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Generalized Additive Model with Bayesian Hyperparameter Selection for Optimized 5G Throughput Data Estimation

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Abstract: The burgeoning complexity and dynamic nature of 5G New Radio (NR) networks necessitate accurate and reliable throughput forecasting for efficient resource allocation, proactive anomaly detection, and robust network planning. Generalized Additive Models (GAMs) offer a powerful, interpretable, and flexible framework for modelling the non-linear relationships inherent in 5G throughput data. However, the performance and interpretability of GAMs are critically dependent on the appropriate selection of their hyperparameters. This paper investigates the influence of various hyperparameter tuning approaches based on Bayesian optimization on the prognostic estimation capabilities of GAMs for real-world 5G-NR throughput data. Through a comparative study, we evaluate these tuning strategies based on key forecasting metrics (e.g., RMSE, MAE, R-squared) and computational efficiency. Our findings reveal that while all methods can identify competitive models, Bayesian optimization with 'all-univariate' and 'all' methods of selecting GAM hyperparameters achieves preferred superior performance with significantly reduced computational effort and precision accuracy, highlighting its efficacy for complex real-world datasets like 5G-NR throughput, where rapid model development and optimization are crucial.

Keywords: 5G-NR Throughput, Generalized Additive Models (GAMs), Hyperparameter Tuning, Prognostic Estimation, Bayesian Optimization, Network Optimization.

1. Introduction

The advent of 5G New Radio (NR) technology promises unprecedented speeds, ultra-low latency, and massive connectivity, fundamentally transforming various industries. To fully realize these benefits, precise network management and resource optimization are paramount [1, 2]. A critical component of this optimization is the ability to accurately forecast network traffic, particularly throughput, which directly impacts user experience, service quality, and operational expenditure [3, 4]. 5G-NR throughput data is inherently complex, characterized by non-linear relationships, time-varying dynamics, and influences from numerous contextual factors such as user density, channel conditions, interference, and cell load.

Traditional forecasting methods, such as ARIMA models, often struggle with the non-linear and high-dimensional nature of telecommunications data. While complex machine learning (ML) and deep learning (DL) models can capture intricate patterns, their "black-box" nature often hinders interpretability, making it challenging for network operators to understand the underlying drivers of throughput fluctuations. Generalized Additive Models (GAMs) emerge as a compelling alternative, offering a balance between predictive power and interpretability. GAMs extend Generalized Linear Models (GLMs) by allowing the linear predictor to be dependent on smooth, non-linear functions of the predictor variables, thereby capturing complex relationships without sacrificing the ability to visualize and understand individual covariate effects.

However, the effectiveness of GAMs hinges significantly on the appropriate selection of their hyperparameters. Key hyperparameters include the choice of basis functions (e.g., cubic regression splines, thin plate splines) and, crucially, the smoothing parameters associated with these functions. Incorrectly chosen smoothing parameters can lead to either underfitting (over-smoothing, missing important patterns) or overfitting (undersmoothing, capturing noise), both of which degrade prognostic accuracy. The challenge lies in efficiently exploring the vast hyperparameter space to identify optimal configurations that yield robust and accurate forecasts.

This paper addresses this challenge by systematically investigating the influence of different hyperparameter tuning approaches on the prognostic estimation capabilities of GAMs for 5G-NR throughput data. Our objective is to quantify the performance gains and computational trade-offs associated with each tuning method, providing practical guidance for academics and practitioners in the telecommunications domain. The insights derived will contribute to building more reliable and interpretable forecasting models for the dynamic 5G ecosystem.

2. Background and Related Work

2.1. 5G-NR Throughput Data Characteristics

5G-NR throughput is influenced by a multitude of factors, including radio conditions (e.g., Signal-to-Interference-plus-Noise Ratio (SINR), Reference Signal Received Power (RSRP)), network load, user equipment capabilities, applied modulation and coding schemes (MCS), and available bandwidth.

Prior work in 5G network analytics has explored various forecasting techniques, ranging from statistical models (e.g., ARIMA, Exponential Smoothing) [5] to traditional machine learning (e.g., Support Vector Regression, Random Forests) [6] and deep learning approaches (e.g., GRUs, Transformers) [7]. While DL models show promise, their lack of clarity in how they arrive at their decisions often remains a significant hurdle for operational deployment [8-13].

The concept of using GAMs in telecommunications has been explored in several previous works. Lai et al. (2024) [14] introduced the idea of using GAMs for modelling non-linear relationships in environmental data, showcasing the model's ability to handle complex predictors effectively. Clark and Wells (2023) [15] utilized GAMs to forecast ecological time series data. Chen et al. (2020) [16] examined flow data in 5G networks using a modified GAM approach that integrated machine learning techniques, yielding promising results in estimating throughput. The prediction of 5G throughput with a boosted additive model f is studied by the authors in [17]. These studies underscore the applicability of GAMs in telecommunications and provide a foundation for further exploration in the context of 5G-NR throughput data estimation. In this paper, our contributions are as follows:

- Provision of GAM with Bayesian optimisation that provides valuable insights into the non-linear relationships between 5G throughput and its predictors.
- The influence of Hyperparameter selection approaches on GAM performance with the Bayesian Optimisation method for Optimized 5G-NR Throughput Data Estimation has been revealed
- An adept precision, accuracy and computational efficiency performance of GAM has been shown using four series of throughput data sets.

3. Methodology

This section details the proposed methodology for estimating 5G throughput using a Generalized Additive Model with Bayesian hyperparameter selection. Specifically, the section outlines how the throughput data was obtained, the GAM formulation, hyperparameter selection methods and tuning strategies, and the evaluation metrics employed in this study.

3.1. Data Acquisition and Preprocessing

The throughput data utilized in this paper were sourced from an online repository [19], made accessible to researchers following a series of real-time measurements conducted across various urban environments in Minneapolis, United States. These measurements were gathered using two 5G smartphones: the Motorola

Moto Z3 and the Samsung Galaxy S10 5G (SM-G977U). The researchers specifically focused on the 5G networks of three major carriers in three large U.S. cities.
Among the parameters examined were the handoff mechanisms within the 5G network and their impact on overall network performance. The authors also evaluated the performance of various applications over the tested 5G wireless networks during activities such as web browsing, online downloading, and video streaming. A substantial dataset of 15 terabytes was employed for these comprehensive experiments, which were conducted on Verizon, T-Mobile, and Sprint 5G networks. Notably, the Verizon network utilized mmWave 5G services in the tested environments, while T-Mobile also operated within the mmWave band, and Sprint functioned at 2.5 GHz. The measurements were conducted against a Microsoft Azure server, achieving remarkably high 5G throughput rates of up to 3 Gbps [19].
This extensive research not only sheds light on the capabilities of 5G technology but also provides valuable insights into the performance variations across different carriers and urban settings.
The data will undergo the following preprocessing steps:

- **Missing Value Imputation:** Address any missing data points using appropriate techniques (e.g., interpolation for time series).
- **Outlier Detection and Treatment:** Identify and mitigate extreme values that could skew model training.

3.2. Generalized Additive Model (GAM) Formulation

A generalized additive model (GAM) is an explicable statistical model that explains a response variable using a sum of univariate and bivariate shape functions of predictors. The GAMs were introduced by Hastie and Tibshirani [4], to provide a flexible framework for modelling the relationship between a response variable and multiple predictor variables.
Here, the GAM is formulated with throughput as the response variable and the data point, x is represented as the independent variable. The standard GAM uses a univariate shape function for each predictor.

$$y \sim N(\mu, \sigma^2) \tag{1}$$

$$g(\mu) = \mu = c + f_1(x_1) + f_2(x_2) + \cdots + f_p(x_p) \tag{2}$$

where y is a response variable that follows the normal distribution with mean μ and standard deviation σ. $g(\mu)$ is an identity link function, and c is an intercept (constant) term. $f_i(x_i)$ is a univariate shape function for the ith predictor, which is a boosted tree for a linear term for the predictor (predictor tree).

In this paper, we used the fitrgam function in MATLAB 2024B software and computational environment to engage the GAM for the prognostic throughput data estimation. The fitrgam utilises a boosted tree as a shape function for each predictor and pair of predictors, therefore, enabling it adaptive capture the nonlinear relation between the response variable and the predictor

2.3. Hyperparameter Tuning Approaches Hyperparameter tuning is the process of finding the optimal set of hyperparameters for a model that yields the best performance on a given dataset. Some core approaches include:

- **Grid Search:** This method exhaustively explores every combination of hyperparameter values within a predefined, discrete search space. While guaranteed to find the best combination within the defined grid, it becomes computationally prohibitive as the number of hyperparameters or their possible values increase.
- **Random Search:** Random Search samples hyperparameter combinations randomly from the specified search space for a fixed number of iterations. It has been shown to be more efficient than Grid Search in high-dimensional hyperparameter spaces, often finding near-optimal solutions much faster, as optimal values are often concentrated in a small region of the space.
- **Bayesian Optimization (BO):** This is a sequential model-based optimization strategy that attempts to find the global optimum of an objective function that is expensive to evaluate. BO builds a probabilistic surrogate model (e.g., Gaussian Process) of the objective function and uses an acquisition function (e.g., Expected Improvement) to decide which hyperparameter configuration to evaluate next. By intelligently balancing exploration (trying new, uncertain regions) and exploitation (refining promising regions), BO often finds better solutions with significantly fewer evaluations compared to Grid or Random Search, making it particularly suitable for computationally expensive models or objective functions.

While these tuning methods have been widely applied to various machine learning models, their specific impact on GAM performance for complex time-series data like 5G-NR throughput, especially concerning prognostic estimation and cognitive state quantification, warrants a dedicated investigation.

The primary hyperparameters for GAMs used in this paper via Bayesian optimisation are shown in Table 1.

Table 1: GAM Hyperparameters and their selection Method based on Bayesian Optimisation

Selection Method	**Hyperparameters**	**Interpretation**
Auto	Initial Learning Rate for Predictors, Number of Trees per Predictor, Interactions, Initial Learning Rate for Interactions, and Number of Trees per Interaction	Optimize Initial Learning Rate for Predictors, Number of Trees, Interactions, Initial Learning Rate for Interactions, and Number of Trees per Interaction
Auto-univaraiate	Initial Learning Rate for Predictors and Number of Trees per Predictor	Optimize Initial Learning Rate and Number of Trees only
All-univariate	Interactions, Initial Learn Rate for Interactions,	Optimize all eligible univariate parameters
all	Initial Learning Rate for Predictors, Number of Trees per Predictor, Interactions, Initial Learning Rate for Interactions and Number of Trees per Interaction	Optimise all eligible hyperparameters

3.3. Hyperparameter Tuning Approaches

For each tuning approach, the objective function to minimize will be the Root Mean Squared Error (RMSE) on the throughput datasets, determined via cross-validation. Due to the time-series nature of the data, a blocked or rolling origin cross-validation strategy will be employed to respect temporal dependencies and prevent data leakage.

3.4 Bayesian Optimization (BO) implementation:

- We employ a Gaussian Process (GP) as the surrogate model to approximate the objective function (RMSE).
- The Expected Improvement (EI) is explored as the acquisition function to determine the next hyperparameter configuration to evaluate.
- The search space for hyperparameters is designed to be continuous, allowing BO to explore a finer granularity than discrete grids.
- The number of BO iterations is set to 30 iterations.

3.5. Prognostic Estimation and Evaluation Metrics

After tuning, the best model from each tuning approach (i.e., the GAM with the optimal set of hyperparameters found by Grid, Random, or BO) will be re-trained on the full training dataset. Prognostic estimation will then be performed on the unseen test set for a defined forecasting horizon (e.g., 24-48 hours ahead).

3.6 Performance Evaluation Metrics

The performance of the GAM models is evaluated using the following metrics on the test set:

- **Minimum Objective function value (MOV):** Measures the minimum value or the lowest value the function that the can GAM can achieve within a defined set of hyperparameter constraints via the Bayesian optimisation process.
- **Root Mean Squared Error (RMSE):** Measures the average magnitude of the prediction errors.

- **R-squared (R2):** Represents the proportion of variance in the target variable explained by the model.
- **Mean Absolute Error (MAE):** Measures the average difference between throughput values and actual throughput values.

4. Results and Discussion

This section will present the empirical results of our comparative analysis. We conducted four series of GAM prognostic estimation of the throughput datasets to compare the performance of different hyperparameter selection methods for GAMs that has been revealed in table 1. For each method, we evaluated the performance of GAMs in terms of both computational efficiency and precision accuracy.

(a) Performance of GAM with Bayesian Optimisation in terms of computational efficiency

Plotting the objective function value against the iteration number is a standard and effective method for evaluating the computational efficiency of iterative algorithms, allowing for the assessment of convergence speed and performance comparison between different approaches. The graphs in Figs.1-4 wherein the objective function value is on the y-axis and iteration number on the x-axis, are plotted to visualize the convergence of the four hyperparameter selection methods with the Bayesian optimization algorithm. The graphs clearly demonstrate how the "goodness" of each selection method improves or changes with every step. The visualization also reveals how quickly each selection method with the Bayesian algorithm approaches an optimal solution. Thus, attaining the lowest objective function value is the target. From the graphs, it can be seen that each selection method behaves differently in terms of the minimum objective function value during the iteration process progression. However, from the results, the 'all-univariate' and 'all' hyperparameter selection methods attain the lowest objective function value with the estimated 5G-NR throughput at 25m, 50m, 75m, and 100m, compared to the other two methods, which are 'auto' and 'auto-univariate'. The results reveal that the relative performance of each selection method is dependent on the characteristics of the throughput dataset and the computational resources available.

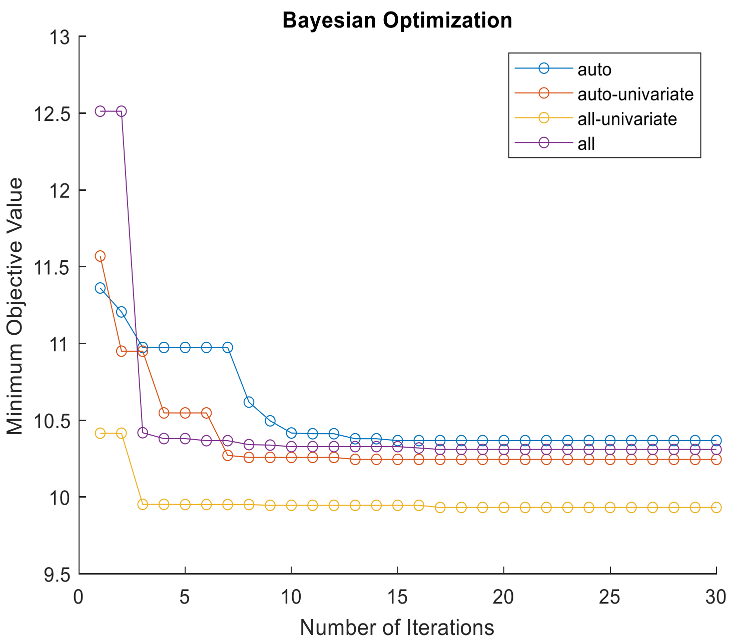

Fig.1: Objective function value vs the iteration number performance plot of GAM for the four hyperparameter selection methods at 25m.

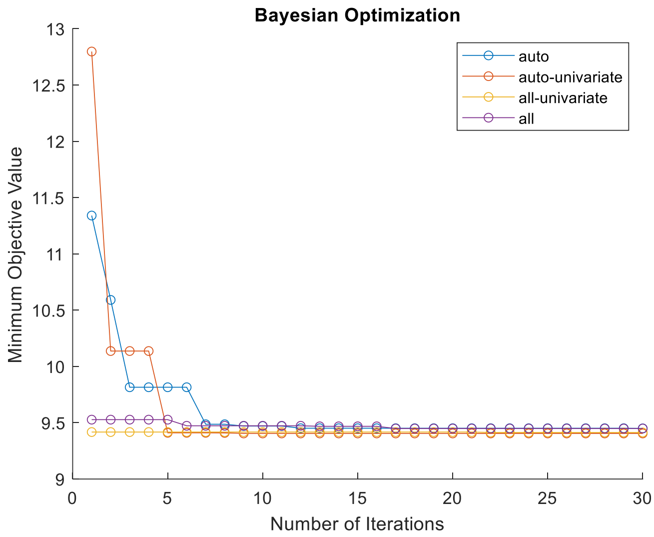

Fig.2: Objective function value vs the iteration number performance plot of GAM for the four hyperparameter selection methods at 50m.

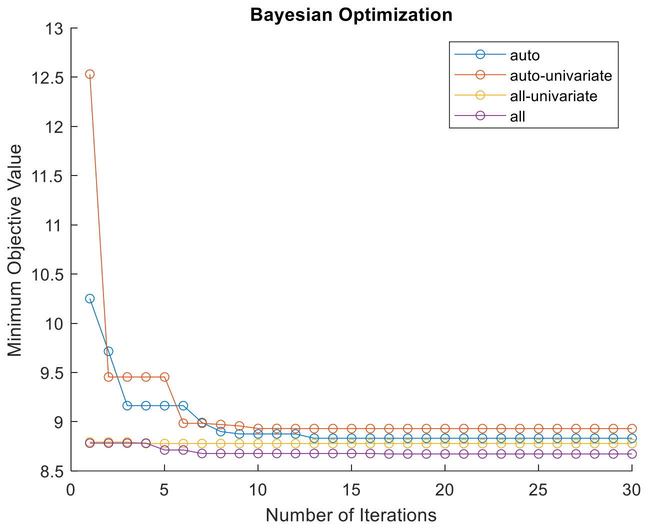

Fig.3: Objective function value vs the iteration number performance plot of GAM for the four hyperparameter selection methods at 75m.

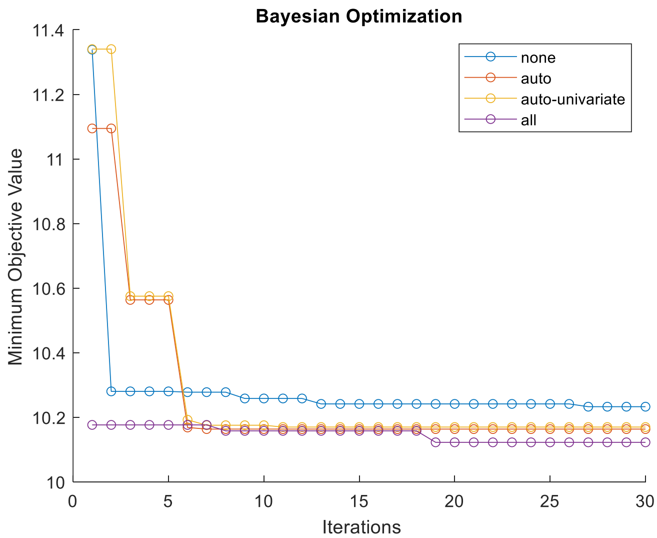

Fig.4: Objective function value vs the iteration number performance plot of GAM for the four hyperparameter selection methods at 100m.

(b) **Performance of GAM with Bayesian Optimisation in terms of Precision Accuracy**

The graphs in Figs. 5-8 and Figs.9-12 are plotted to display how each GAM hyperparameter selection method precisely performs on the throughput data estimation via the GAM based Bayesian optimisation algorithm. For the four selection methods used, see Table 1 for reference. The eight graphs also show that the GAM based Bayesian optimisation algorithms with ‘all-univariate’ and ‘all’ hyperparameter selection methods attain the lowest RMSE and best R values on the estimated 5G-NR throughput at 25m, 50m, 75m and 100m, compared to other two methods, which are ‘auto’ and ‘auto-univariate’. The summary of the selection method in terms of RMSE, MAE, and R values is presented in Table 2. Our results show that the choice of hyperparameter selection method can significantly affect the performance of GAMs.

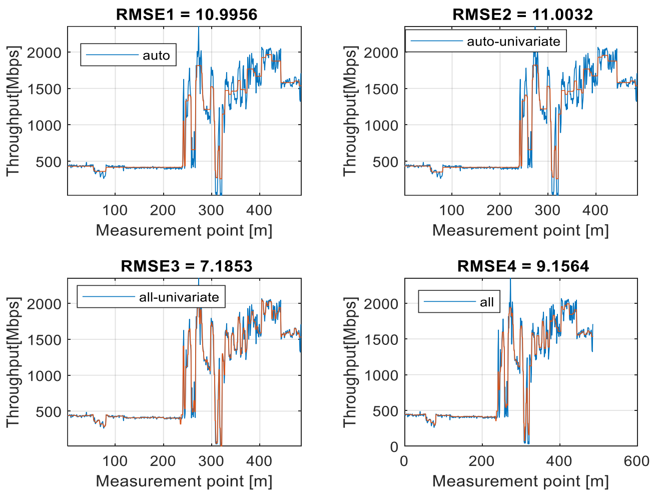

Fig.5: Estimated Throughput vs Measurement using GAM for the four hyperparameter selection methods at 25m.

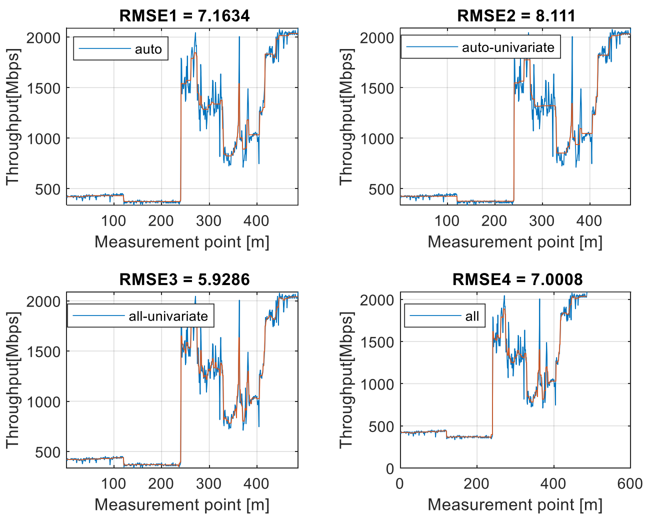

Fig.6: Estimated Throughput vs Measurement using GAM for the four hyperparameter selection methods at 50m.

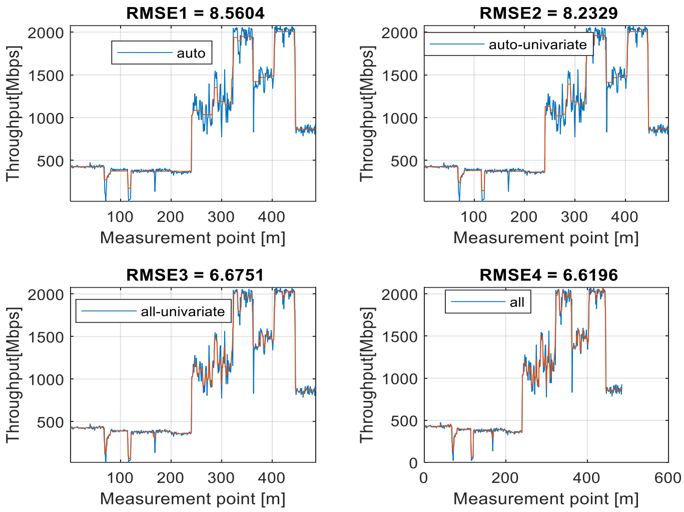

Fig.7: Estimated Throughput vs Measurement using GAM for the four hyperparameter selection methods at 75m.

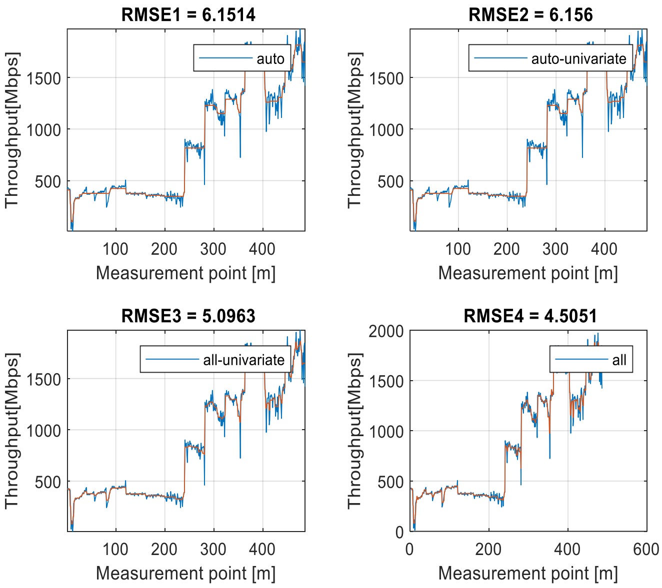

Fig.8: Estimated Throughput vs Measurement using GAM for the four hyperparameter selection methods at 100m.

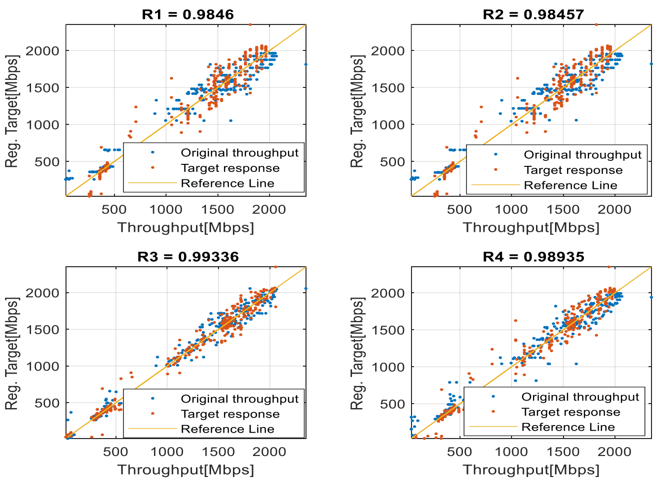

Fig.9: Estimated Throughput vs Actual Throughput using GAM

for the four hyperparameter selection methods at 25m.

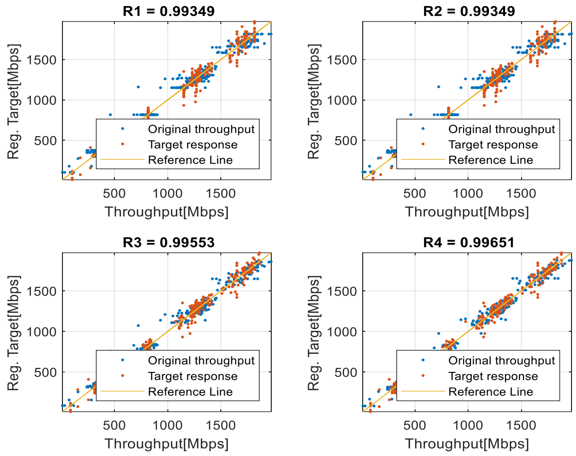

Fig.10: Estimated Throughput vs Actual Throughput using GAM for the four hyperparameter selection methods at 50m.

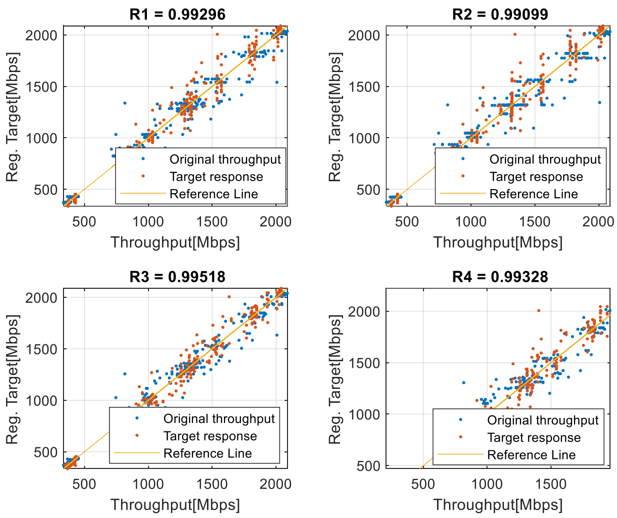

Fig.11: Estimated Throughput vs Actual Throughput using GAM for the four hyperparameter selection methods at 75m.

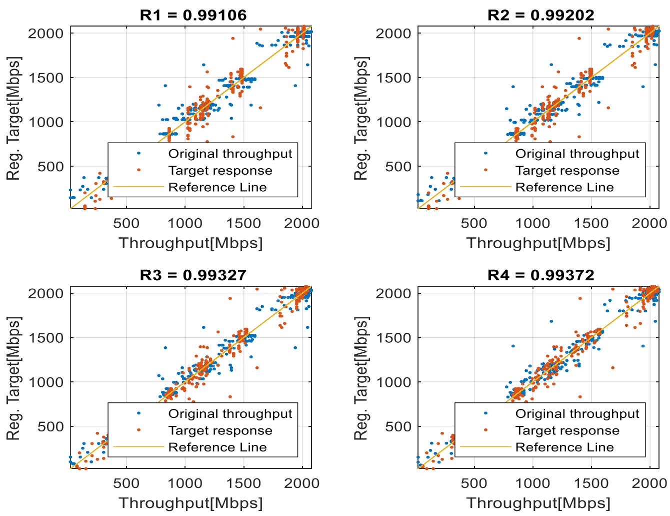

Fig.12: Estimated Throughput vs Actual Throughput using GAM

for the four hyperparameter selection methods at 100m.

Table: Estimated Throughput Precision performance using GAM
for the four hyperparameter selection methods at 25m, 50m,75m and 100m.

	25m			
Metric	**Auto**	**Auto-univariate**	**All-univariate**	**All**
RMSE	10.99	11.00	7.18	9.15
MAE	6.63	6.65	3.96	5.04
R	0.9846	0.9846	0.9934	0.9894
	50m			
	Auto	**Auto-univariate**	**All-univariate**	**All**
RMSE	7.16	8.11	5.92	7.00
MAE	3.69	4.21	3.16	3.55
R	0.9930	0.9910	0.9952	0.9933
	75m			
	Auto	**Auto-univariate**	**All-univariate**	**All**
RMSE	8.56	8.23	6.67	6.61
MAE	4.50	4.10	3.57	3.42
R	0.9911	0.9920	0.9933	0.9937
	100m			
	Auto	**Auto-univariate**	**All-univariate**	**All**
RMSE	6.15	6.16	5.09	4.50
MAE	3.78	3.99	3.02	2.68
R	0.9935	0.9935	0.9955	0.9965

5. Conclusion

Generalized Additive Models (GAMs) offer a powerful, interpretable, and flexible framework for modelling complex, non-linear relationships in data. Their effectiveness, however, is significantly influenced by the proper selection of hyperparameters, particularly those governing the smoothness of the component functions. In this paper, we investigated the impact of different hyperparameter selection methods on the adaptive estimation performance of GAM applied to 5G-NR throughput prediction. Using a real-world 5 G-NR throughput dataset, we evaluate models based on key metrics such as Root Mean Squared Error (RMSE), R-squared, and computational efficiency. Our findings reveal that while all methods can identify competitive models, Bayesian Optimization with 'all-univariate' and 'all' method of selecting GAM hyperparameters achieves comparable superior performance with significantly reduced computational effort and precision accuracy, highlighting its efficacy for complex real-world datasets like 5G-NR throughput, where rapid model development and optimization are crucial. Future research directions include:

- **Exploring other hyperparameter optimization techniques:** Investigating the performance of more advanced optimization algorithms, such as genetic algorithms and particle swarm optimization.
- **Incorporating more features:** Expanding the feature set to include additional factors that influence 5G-NR throughput, such as channel type, environment type, and user mobility patterns.
- **Developing adaptive hyperparameter optimization strategies:** Designing methods that dynamically adjust the hyperparameter search space based on the characteristics of the data.
- **Applying GAMs to real-world 5G-NR data:** Validating the findings of this research on real-world 5G-NR throughput data collected from operational networks.
- **Investigating different basis function types:** Explore other smoothing function options within GAMs, such as Thin Plate Regression Splines (TPRS) and Duchon splines.

By addressing these research directions, we can further enhance the accuracy and robustness of GAM models for 5G-NR throughput prognostic estimation, enabling more effective resource management, optimized network planning, and improved user experience in 5G-NR networks.

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