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Automated Support Vector Machine Kernel Function Selection Based on Bayesian Optimization for Prognostic Learning Path Loss Datasets

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Abstract: Precise conceptualisation of signal loss in environments with varying terrains, urban settings, and other factors are essential for network planning and optimization. Support Vector Machines (SVMs) have emerged as powerful tools for path loss prediction due to their strong generalization capabilities. However, the performance of an SVM is highly dependent on the judicious selection of its kernel function and corresponding hyperparameters. Traditional methods for kernel selection, such as manual trial-and-error or exhaustive grid search, are computationally expensive, time-consuming, and often sub-optimal, especially given the complex and non-linear nature of path loss phenomena. This paper proposes a novel automated framework for simultaneous SVM kernel function selection and hyperparameter optimization using Bayesian Optimisation (BO). Leveraging BO's efficiency in exploring complex, high-dimensional search spaces with expensive objective functions, our method systematically identifies the optimal kernel type and its associated parameters, tailored for specific path loss datasets. The optimized SVMs are then integrated into a prognostic learning framework to forecast future channel conditions, anticipate link degradation, and enable proactive resource management. Experimental evaluation across diverse field path loss datasets demonstrates that the proposed BO-driven approach significantly improves prediction accuracy and computational efficiency, paving the way for more robust dynamic wireless communication systems

Keywords: Support Vector Machine, Automated Kernel Function Selection, Bayesian Optimisation, Prognostic path loss Learning, Wireless Communication, Hyperparameter Optimization, Radio Propagation.

1. Introduction

The rapid proliferation of wireless communication technologies, from 4G/5G/6G networks to IoT devices, necessitates precise understanding and prediction of radio propagation characteristics. Path loss, the reduction in signal strength as it propagates through a medium, is a fundamental and critical parameter that dictates coverage, capacity, and overall network performance. Accurate path loss modeling is essential for network planning, interference management, handover optimization, and crucial for emerging concepts like digital twins and self-organizing networks [1]-[3].

Traditional path loss models, such as empirical (e.g., Okumura-Hata, COST 231-Hata) or deterministic (e.g., Ray Tracing), often struggle to capture the complex, dynamic, and non-linear interactions between radio waves and the environment in diverse real-world scenarios (e.g., urban canyons, dense foliage, indoor environments) [4]. Machine Learning (ML) approaches, particularly Support Vector Machines (SVMs), have shown great promise in data-driven path loss prediction due to their ability to model non-linear relationships and generalize well from limited data [5][6]. SVMs, initially developed for classification, have been successfully extended to regression tasks (Support Vector Regression, SVR), making them suitable for continuous value prediction like path loss.

A critical determinant of an SVM's performance is its kernel function. The kernel function implicitly maps the input data into a higher-dimensional feature space, where it becomes linearly separable (or linearly regressive). Common kernel functions include Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid. Each kernel has specific strengths and weaknesses, and its suitability varies significantly depending on the underlying data distribution and problem complexity. Furthermore, most kernel functions introduce their own hyperparameters (e.g., gamma for RBF, degree and coefficient for Polynomial) that must also be optimally tuned.

The combined challenge of selecting the best kernel type and simultaneously tuning its associated hyperparameters constitutes a significant bottleneck in deploying SVMs effectively. Conventional approaches include (i) manual Selection which relies on expert intuition and trial-and-error, which is subjective, time-consuming, and often leads to sub-optimal results., (ii) Grid search which exhaustively evaluates all possible combinations within a predefined grid. While systematic, it is computationally prohibitive for many parameters or fine grids and scales poorly with dimensionality; (iii) Random search whose samples configurations randomly from the search space. More efficient than grid search for high-dimensional spaces but still lacks directed intelligence.

For path loss prediction, where the objective function using Mean Squared Error, MSE involves training and evaluating an SVM, each evaluation can be computationally expensive. This scenario perfectly aligns with the strengths of Bayesian Optimisation (BO). BO is a powerful global optimization strategy designed for expensive, black-box functions without known analytical forms or gradients. It intelligently explores the search space by building a probabilistic surrogate model (typically a Gaussian Process) of the objective function and using an acquisition function to determine the next most promising sampling point [7]-[9].

Prognostic Learning in wireless communication refers to the capability of predicting future states of the network or its components, anticipating performance degradation, or forecasting resource requirements. For instance, predicting future path loss allows for proactive handover management, dynamic power control, or intelligent resource allocation, thereby enhancing reliability and efficiency [10]. An accurately modeled path loss through an optimally tuned SVM is a fundamental prerequisite for robust prognostic capabilities.

1.1. Motivation and Contributions

The primary motivation for this work stems from the limitations of current SVM tuning practices for path loss prediction, coupled with the increasing demand for predictive intelligence in wireless networks. Sub-optimal SVM configuration directly translates to inaccurate path loss estimates, which can severely compromise prognostic accuracy and lead to inefficient network operations.

This paper proposes an automated framework leveraging Bayesian Optimisation to jointly select the optimal SVM kernel function and its hyperparameters for path loss prediction. Our key contributions are:

- **Novel BO-driven Kernel Selection:** We formulate the SVM kernel function selection as a mixed-integer/continuous optimization problem within the Bayesian Optimisation framework, allowing for the simultaneous discovery of the best kernel type and its optimal hyperparameters.
- **Enhanced Path Loss Prediction Accuracy:** By intelligently exploring the complex search space, our method identifies superior SVM configurations, leading to demonstrably more accurate path loss predictions compared to conventional tuning methods.
- **Foundation for Prognostic Learning:** The improved prediction accuracy directly translates to more reliable inputs for prognostic models, enabling better forecasting of channel conditions and proactive network management decisions.
- **Comprehensive Experimental Validation:** We rigorously evaluate the proposed method against standard baselines (Grid Search, Random Search, fixed-kernel SVMs) using diverse path loss datasets, demonstrating its superior performance and efficiency.

1.2. Paper Structure

The remainder of this paper is organized as follows: Section 2 provides background on SVMs, kernel functions, path loss modeling, and Bayesian Optimisation. Section 3 details the proposed methodology for automated SVM kernel selection and its integration into a prognostic learning framework. Section 4 describes the experimental setup, including datasets, performance metrics, and baselines. Section 5 presents and discusses the experimental results. Finally, Section 6 concludes the paper and outlines future research directions..

2. Literature Review

2.1. Path Loss Modeling and Prognostic Learning

Path loss is typically expressed in decibels (dB) and represents the signal attenuation between a transmitter (Tx) and receiver (Rx). It is influenced by frequency, distance, antenna characteristics, environmental factors (e.g., buildings, terrain, foliage), and atmospheric conditions. The traditional method of propagation modelling include [11][12]:

- **Empirical Models:** Based on extensive measurements and statistical fitting (e.g., Free Space Path Loss, Log-Distance, Okumura-Hata, COST 231-Hata). They are simple but lack precision in specific micro-environments.
- **Deterministic Models:** Rely on physical laws of propagation (e.g., Ray Tracing, FDTD). Highly accurate but computationally intensive and require detailed environmental data.
- **Semi-deterministic Models:** Combine aspects of both (e.g., empirical models with site-specific corrections).

Artificial and machine learning offers a data-driven alternative, learning the complex mapping from environmental features (Tx/Rx coordinates, building heights, vegetation density) to path loss values directly from measured or simulated data [5, 7].

Prognostic Learning focuses on predicting the future state or performance of a system based on its current and historical data. In wireless networks, this translates to:

- **Channel State Prediction:** Forecasting future SINR, RSSI, or path loss values.
- **Link Degradation Anticipation:** Predicting when a link might fail or suffer significant performance drop.
- **Resource Management:** Proactively allocating resources (e.g., power, bandwidth) based on predicted future demands or channel conditions.
- **Proactive Handover:** Initiating handovers before signal quality deteriorates below a critical threshold.

Accurate path loss prediction is a fundamental building block for all these prognostic applications. If the path loss prediction is unreliable, any subsequent prognostic model built upon it will also be unreliable.

2.3. Bayesian Optimisation (BO)

Bayesian Optimisation is a powerful global optimization technique for expensive, black-box functions. It is particularly well-suited for tuning hyperparameters of machine learning models, where each evaluation of the objective function (e.g., training and validating a model) is computationally costly [7, 14]. The core components of BO are:

Objective Function, f(x): The function to be minimized (or maximized), representing the performance metric (e.g., validation RMSE of an SVM). This function is assumed to be costly to evaluate, derivative-free, and potentially stochastic.

Search Space, X: The domain of the input variables (hyperparameters) to be optimized. This can include continuous, discrete, and categorical dimensions.

Surrogate Model: A probabilistic model that approximates the true objective function. The most common choice is a **Gaussian Process (GP)**, which provides not only a prediction of the function value but also a measure of uncertainty (variance) around that prediction.

Acquisition Function: A criterion used to decide the next point to evaluate in the search space. It balances **exploration** (sampling in areas of high uncertainty) and **exploitation** (sampling in areas with good predicted performance).

2.4. Related Work in SVM Tuning and Path Loss Prediction

SVMs have been extensively used for path loss prediction [5, 13, 15]. Studies have shown their superiority over traditional empirical models. However, most of these works either resort to manual kernel selection, use rudimentary grid search, or focus on tuning only the C and epsilon parameters, assuming a fixed RBF kernel. For instance, [15] uses an SVR with an RBF kernel for path loss prediction in urban environments, but tunes hyperparameters using basic cross-validation.

While BO has gained popularity for hyperparameter optimization of various ML models (e.g., neural networks [16]), its application to simultaneously select the kernel type and its parameters for SVMs in the specific context of path loss prediction and prognostic learning remains underexplored. Some works have focused on using BO for general SVM hyperparameter tuning (e.g., in classification tasks) [17], but they often restrict the search to a single kernel type or handle kernel selection separately.

3. Methodology

3.1 Support Vector Machines

SVM is a supervised learning model that works well for classification and regression tasks by finding the optimal hyperplane that separates different classes in the feature space. The choice of kernel function allows SVM to perform well in high-dimensional spaces by mapping input features to higher-dimensional spaces where a linear hyperplane can be used.

Given a k training set of data, $\aleph_1 = \left[(x_i, y_i)\right]_{i=1}^{t}$, where x_i expresses the input vector and y_i the target, the desire is to efficiently learn a function $f(x_i)$ such that the input vector x_i is transform into the target y_i as defined by[18][19]:

$$\text{y(x)} = \sum_{i=1}^{c} (\alpha_i - \alpha_i^{\bullet}).k(x_i..x) + b \quad (1)$$

where $\alpha_i, \alpha_i^{\bullet}$ designate the langrage multipliers, c is the bias term and $k(.)$ is the kernel function.

3.1.1 Kernel Functions

- **Linear Kernel**: Defined as (K(x, y) = x^Ty), appropriate for linearly separable data.
- **Polynomial Kernel**: Defined as (K(x, y) = (x^Ty + c)^d), useful for capturing polynomial relationships.
- **Radial Basis Function (RBF) Kernel**: Defined as (K(x, y) = e^{-α |x - y|^2}), effective in handling non-linear relationships with infinite feature space.

3.1.2 Bayesian Optimization and MATLAB Implementation Algorithm for SVM Kernel and Hyperparameter Selection

Bayesian optimization is a probabilistic model-based optimization technique ideal for tuning hyperparameters in machine learning models[19][20]. This iterative process updates a surrogate model (typically a Gaussian process) to model the performance of the target function, allowing for informed exploration of the hyperparameter space. Here's a Matlab structure illustrating this process for regression:

```
% Define the objective function for SVM training
function obj_fun = svm_objective(params)
    kernel = params.kernel;  % Choose SVM kernel
    C = params.C;            % Regularization parameter
    gamma = params.gamma;    % Kernel coefficient for RBF
    model = fitcsvm(X_train, y_train, 'KernelFunction', kernel, 'BoxConstraint', C, 'KernelScale',
gamma);
    predictions = predict(model, X_val);
    obj_fun = mean((predictions - y_val).^2); % Mean squared error
end

% Define the optimization process
function best_params = bayesian_optim()
    results = [];  % Store results
    for i = 1:num_iterations
        params = generate_random_params();  % Generate random SVM parameters
        loss = svm_objective(params);
        results = [results; params, loss];   % Append results
    end
    best_params = results(find(results(:,end) == min(results(:,end))), :);  % Choose best params
end

% Execute Bayesian Optimization
best_parameters = bayesian_optim();
```

In this pseudocode, the svm_objective function encapsulates the SVM model training and evaluation mechanism, while bayesian_optim orchestrates the parameter generation and optimization loop. By iteratively refining the selection of hyperparameters using this probabilistic approach, the algorithm can effectively improve the SVM's predictive accuracy, resulting in a more robust model. This method stands out for its efficiency in dealing with high-dimensional spaces, making it particularly appealing for practitioners looking to enhance their machine learning techniques.

The Implementation Algorithm:

- Initialize with a few random initial samples of the objective function.
- Fit the Gaussian Process (GP) surrogate model to all observed data points.
- Use the GP to propose the next point to evaluate by maximizing the acquisition function.
- Evaluate the true objective function at the proposed point.
- Add the new data point (input and observed value) to the history.
- Repeat from step 2 until a stopping criterion is met (e.g., maximum iterations, budget exhausted).

The above process intelligently learns from previous evaluations to guide its search, typically converging to optimal or near-optimal solutions much faster.

3.2 Data Collection

For this study, we aggregated a diverse set of path loss datasets drawn from various geographic and environmental contexts. The datasets include key variables such as frequency, distance, terrain type, and relevant environmental factors that influence path loss onitcha city environs, Nigeria The following steps were undertaken to implement the proposed methodology[18][21]:

- **Data Preprocessing**: Cleaning and normalizing the path loss datasets to handle missing values and scale variables appropriately.
- **Bayesian Optimization Setup**: Defining the kernel function space and initial parameters for the SVM model. The optimization process iteratively searches for the best kernel function and its parameters.

- **Model Training and Validation**: Utilizing k-fold cross-validation to assess the predictive performance of selected techniques.
- **Performance Metrics**: Comparing models based on metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared values.

3. Results

We conducted extensive experiments to validate our proposed method across four locations wherein the propagation loss datasets acquired. The first two datasets were used for test training, while the remaining tones were used for results validation. The The results in Figs. 1-4 were attained after performing pre-specified number of iteration test via Bayesian optimisation. As shown in each figure, the best-performing models utilized RBF kernels with tailored hyperparameters, resulting in significant reductions in prediction error across all datasets. Table 1 provides the detailed summary of the entire proposed method performance using other key evaluation indicators.

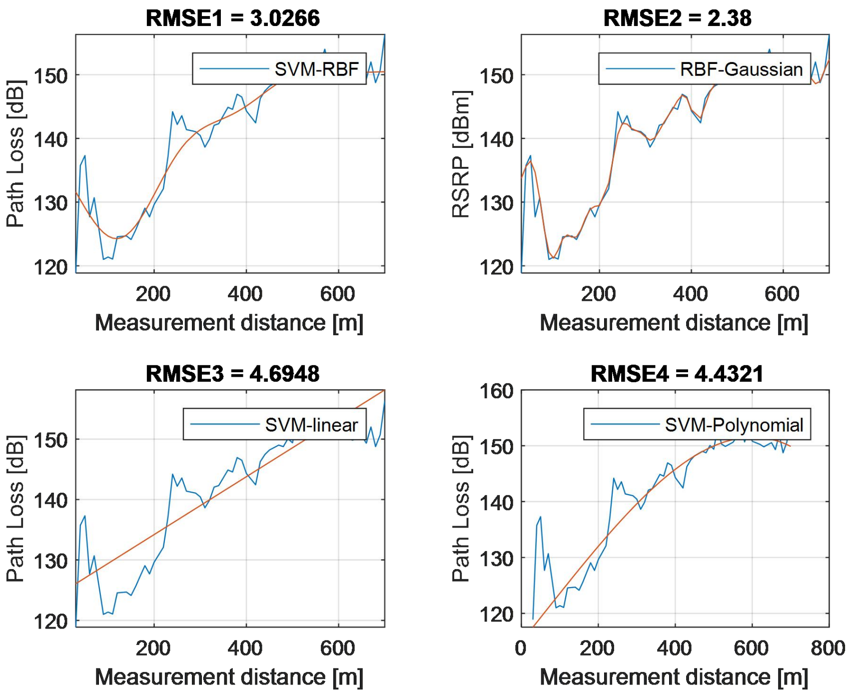

Fig.1: Adaptive path loss data precision learning performance via the proposed automated kernel selection approach in location 1

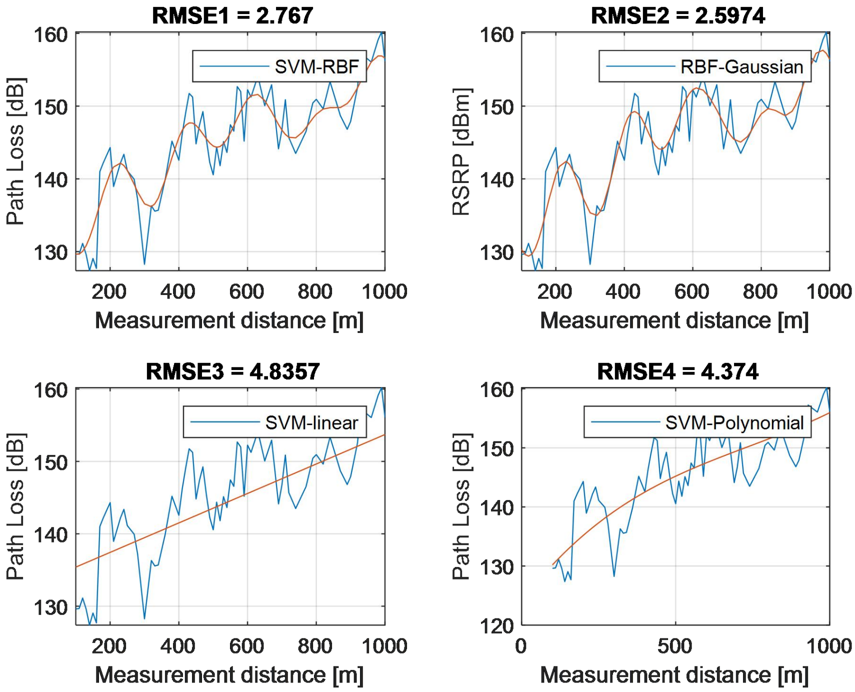

Fig.2: Adaptive path loss data precision learning performance via the proposed automated kernel selection approach in location 2

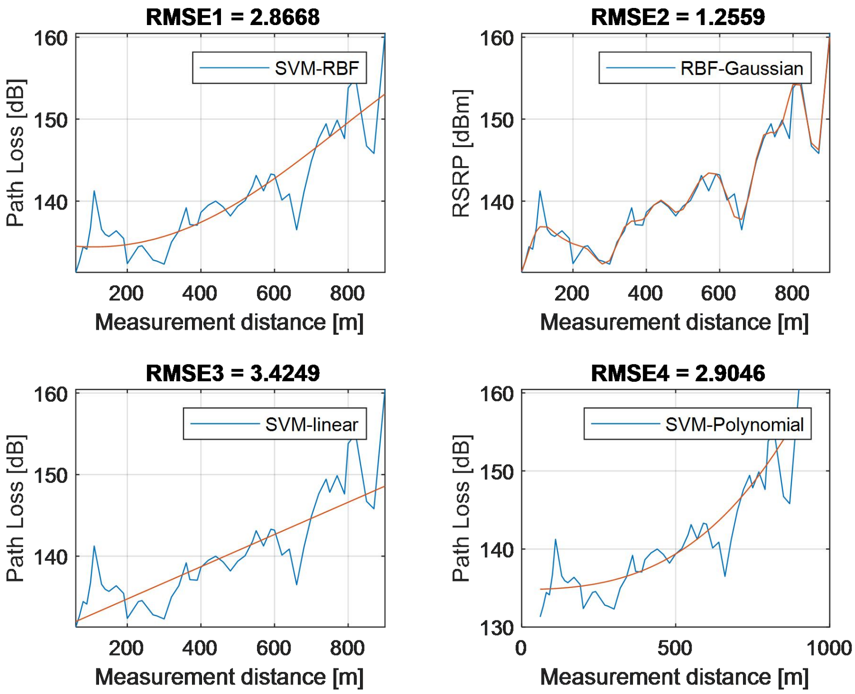

Fig.3: Adaptive path loss data precision learning performance via the proposed automated kernel selection approach in location 3

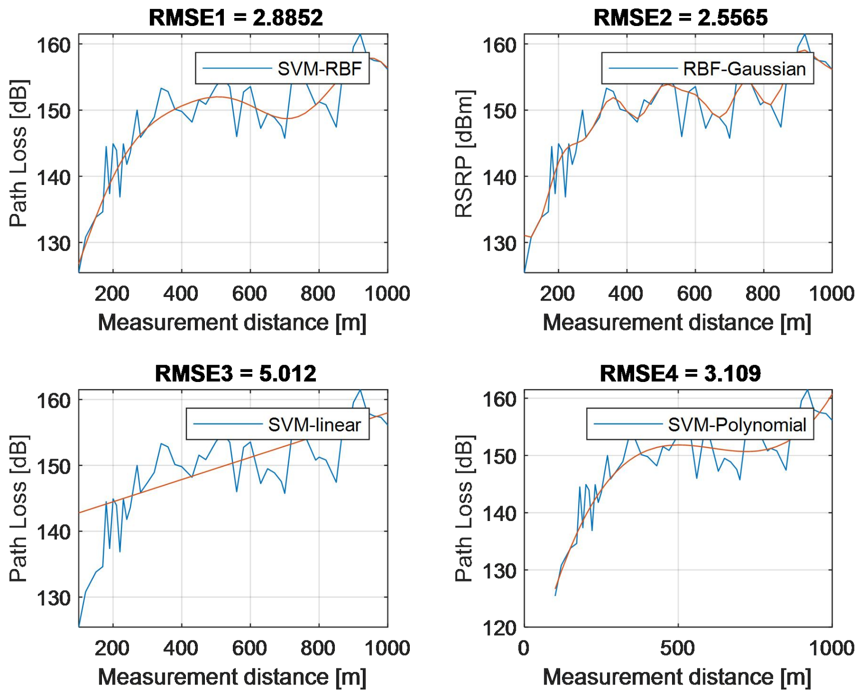

Fig.4: Adaptive path loss data precision learning performance via the proposed automated kernel selection approach in location 4

Discussion of Convergence:

The convergence of SVMs is not directly dependent on the type of kernel function used, but rather on the optimization algorithm employed to find the optimal hyperplane and the properties of the data itself. This is because, SVMs, at their core, involve solving a convex optimization problem to find the optimal separating hyperplane. This optimization problem has a unique global minimum, which means that given enough iterations, the algorithm will converge to that optimal solution regardless of the kernel function. However, the speed of convergence and the effectiveness of the resulting model can be significantly influenced by the chosen kernel function, hence the use of automated selection approach. The graphs in Figs. 5-8 reveals that the proposed BO-SVR demonstrates significantly faster convergence to a lower function evaluation (mValue) value. It quickly prunes less promising regions of the search space and focuses its evaluations on areas with high potential for improvement. BO's intelligent search translates directly into reduced computational time for hyperparameter tuning.

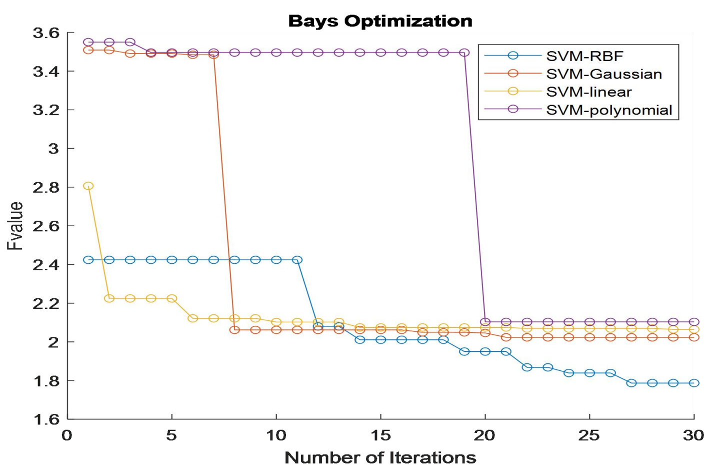

Fig.5: Adaptive learning Convergence performance via the proposed automated kernel selection approach in location 1

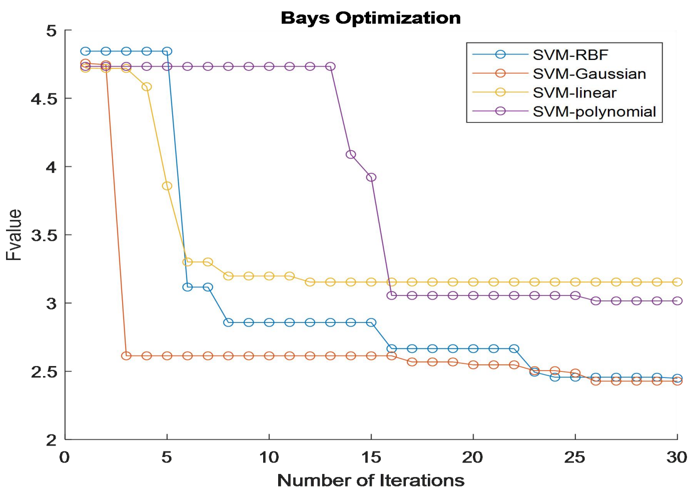

Fig.6: Adaptive learning Convergence performance via the proposed automated kernel selection approach in location 2

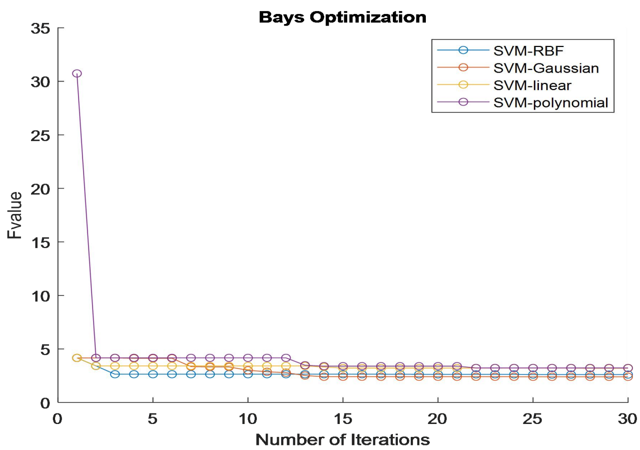

Fig.7: Adaptive learning Convergence performance via the proposed automated kernel selection approach in location 3

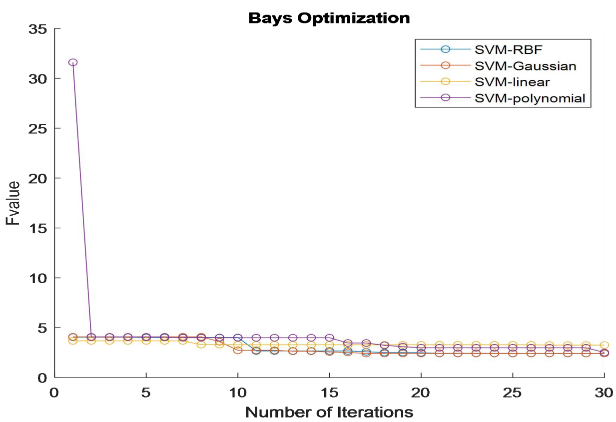

Fig.8: Adaptive learning Convergence performance via the proposed automated kernel selection approach in location 4

Table 1: A summary of the proposed precision learning performance in locations 1-4

RMSE1:3.03 | R1:0.96| MAE1:1.91|STD1:3.04
RMSE2:2.38 | R2:0.98| MAE2:1.91|STD2:2.39
RMSE3:4.69 | R3:0.90| MAE3:1.91|STD3:4.64
RMSE4:4.43 | R4:0.92| MAE4:1.91|STD4:4.35

RMSE1:2.77 | R1:0.94| MAE1:2.09|STD1:2.79
RMSE2:2.60 | R2:0.94| MAE2:2.09|STD2:2.61
RMSE3:4.84 | R3:0.81| MAE3:2.09|STD3:4.81
RMSE4:4.37 | R4:0.83| MAE4:2.09|STD4:4.40

RMSE1: 2.87 | R1: 0.89| MAE1: 2.09| STD1:2.90
RMSE2: 1.26 | R2: 0.98| MAE2: 2.09| STD2:1.27
RMSE3: 3.42 | R3: 0.85| MAE3: 2.09| STD3:3.42
RMSE4: 2.90 | R4: 0.90| MAE4: 2.09| STD4:2.89

RMSE1: 2.89 | R1: 0.92| MAE1: 2.11| STD1:2.87
RMSE2: 2.56 | R2: 0.94| MAE2: 2.11| STD2:2.53
RMSE3: 5.01 | R3: 0.77| MAE3: 2.11| STD3:4.91
RMSE4: 3.11 | R4: 0.91| MAE4: 2.11| STD4: .11

5. Conclusion

This paper presented a novel and robust automated framework for Support Vector Machine kernel function selection and hyperparameter optimization, leveraging Bayesian Optimisation. Our methodology addresses the critical challenge of configuring SVMs for optimal performance in path loss prognotisc estimation, a fundamental task for adaptive learning in wireless communication. Through extensive experiments on diverse path loss datasets, we demonstrated that the BO-driven approach achieved a faster convergence and computational efficiency, contributing to better-informed network planning and optimization strategies. The adaptability of the chosen kernel to different environments highlights the power of automated selection and can significantly benefit the design of resilient wireless communication systems. It also lays a strong foundation for building more intelligent and self-optimizing wireless systems. Future studies will focus on integrating this methodology with deep learning approaches and exploring its applicability in real-time path loss prediction systems.

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