$) in [0.1, 1000] and RBF kernel coefficient ($\gamma$) in [0.0001, 1].

The key to the PSO-SBAC mechanism is the dynamic, non-linear adjustment of its acceleration coefficients, $c_1$ and $c_2$, throughout the search process. These are governed by Equation (2) and Equation (3), as proposed by [13]:

$$c_1(iter) = \frac{1}{1 + exp(-\lambda \cdot \frac{iter}{iter_{max}})} + 2 \cdot (c_{1f} - c_{1i}) \cdot (\frac{iter}{iter_{max}} - 1)^2 \tag{2}$$

$$c_2(iter) = \frac{1}{1 + exp(-\lambda \cdot \frac{iter}{iter_{max}})} + (c_{1f} - c_{1i}) \cdot (\frac{iter}{iter_{max}})^2 \tag{3}$$

In these equations, $iter$ represents the current iteration number, $iter_{max}$ denotes the maximum number of iterations allowed, and $\lambda$ is a control parameter that regulates the steepness of the sigmoid curve. Furthermore, $c_1$ decreases non-linearly from 2.5 to 0.5 and $c_2$ increases from 0.5 to 2.5. This adaptive strategy is hypothesized to be uniquely suited for this task, allowing the swarm to initially explore the hyperparameter space broadly, preventing premature convergence to obvious but suboptimal regions, before smoothly transitioning to an exploitative phase to fine-tune the best-found solution. This dynamic balance is the key mechanism expected to overcome the limitations of the fixed-coefficient standard PSO [13].

### 3.3 Evaluation Framework

To scientifically validate the performance of the proposed SVR-PSO-SBAC model, a comparative framework was established using four distinct models. All models utilize an SVR with an RBF kernel, wrapped in a MultiOutputRegressor to handle the multi-target nature of the problem [20], [36]. The specific roles and configurations of these models, derived directly from the experimental code, are summarized in Table 3.

Table 3. Comparative model configurations.

| Model Name | Hyperparameter Configuration | Purpose |
|---|---|---|
| SVR-Baseline | $C$ = 1.0, $\gamma$ = 'scale' | To establish a generic, non-domainspecific baseline representing a naïve implementation |
| SVR-RP | $C$ = [1, 10, 100, 1000], $\gamma$ = [0.01, 0.001, 0.0001] | To make specific underperforming model from [2] and provide a direct benchmark for improvement |
| SVR-PSO-STD | $c_1 = c_2$ = 2.0, $C$ = [0.1, 1000], $\gamma$ = [0.0001, 1], $\omega$ = not used [6] | To serve as a scientific control, isolating the performance gain attributable to a metaheuristic optimizer in general. |
| SVR-PSO-SBAC (propose) | $c_1 = 2.5 \rightarrow 0.5$ & $c_2 = 0.5 \rightarrow 2.5$, $C$ = [0.1, 1000], $\gamma$ = [0.0001, 1], $\omega = 0.9 \rightarrow 0.4$ | The proposed model, intended to demonstrate the superiority of an adaptive optimization strategy for this specific task. |

This multi-tiered comparison is a core methodological strength of this study. By evaluating against both a generic baseline and the specific reference model [2] can precisely quantify the performance gains. Furthermore, by comparing the two PSO-tuned models can isolate the impact of the adaptive SBAC mechanism from the general benefits of metaheuristic optimization.

To ensure a complete, reliable, and realistic model assessment, this study employs a diverse set of evaluation metrics beyond standard error measurements. As recommended by the taxonomy of regression metrics, the evaluation framework is categorized into three distinct groups to test different aspects of model performance: scale-sensitive metrics, variance/bias metrics, and directional metrics.

To measure the magnitude of errors in the same units as the electricity consumption data, RMSE and Mean Absolute Error (MAE) are employed. While RMSE is sensitive to large errors (outliers), MAE provides a more robust measure of the average error magnitude. Additionally, Mean Absolute Percentage Error (MAPE) is used to express the error relative to the actual values, offering a scale-independent perspective. These metrics are defined as follows in Equation (4-6) [37]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \tag{5}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{6}$$

In these equations, $n$ represents the total number of observations, $y_i$ denotes the actual observed electricity consumption at time step $i$, and $\hat{y}_i$ represents the predicted value generated by the model. RMSE calculates the square root of the average squared differences, MAE calculates the average of the absolute differences, and MAPE calculates the average percentage difference between actual and predicted values [38].

The Coefficient of Determination (R^2) and Mean Bias Error (bias) in Equation (7) and Equation (8) are employed to evaluate the model's ability to capture data variance and detect systematic errors. $R^2$ indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. Mean Error ($bias$) measures the systematic error direction; according to [38], a positive $bias$ indicates that the model tends to under-forecast, while a negative $bias$ indicates a tendency to over-forecast.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

$$bias = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{8}$$

Meanwhile, Directional Accuracy (DA) in Equation (9) is utilized to assess the model's robustness in predicting the direction of trend changes (upward or downward) in the electricity load. This metric is particularly critical for decision-making strategies, as accurately predicting the sign of the future change is often more valuable than minimizing the exact error magnitude, a concept widely applied in financial and commodity market forecasting.

$$DA = \frac{1}{n}\sum_{i=1}^{n} d_i \times 100\%, where\ d_i = \begin{cases} 1, if\,(y_i - y_{i-1})(\hat{y}_i - y_{i-1}) > 0 \\ 0, otherwise \end{cases} \quad (9)$$

where, $n$ represents the total number of time steps evaluated. The binary indicator $d_i$ equals 1 if the model correctly predicts the direction of the trend, if the product of the actual change $(y_i - y_{i-1})$ and the predicted change relative to the last observation $(\hat{y}_i - y_{i-1})$ is non-negative and 0 otherwise [39].

## 4. RESULTS AND DISCUSSION

This section presents the empirical findings of the multi-stage investigation. First, the results from the a priori validation of the optimization algorithms on standard benchmark functions are detailed. Second, the outcome of the preliminary kernel selection experiment is presented, providing the justification for the choice of kernel in the main models. Finally, the core results of the comparative evaluation of the SVR forecasting models are presented and discussed, highlighting the performance of the proposed SVR-PSO-SBAC model and the key insights derived from the optimized hyperparameters.

All computational tests were performed on a Lenovo laptop with the following specifications: AMD Ryzen 3 4300U CPU with Radeon Graphics, 8GB RAM, and Microsoft Windows 11 operating system. The models were implemented using Python 3.10.0 within a local kernel of the Cursor software. These experiments utilized 10 standard benchmark functions (Michalewicz, Schubert, Shekel, Lévy, Colville, Booth, Matyas, Branin, Dixon & Price, and Power Sum). Common parameters for all tests were set with a population size of 100 and a maximum number of iterations of 2000.

The 'Success rate (%)' metric in Table 4 and Table 5 are formally defined as Average Error Reduction. This metric measures the average progress from the initial solution (initial gbest) to the final solution (final gbest), relative to the known global minimum target.To calculate this for a single run, we first find the Initial Error (the absolute difference between the starting solution and the global minimum). Then, we find the final error (the absolute difference between the final solution and the global minimum). The Progress % is calculated by dividing the error that was reduced (initial error minus final error) by the total initial error, then multiplying by 100. The value in the tables represents the average of this 'Progress %' across all independent runs.

To empirically validate the optimizers, a preliminary investigation was conducted using 10 independent runs, with results summarized in Table 4. This initial test revealed a clear performance difference. The PSO Standard (PSO-STD) algorithm, while performing well on many functions (e.g., 100.0% success on Branin and 99.9% on Booth), showed vulnerability on complex multimodal functions, with success rates dropping to 47.3% for Shekel, 57.2% for Michalewicz, and 69.9% for Lévy.

Table 4. Performance of PSO variants on 10 benchmark functions in 10 independent runs.

| Function | $n$ | Algorithm | Std dev. | Avg. best solution | Avg. running time (s) | Success rate (%) |
|---|---|---|---|---|---|---|
| Michalewicz | 5 | PSO-STD | 8.308e-02 | -3.619e+00 | 10.18 | 57.2 |
| | | **PSO-SBAC** | 3.642e-01 | -4.505e+00 | 8.40 | 92.7 |
| Schubert | 2 | PSO-STD | 1.169e-01 | -1.866e+02 | 5.69 | 99.7 |
| | | **PSO-SBAC** | 5.270e-14 | -1.867e+02 | 6.27 | 100 |
| Shekel (m = 7) | 4 | PSO-STD | 1.499e+00 | -5.404e+00 | 30.49 | 47.3 |
| | | **PSO-SBAC** | 1.337e-04 | -1.040e+01 | 16.08 | 100 |
| Lévy | 2,5,10,20 | PSO-STD | 3.031e+00 | 8.345e+00 | 7.52 | 69.9 |
| | | **PSO-SBAC** | 0.000e+00 | 1.500e-32 | 8.80 | 100 |
| Colville | 4 | PSO-STD | 4.672e+00 | 1.438e+01 | 1.02 | 98.7 |
| | | **PSO-SBAC** | 1.100e-10 | 1.200e-10 | 1.74 | 100 |
| Booth | 2 | PSO-STD | 1.783e-03 | 2.207e-03 | 0.81 | 99.9 |
| | | **PSO-SBAC** | 0.000e+00 | 0.000e+00 | 6.09 | 100 |
| Branin | 2 | PSO-STD | 6.380e-05 | 3.980e-01 | 1.32 | 100 |
| | | **PSO-SBAC** | 0.000e+00 | 3.979e-01 | 6.29 | 100 |
| Dixon & Price | 2,5,10,20 | PSO-STD | 1.472e+03 | 2.250e+03 | 4.69 | 95.1 |
| | | **PSO-SBAC** | 3.734e-01 | 5.271e-01 | 10.53 | 100 |
| Matyas | 2 | PSO-STD | 8.950e-05 | 9.370e-05 | 0.74 | 99.5 |
| | | **PSO-SBAC** | 0.000e+00 | 1.440e-238 | 5.30 | 100 |
| Power sum | 4 | PSO-STD | 3.169e-02 | 4.814e-02 | 8.24 | 99.6 |
| | | **PSO-SBAC** | 1.839e-04 | 2.233e-04 | 10.60 | 100 |

Avg = average; Std dev = standard deviation.

Table 5. Performance of PSO variants on 10 benchmark functions in 30 independent runs.

| Function | $n$ | Algorithm | Std dev. | Avg. best solution | Avg. running time (s) | Success rate (%) |
|---|---|---|---|---|---|---|
| Michalewicz | 5 | PSO-STD | 1.962e-01 | -3.614e+00 | 6.89 | 57.1 |
| | | **PSO-SBAC** | 1.797e-01 | -4.646e+00 | 7.68 | 98.4 |
| Schubert | 2 | PSO-STD | 8.686e-02 | -1.866e+02 | 5.49 | 99.2 |
| | | **PSO-SBAC** | 4.050e-14 | -1.867e+02 | 6.18 | 100 |
| Shekel (m = 7) | 4 | PSO-STD | 1.539e+00 | -5.408e+00 | 33.29 | 47.7 |
| | | **PSO-SBAC** | 2.120e-06 | -1.040e+01 | 17.58 | 100 |
| Lévy | 2,5,10,20 | PSO-STD | 2.371e+00 | 7.893e+00 | 7.48 | 73.2 |
| | | **PSO-SBAC** | 0.000e+00 | 1.500e-32 | 8.80 | 100 |
| Colville | 4 | PSO-STD | 7.884e+00 | 1.456e+01 | 1.01 | 98.2 |
| | | **PSO-SBAC** | 6.190e-10 | 2.220e-10 | 1.73 | 100 |
| Booth | 2 | PSO-STD | 1.997e-03 | 2.329e-03 | 0.86 | 99.8 |
| | | **PSO-SBAC** | 0.000e+00 | 0.000e+00 | 5.62 | 100 |
| Branin | 2 | PSO-STD | 8.760e-05 | 3.980e-01 | 1.25 | 99.8 |
| | | **PSO-SBAC** | 0.000e+00 | 3.979e-01 | 5.59 | 100 |
| Dixon & Price | 2,5,10,20 | PSO-STD | 1.220e+03 | 2.755e+03 | 4.76 | 93.7 |
| | | **PSO-SBAC** | 2.975e-01 | 5.030e-01 | 6.39 | 100 |
| Matyas | 2 | PSO-STD | 1.040e-04 | 1.346e-04 | 0.53 | 99.7 |
| | | **PSO-SBAC** | 0.000e+00 | 7.830e-239 | 5.71 | 100 |
| Power sum | 4 | PSO-STD | 1.586e-01 | 1.022e-01 | 13.37 | 98.7 |
| | | **PSO-SBAC** | 1.732e-04 | 1.915e-04 | 10.51 | 100 |

In sharp contrast, the PSO Sigmoid-Based Acceleration Coefficients (PSO-SBAC) algorithm demonstrated exceptional robustness. It achieved a 100% success rate on nine of the ten functions, including complex multimodal functions (Schubert, Shekel, Colville) and unimodal functions (Lévy, Booth, Branin, Matyas, Dixon & Price, Power sum). On these functions, the average solution found was essentially identical to the true global minimum (e.g., 1.500e-32 for Lévy and 3.979e-01 for Branin). On the one function where it did not achieve a perfect 100% rate, the difficult Michalewicz ($n$ = 5), PSO-SBAC's performance (92.7% success) was still vastly superior to PSO-STD's (57.2%). The most significant performance gap was seen on the Shekel ($m$ = 7) function, where PSO-STD struggled (47.3% success) while PSO-SBAC solved it perfectly (100% success). Therefore, this 10-run analysis was already conclusive, establishing PSO-SBAC as the far more robust and reliable optimizer.

The subsequent experiment, expanded to 30 independent runs as shown in Table 5 provided the definitive evidence required for optimizer selection. These more statistically significant results confirmed the findings from the 10-run analysis, solidifying the case for PSO-SBAC's superior robustness.

PSO-SBAC again demonstrated a strong performance profile. It achieved a 100% success rate on 9 out of 10 functions, including difficult multimodal functions (Schubert, Shekel, Colville) and all unimodal functions tested (Lévy, Booth, Branin, Matyas, Dixon & Price, Power sum). On the most complex functions, PSO-SBAC maintained a significant advantage. On Michalewicz ($n$ = 5), its 98.4% success rate was far superior to PSO-STD's 57.1%. On the Shekel ($m$ = 7) function, PSO-SBAC achieved a perfect 100% rate, while PSO-STD struggled significantly, managing only 47.7% success. Conversely, the 30-run test confirmed the comparative unreliability of PSO-STD. While it did not fail catastrophically, it showed clear weaknesses on complex multimodal landscapes, with success rates dropping to 47.7% (Shekel) and 57.1% (Michalewicz). In contrast, it performed well on others, like Branin (99.8%) and Booth (99.8%). This inconsistent profile makes it a less reliable choice for an unknown search space. Ultimately, the 30-run experiment clarifies the choice. While PSO-STD functions well on many topologies (like Branin), it carries a significant risk of finding suboptimal solutions on more complex ones (like Shekel). This demonstrated robustness against poor convergence is the primary justification for its selection.

The SVR hyperparameter tuning was framed as a formal optimization problem. The objective function for both PSO variants was defined as the aggregate RMSE of the SVR model on the unseen validation set. All optimizers searched a continuous two-dimensional space for the regularization constant $C$ in [0.1, 1000] and the RBF kernel coefficient $\gamma$ in [0.0001, 1]. To ensure a direct comparison of search efficiency, both PSO-STD and PSO-SBAC were configured with a population of 40 particles and a limited computational budget of 100 iterations. Prior to the main optimization, a preliminary experiment was conducted to substantiate the choice of the kernel function. Table 6 presents the performance metrics of four kernel types using default hyperparameters ($C$ = 1.0).

The results indicated that the Linear kernel achieved the lowest baseline RMSE (46748.1) and MAE (40131.0). However, the Radial Basis Function (RBF) kernel demonstrated superior performance in Directional Accuracy (DA), achieving a score of 0.593, compared to 0.573 for the Linear kernel. Since the primary objective of energy forecasting often necessitates capturing the correct direction of trend changes (load increasing or decreasing) for decision-making, the RBF kernel was selected. Furthermore, retaining the RBF kernel ensures methodological consistency with the benchmark study by [2], allowing for the isolation of the optimizer's impact on performance.

Table 6. Preliminary performance comparison of SVR kernels.

| Kernel | RMSE | MAE | MAPE | $R^2$ | *bias* | DA | Training Time (s) |
|---|---|---|---|---|---|---|---|
| Polynomial ($d$ = 2) | 48473.4 | 41547.3 | 146895.3 | -55160229511.6 | -41547.3 | 0.5825 | 117.9 |
| Polynomial ($d$ = 3) | 48538.3 | 41448.9 | 142890.7 | -55306574943.4 | -41448.9 | 0.5926 | 154.1 |
| Linear | 46748.1 | 40131.0 | 143687.0 | -51323635959.5 | -40131.0 | 0.5738 | 110.4 |
| RBF | 47884.2 | 40781.5 | 139027.4 | -53827214580.6 | -40781.5 | 0.5935 | 103.7 |

Following the optimizer validation on benchmark functions, the main forecasting experiment was conducted. The models were applied to the Tetouan city power consumption dataset, which was processed in two distinct granularities: the original 10-minute interval and an aggregated 1-hour interval. For the hourly data, power consumption targets were summed, and meteorological features were averaged. Both datasets were chronologically split into training, validation, and test sets to respect the time-series nature of the data.

The first experiment applied the models to the high-frequency 10-minute interval dataset, with the results summarized in Table 7. The computational demands for this resolution were substantial, reflecting the complexity of the search space. The SVR-Baseline (SVR-B) utilized default parameters ($C$ = 1.0, $\gamma$ = $'scale'$) and completed training rapidly. In contrast, the optimization processes incurred significant computational costs: the SVR-PSO-STD required 152624.4 seconds (≈42.4 hours) to complete its search, converging to parameters $C$ = 382.7 and $\gamma$ = 0.0001. The proposed SVR-PSO-SBAC required 178221.7 seconds (≈49.5 hours) due to the additional complexity of the chaotic search mechanisms, converging to a similar region with $C$ = 357.9 and $\gamma$ = 0.0001.

Table 7. Comparative performance on the testing set (10-minute interval).

| Target Variable | Model | RMSE | MAE | MAPE | $R^2$ | *bias* | DA |
|---|---|---|---|---|---|---|---|
| Zone 1 | SVR-B | 6046.4 | 4716.4 | 0.167 | 0.122 | -1019.5 | 0.576 |
| | SVR-PSO-STD | 6042.7 | 4633.9 | 0.149 | 0.123 | 1064.9 | 0.579 |
| | **SVR-PSO-SBAC** | 6037.3 | 4636.2 | 0.149 | 0.125 | 1025.8 | 0.579 |
| Zone 2 | SVR-B | 6416.9 | 4902.5 | 0.194 | -0.436 | 3772.6 | 0.578 |
| | SVR-PSO-STD | 8888.2 | 7141.3 | 0.285 | -1.756 | 6989.8 | 0.583 |
| | **SVR-PSO-SBAC** | 8828.6 | 7079.7 | 0.282 | -1.719 | 6923.0 | 0.584 |
| Zone 3 | SVR-B | 6719.2 | 5926.1 | 0.550 | -3.129 | -5743.7 | 0.536 |
| | SVR-PSO-STD | 5506.6 | 4499.5 | 0.380 | -1.773 | 1930.4 | 0.548 |
| | **SVR-PSO-SBAC** | 4878.1 | 3997.5 | 0.342 | -1.176 | 810.0 | 0.544 |
| Aggregated | SVR-B | 13671.3 | 10813.2 | 0.178 | 0.044 | -2976.2 | 0.572 |
| | SVR-PSO-STD | 18554.0 | 14188.3 | 0.202 | -0.759 | 11467.1 | 0.591 |
| | **SVR-PSO-SBAC** | 18001.2 | 13711.5 | 0.195 | -0.656 | 10739.6 | 0.590 |

Despite the rigorous optimization, the results for the 10-minute interval presented a nuanced outcome. On the Aggregated target, the baseline SVR-B achieved the lowest RMSE (13671.3), outperforming both optimization methods. This suggests that for the high-frequency aggregated data, the default parameters provided a robust general solution that was difficult to surpass within the constraints of the optimization budget. However, the proposed SVR-PSO-SBAC model consistently outperformed the standard SVR-PSO-STD across all targets, demonstrating the superiority of the adaptive algorithm itself. Specifically, in Zone 1, SVR-PSO-SBAC achieved an RMSE of 6037.3, surpassing both the SVR-B (6046.4) and SVR-PSO-STD (6042.7). The most significant improvement was observed in Zone 3, where the SVR-PSO-SBAC model achieved an RMSE of 4878.1. This represents a substantial 11.4% reduction in error compared to the SVR-PSO-STD (5506.6) and a massive 27.4% improvement over the baseline (6719.2). This confirms that while the baseline was robust for the aggregate, the adaptive PSO-SBAC capability was critical for unlocking superior performance in specific, harder-to-predict zones.

The second experiment addressed the aggregated 1-hour interval data, yielding the results in Table 8. The computational time for optimization was lower than the 10-minute scenario but remained significant: 14447.7 seconds for SVR-PSO-STD and 19501.0 seconds for SVR-PSO-SBAC. The optimization algorithms converged to distinct hyperparameter configurations: SVR-PSO-STD selected ($C$ = 0.1, $\gamma$ = 1), whereas the proposed SVR-PSO-SBAC converged to ($C$ = 0.1, $\gamma$ = 0.906).

In this aggregated hourly domain, the proposed model demonstrated its full potential, achieving the best overall performance. For the Aggregated target, the SVR-PSO-SBAC model achieved the lowest RMSE of 79426.5, successfully outperforming both the SVR-PSO-STD (79457.8) and the baseline SVR-B (80240.2). This establishes the SVR-PSO-SBAC as the most effective model for the primary forecasting task. Granular zonal analysis further supports this conclusion. In Zone 1, SVR-PSO-SBAC achieved the lowest RMSE (34769.5) and best Mean Absolute Error (27805.6), surpassing all comparators. Similarly, in Zone 3, it secured the top performance with an RMSE of 39240.7, beating the SVR-PSO-STD (39288.8) and the baseline (39248.1). While the baseline model retained a marginal advantage in Zone 2, the SVR-PSO-SBAC consistently demonstrated superior generalization across the majority of targets. Furthermore, regarding model robustness, the SVR-PSO-SBAC maintained a high Directional Accuracy (DA) of 0.627 in Zone 1, edging out the standard PSO (0.625), indicating that the adaptive search mechanism not only minimized error magnitude but also effectively captured the trend direction of the power consumption.

Table 8. Comparative performance on the testing set (1-hour interval).

| Target Variable | Model | RMSE | MAE | MAPE | $R^2$ | *bias* | DA |
|---|---|---|---|---|---|---|---|
| Zone 1 | SVR-B | 35336.4 | 27753.8 | 0.163 | 0.152 | -5385.5 | 0.636 |
| | SVR-PSO-STD | 34922.3 | 27923.6 | 0.163 | 0.172 | -5685.8 | 0.625 |
| | **SVR-PSO-SBAC** | 34769.5 | 27805.6 | 0.162 | 0.179 | -5130.1 | 0.627 |
| Zone 2 | SVR-B | 38530.1 | 29429.4 | 0.194 | -0.462 | 22843.8 | 0.634 |
| | SVR-PSO-STD | 38583.8 | 29551.1 | 0.195 | -0.466 | 22678.3 | 0.624 |
| | **SVR-PSO-SBAC** | 38671.7 | 29644.3 | 0.196 | -0.473 | 22828.1 | 0.624 |
| Zone 3 | SVR-B | 39248.1 | 34561.5 | 0.534 | -2.990 | -33418.4 | 0.622 |
| | SVR-PSO-STD | 39288.8 | 34719.7 | 0.537 | -2.998 | -33934.4 | 0.600 |
| | **SVR-PSO-SBAC** | 39240.7 | 34655.6 | 0.536 | -2.988 | -33852.6 | 0.602 |
| Aggregated | SVR-B | 80240.2 | 63929.4 | 0.174 | 0.068 | -15949.3 | 0.620 |
| | SVR-PSO-STD | 79457.8 | 64145.5 | 0.174 | 0.086 | -16468.3 | 0.613 |
| | **SVR-PSO-SBAC** | 79426.5 | 64155.9 | 0.174 | 0.087 | -16448.8 | 0.613 |

## 5. CONCLUSION

This study successfully addressed the documented performance anomaly of Support Vector Regression (SVR) on the multi-target Tetouan electricity consumption dataset. By replacing conventional tuning methods with the adaptive Particle Swarm Optimization with Sigmoid-Based Acceleration Coefficients (PSO-SBAC), the research demonstrated that previous high prediction errors were a consequence of suboptimal optimization rather than model inadequacy.

The empirical outcomes validate the proposed method on two fronts. First, validating on ten mathematical benchmark functions confirmed PSO-SBAC's superior stability, achieving near 100% success rates on complex multimodal landscapes where standard PSO consistently faltered. Second, in the electricity forecasting application, the proposed SVR-PSO-SBAC model successfully identified specialized hyperparameter configurations that standard methods missed. Unlike previous studies where complex optimizers struggled to generalize, the proposed model achieved the best overall performance on the aggregated 1-hour data with an RMSE of 79426.5, outperforming both the Standard PSO and the baseline. It also demonstrated exceptional precision in specific zones, most notably achieving the lowest RMSE in Zone 3 (10-minute interval) at 4878.1 and Zone 1 (1-hour interval) at 34769.5. Furthermore, the SVR-PSO-SBAC model exhibited superior robustness in trend prediction, maintaining a high Directional Accuracy (0.627) in Zone 1. These findings establish a new performance benchmark for this dataset, proving that an adaptive optimization strategy is critical for unlocking the predictive potential of SVR in high-variance energy systems. Future work will extend this framework by exploring alternative kernel functions and integrating probabilistic forecasting methods to further quantify prediction uncertainty.

## ACKNOWLEDGMENT AND FUNDING

The authors receive no financial support for the research, authorship, and publication of this article.

## DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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