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Optimization of UAV Deployment for Enhanced Communication Coverage

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Abstract

This paper addresses the challenge of optimizing communication coverage in multi-unmanned aerial vehicle (UAV) networks. Our primary focus is maximizing the secrecy rate by jointly optimizing UAV trajectories and transmission power within a defined timeframe. We employ a dual-method approach to tackle this complex, non-convex problem. Firstly, we apply advanced iterative methods, including the Gradient Descent technique, to identify the most effective strategy. Secondly, we introduce a novel machine learning-based model as an alternative approach. This model aims to enhance optimization, offering faster and more efficient solutions than traditional methods. We assess both strategies regarding computational efficiency, memory usage, and effectiveness in solving the optimization challenge. The performance of both methods is critically evaluated in terms of computational speed, memory demands, and optimization effectiveness. This approach demonstrates a potential for improved solutions in UAV network operations compared to traditional optimization techniques.

Keywords: *Unmanned Aerial Vehicles (UAVs), Trajectory Optimization, Communication Coverage, Gradient Descent (GD), Machine Learning, Non-Convex Optimization, Power Transmission Optimization, Computational Efficiency.*

I. Introduction

A. Context and Relevance

Introducing unmanned aerial vehicles (UAVs) marks a significant turning point in technology and its application across diverse sectors. Their versatility and flexibility have opened new frontiers in surveillance and logistics, especially in wireless communication networks. UAVs have emerged as a dynamic solution to the challenges posed by the need for robust and expansive communication networks [1], particularly in remote or disaster-hit areas where traditional infrastructure is infeasible or compromised.

One of the critical areas where UAVs have shown immense potential is in augmenting existing communication networks. UAVs can provide enhanced coverage by acting as aerial base stations or relays, especially in densely populated urban areas or regions with complex topographies. Their ability to dynamically reposition allows for adaptive network coverage, catering to fluctuating demand or changing environmental conditions.

However, the effectiveness of UAVs in communication roles heavily relies on two critical aspects: trajectory optimization and power management. The trajectory of a UAV determines its coverage area, signal quality, and the duration of service it can provide. Optimizing this trajectory is not just about finding the shortest path or the best vantage point; it involves a complex calculus that balances multiple factors. These include maximizing the coverage area, maintaining optimal signal strength, ensuring line-of-sight connectivity, and avoiding obstacles.

Furthermore, power management is an equally critical component. UAVs are constrained by their battery life, impacting their operational duration and effectiveness. Efficient power management ensures that UAVs can perform their tasks for extended periods, thereby enhancing the reliability and stability of the communication networks they support.

In summary, deploying UAVs in communication networks presents a promising solution to several modern challenges. However, realizing their potential hinges on effectively addressing the intricacies of UAV trajectory optimization and power management. This maximizes their coverage and efficiency and extends their operational endurance, thus making them more viable and practical in diverse applications. This paper delves into these challenges, offering new insights and solutions in UAV trajectory optimization for enhanced communication networks.

B. Challenges in UAV Trajectory Optimization

Optimizing unmanned aerial vehicle (UAV) trajectory presents many intricate and multifaceted challenges. Central to these challenges is the non-convex nature of the optimization problems inherent in UAV operations. This non-convexity stems from the complex interplay of various factors, such as the UAVs' flight dynamics, environmental constraints, and the mission's objectives, whether for surveillance, delivery, or communication.

One of the primary hurdles in UAV trajectory optimization is balancing energy consumption against adequate communication coverage judiciously. UAVs, typically powered by batteries, have a limited operational lifespan determined by their energy reserves. This limitation imposes a stringent constraint on how long a UAV can stay airborne and operational, directly influencing the scope and efficiency of its mission. The challenge, therefore, lies in devising flight paths that minimize energy expenditure while maximizing the area and quality of communication coverage.

This energy-coverage trade-off is further complicated by factors such as varying payload weights, changing weather conditions, and potential obstacles in the flight path. These elements can significantly impact the UAV's energy consumption and operational efficiency. For instance, avoiding obstacles or compensating for strong winds requires additional power, reducing the UAV's working time.

Moreover, the optimization process must consider the dynamic nature of communication demands. In significant public events or disaster response scenarios, the demand for communication coverage can change rapidly, spatially, and temporally. The UAV's trajectory must be adaptable in real-time to these changing requirements, a challenge that demands sophisticated and responsive computational strategies.

The complexity of these challenges necessitates advanced computational approaches that can accurately model the UAVs' flight dynamics, predict energy consumption, and dynamically adapt to changing conditions and requirements. This paper addresses these challenges by exploring and developing such computational strategies, focusing on optimizing UAV trajectories for enhanced communication coverage in various operational contexts.

C. Literature Gap and Research Motivation

Recent advancements in wireless communication have underscored the significance of unmanned aerial vehicles (UAVs) in enhancing network performance, particularly in 5G and beyond networks. As aerial base stations, UAVs offer unique advantages like dynamic deployment, on-demand coverage, line-of-sight, and solid connectivity. However, the optimal placement of UAVs in such networks is a complex challenge involving multi-dimensional decision-making to ensure efficient coverage and communication performance [2-4].

Several studies have explored various aspects of UAV deployment, focusing on issues like trajectory optimization, interference management, energy efficiency, and quality-of-service (QoS) enhancement. In [5], a coordinated multi-UAV strategy for optimizing coverage area in the presence of co-channel interference was proposed. [6] provided a comprehensive survey on UAV placement optimization, highlighting key design issues and solution techniques in UAV-assisted wireless networks.

Despite these advancements, there remains a significant gap in addressing the non-convex nature of UAV placement problems. The complexity of these problems escalates with the inclusion of factors like UAV mobility, user distribution, and dynamic network conditions. This research is motivated by the need to develop and compare advanced computational methods, including iterative optimization techniques and machine learning approaches, to solve these non-convex optimization problems more efficiently. The goal is to enhance the efficacy and efficiency of UAV trajectory planning and power management, thus improving the overall performance of 5G and beyond wireless networks.

This study aims to address these gaps and explore the potential of machine learning in simplifying and accelerating the UAV deployment process. By comparing traditional optimization techniques with modern machine learning approaches, we seek to offer a new perspective on UAV placement optimization, opening avenues for future research and practical implementations in advanced wireless networks.

The comprehensive examination of UAV applications in wireless networks by [7] underscores the diverse applications of UAVs and presents open problems that require innovative computational solutions, including machine learning techniques. [8] explores the potential of UAVs in enhancing vertical backhaul/fronthaul connectivity in 5G+ wireless networks, illustrating the integration of UAVs with existing network structures. The authors in [9] delve into the intricacies of UAV communications, particularly for 5G and beyond, providing a detailed analysis of potential applications and challenges [10] focus on efficiently placing UAVs as aerial base stations in cellular networks, emphasizing the importance of 3D positioning. Lastly, [11] conducted an extensive survey on UAV cellular communications, covering various dimensions, including practical aspects, standardization, regulation, and security challenges.

By building upon these studies, this paper seeks to advance the field of UAV deployment in wireless networks, using machine learning and advanced computational methods to address current challenges and unlock new potentials for UAV applications in complex network environments.

D. Objectives and Scope

The central aim of this research is to fulfill two main objectives. Firstly, it comprehensively analyzes various iterative methods, focusing on the Gradient Descent (GD) technique for optimizing unmanned aerial vehicle (UAV) trajectories. This comparison is directed toward identifying the most effective method for trajectory optimization in terms of coverage efficiency and computational performance.

Secondly, the study aspires to delve into machine learning, investigating its potential and applicability in optimizing UAV trajectories. The exploration of machine learning models in this context is motivated by the need for innovative solutions that can surpass traditional methods in efficiency and effectiveness.

The scope of this paper is primarily centered on optimizing UAV trajectories to enhance communication coverage. The emphasis is placed on addressing the computational challenges inherent in this optimization process. The research aims to contribute valuable insights and advancements in UAV-assisted communication networks by exploring traditional iterative approaches and cutting-edge machine-learning techniques. The ultimate goal is to improve UAV networks' overall performance and reliability, facilitating better communication coverage in various operational scenarios.

E. Contribution and Structure of the Paper

This paper makes a significant contribution to the field of UAV trajectory optimization by introducing innovative optimization models and offering a detailed comparative analysis of both traditional and contemporary computational methods. A key highlight of our work is the pioneering exploration of machine learning techniques for UAV trajectory optimization, marking a new direction in this research area.

The structure of the paper is meticulously designed to provide a clear and coherent presentation of our research. It begins with an introduction that sets the stage for the study, followed by a detailed literature review that contextualizes our work within the existing body of research. The methodology section elaborates on the techniques and approaches employed in our study, including the specifics of the computational models and the machine learning framework.

Subsequent sections present our findings and analyses, where we critically examine the results obtained from both the traditional optimization methods and the machine learning model. This comparative analysis is central to understanding the efficacy and potential of the proposed approaches in UAV trajectory optimization.

The discussion section delves into the implications of our findings, providing insights into the practical applications and limitations of the methods studied. Here, we also explore the broader impact of our research on UAV-assisted communications and potential future developments.

Finally, the paper concludes with a summary of our key contributions, reflecting on the study's outcomes and suggesting avenues for future research. This structured approach ensures that the paper is informative and accessible to readers, providing a comprehensive overview of our study in UAV trajectory optimization.

II. Gradient Descent Method for UAV Network Optimization

This section details an optimization method using gradient descent for a UAV network. It focuses on enhancing communication efficiency through strategic UAV placement and power management.

A. *Initial Setup*

This UAV network optimization study focuses on downlink transmissions between UAVs and ground-based stations (BSs). Each UAV and BS have an omnidirectional antenna for effective communication. The UAVs are strategically positioned in three-dimensional space, with their locations specified for various time slots within a predetermined operational period. This period is equally divided into intervals for systematic analysis. The initial setup was inspired by the [12].

Figure 1 illustrates the initial setup of a UAV communication network, depicting four UAVs (unmanned aerial vehicles.

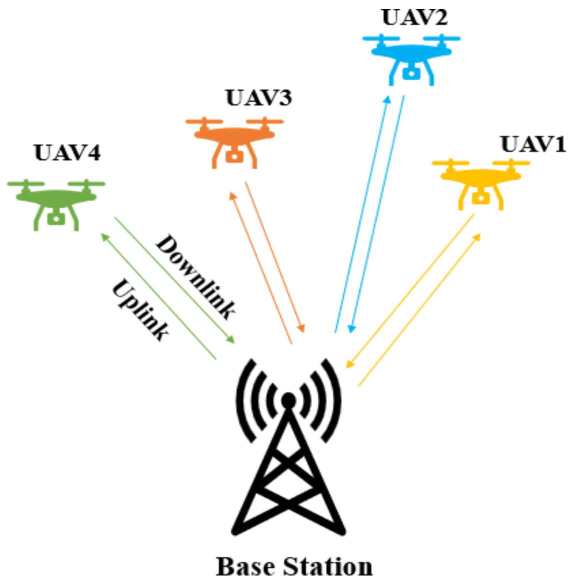

Figure 1: The initial setup of a UAV communication network.

They are positioned around a central base station. Each UAV is represented by a different color, indicating unique flight paths and communication links. The diagram in Figure 1. shows uplink and downlink communication channels, emphasizing the complexity and dynamics of UAV-based communication systems.

We consider the number of Base stations, $K = 4$; fixed base station location, $s = ((250, -250, 0), (-250, 250, 0), (250, -250, 0), (250, 250, 0))$ minimum safe altitude, $H_{min} = 100$, maximum safe altitude, $H_{max} = 300$, level flight speed, $V_L = 20m/s$, vertical ascending level, $V_A = 5$, vertical descending speed, $V_D = 5m/s$, the minimum safe distance between any two UAVs is $d_{min} = 0$, Maximum Power, $P_{max} = 30$, $T = 300$, $M = 30$, $G_0 = -50$, $B = 10$, $N_0 = -160$, the tolerance rate, $\epsilon = 0.001$.

The model sets UAVs' altitude constraints (minimum H_{min} and maximum H_{max} limits), ensuring safe operations. Additionally, spatial boundaries are defined to regulate UAV movement, considering their horizontal and vertical flight speeds. These constraints are crucial to simulating realistic UAV trajectories, considering their dynamic flight characteristics.

Variables involved include the 3D positions ($\boldsymbol{q}[:,k,n]$) and power levels ($\boldsymbol{p}[k,n]$) of each UAV, denoted for K UAVs across N time slots. The model also imposes power constraints, ensuring the power levels remain within a maximum allowable range ($P_{\max}$).

This section lays the groundwork for the subsequent optimization process to enhance communication efficiency within the UAV network. For detailed mathematical equations and formulations, readers are directed to the referenced literature [13].

B. *Objective Function*

The primary aim of this optimization study is to enhance the secrecy rate of the UAV network. This involves optimizing UAVs' positions and power levels to maximize the communication rate with ground-based stations. The secrecy rate, denoted as R [14], is formulated as follows:

$$\text{Maximize} \quad R = \sum_{n=1}^{N} \sum_{k=1}^{K} \text{Bandwidth} \times \log_2\left(1 + \frac{\gamma \times p_{[k,n]}^2}{|q_{[:,k,n]} - s_{[:,k]}|^2}\right) \tag{1}$$

Here, γ represents a constant determined by channel properties, while $\boldsymbol{s}_{[:,k]}$ indicates the location of the k-th base station. The equation aims to find the optimal configuration that yields the highest secrecy rate across all UAVs over the network operation period.

C. *Variables*

This section introduces key variables for UAV optimization. The 3D position of each UAV at specific time slots is $\boldsymbol{q}[:,k,n] \in \mathrm{R}^3$, and its corresponding power level by $\boldsymbol{p}[k,n] \in \mathrm{R}$. The UAV count is denoted by K, and time slots by N.

D. *Constraints*

The model enforces several constraints on UAV operations:

- **Altitude:** Each UAV's altitude must remain between $H_{\text{min and}}$ H_{max}
- **Spatial Boundaries:** UAV positions should stay within predefined spatial limits.
- **Power:** UAV power levels are bounded between 0 and $P_{\text{max.}}$

These variables and constraints form the foundation of the optimization framework, ensuring realistic and safe UAV operation within the designated parameters.

E. *Optimization Method*

Our approach utilizes the gradient descent algorithm to optimize UAV positions and power levels iteratively. This technique involves calculating the gradient of the objective function (secrecy rate) concerning both UAV positions and power levels. The updates are made by adjusting these variables to maximize the objective function. A learning rate, denoted as α, governs the adjustments. This process is iterative, with the algorithm updating positions and power levels until convergence is reached, determined by a predefined tolerance level.

F. *Gradient Descent Algorithm*

The gradient descent algorithm iteratively updates UAV positions and power levels. This process, as shown in Algorithm 1, involves calculating the gradients of the secrecy rate function concerning position and power variables, followed by their incremental adjustment.

Algorithm 1: The summarized version algorithm for Gradient Descent

Initialization: Define initial positions and power levels for UAVs. **Iteration:** At each step, calculate gradients of the secrecy rate concerning positions and power levels. **Update:** Adjust UAV positions and power levels based on gradients and learning rate (alpha).

Convergence Check: Repeat the process until the difference in secrecy rate between iterations is less than a set tolerance. Output: Final optimized UAV positions and power levels.

The Gradient Descent Algorithm 2 iteratively adjusts UAV positions and power levels to maximize the secrecy rate in UAV networks. It begins with initial settings for positions and power, then gradually updates these variables in the direction that increases the secrecy rate the most. This update is controlled by a dynamic learning rate that adapts based on the current rate, ensuring the algorithm remains sensitive to the solution's progress. The process repeats until the change in secrecy rate between iterations is below a defined threshold, signifying convergence.

Algorithm 2: Gradient Descent Algorithm

Set iteration index r = 0, $\alpha_1 = 0.1,\ \alpha_2 = 0.1,\ \epsilon = 0.01$

Initialize $q^0_{[:,k,n]}$ and $p^0_{[k,n]}$ for $k \in K, n \in N_2^M$

Calculate $R^0 = \sum_{k=1}^{K} \sum_{n=2}^{M} R_{[k,n]}(p^0, q^0)$ repeat

Calculate $p^r_{[k,n]}, q^r_{[:,k,n]}$ by

$p^r_{[k,n]} = p^r_{[k,n]} - \alpha_1 \times \frac{d}{dp} R(p^{r-1}, q^{r-1})$

$q^r_{[:,k,n]} = q^r_{[:,k,n]} - \alpha_2 \times \frac{d}{dq} R(p^{r-1}, q^{r-1})$

Set $\alpha_1 = \frac{0.1}{R_r}, \alpha_2 = \frac{0.1}{R_r^2}$

Set r = r + 1

until $e^{-\frac{|(R_{r1} - R_r)|)}{R_{r1})}} < \epsilon$

return $p^r_{[k,n]}, q^r_{[:,k,n]}$

G. Results and Visualization

Post-optimization, the results showcase the effective placement of UAVs in the network. A 3D visualization depicts UAV positions relative to base stations, demonstrating the optimization's impact on network efficiency. Using the Gradient Descent Method, we have successfully calculated the cases we could not solve with the ECOS method, where the problem is treated as a SOCP problem.

Here, observing the results, we can find from Figure 2 that the location change, Δq, is proportional to the initial power assigned. This is because we gave alpha=0.1/Rr, where the secrecy rate is logarithmically proportional to the power value.

Inspecting the two charts, we can see that even though gradient descent takes less iteration, the iteration number is more extended since it deals with 16 parameters, where the ECOS-SOCP method does not differentiate while maximizing.

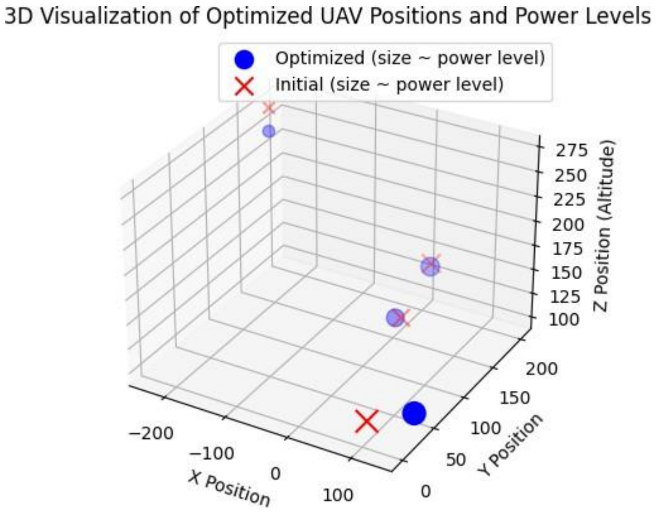

Figure 2: Optimized location with Gradient Descent.

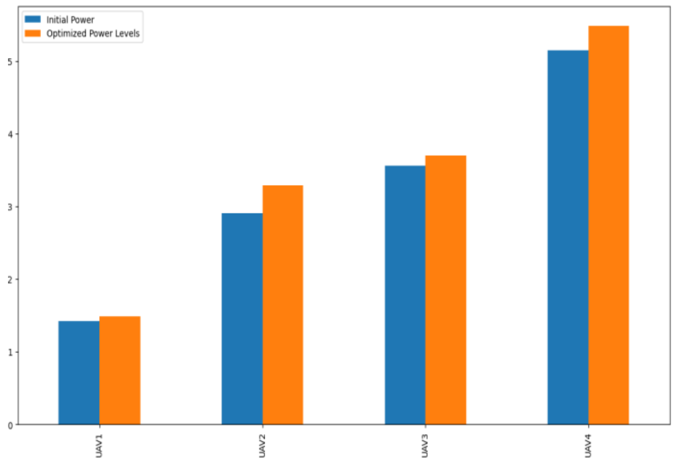

Figure 3: Optimized power after Gradient Descent.

So, we optimized the cases with gradient descent, but we could not do it with the help of ECOS-SOCP.

H. Analysis

This section concludes with an analysis of the algorithm's performance, including its limitations and potential areas for improvement. We used 1000 random data points to analyze the solving method of the Algorithm:

- We used the ECOS method, with 16 variables and 26 constraints in the problem. This is a DPP (disciplined parameterized programming) problem.

	iteration required	Time Required
Mean	20	488
Std	8.09	210.42
Minimum	3	41.00
25% Percentile	14	313.50
50% Percentile	21	482.00
75% Percentile	29	699.00
Maximum	29	872.00

Table I: Statistics of Gradient Descent Method.

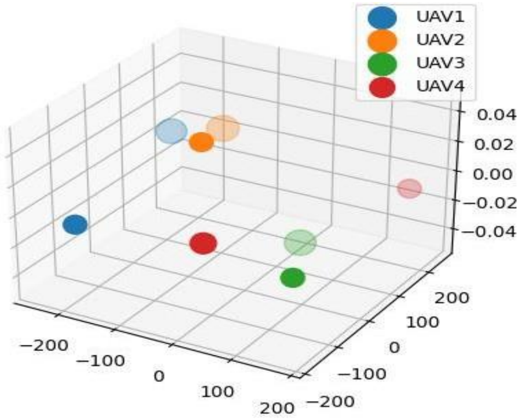

Figure 4: UAV locations optimized with ECOS-SOCP (lighter colors are the initial location, and darker colors are the final locations).

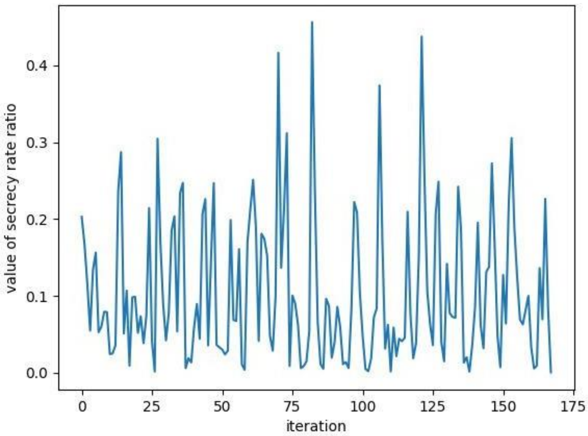

Figure 5: Secrecy Rate Observation of ECOS-SOCP method.

- We inspect the initial location and final location of one of the experiments in Figure: UAV locations:
- We observe the (Rr1-Rr)/Rr value for the ECOS method for the Figure 1 simulation.

Figure 5 illustrates the performance of secrecy rate ratios over a series of iterations. The graph fluctuates significantly across iterations, suggesting a non-steady convergence process in the context of secrecy rate optimization. This could indicate variability in the algorithm's performance or sensitivity to initial conditions and parameters.

After analysis, we found 715 points with feasible solutions and recorded the total time to reach the final solution and the total iteration required. For 715 points, the statistics of total iteration and total time are mentioned in Table II:

Figure 6 displays the progression of convergence ratios over iterations for seven different sample cases using the gradient descent algorithm. The convergence ratio, likely a measure of how close the algorithm is to its optimization goal decreases across iterations, suggesting improvement in the solution. Each sample case, represented by a different color and symbol, shows a trend where the ratio decreases as the number of iterations increases, indicating that the gradient descent is effectively refining the variables toward the desired outcome. This type of graph is often used to validate the efficiency and reliability of optimization algorithms like gradient descent.

	iteration required	Time Required
Mean	143	38.01
Std	151	40.39
Minimum	2	0.00
25% Percentile	47	12.00
50% Percentile	98	26.00
75% Percentile	182	48.25
Maximim	1464	382.00

Table II: Statistics of The ECOS Method.

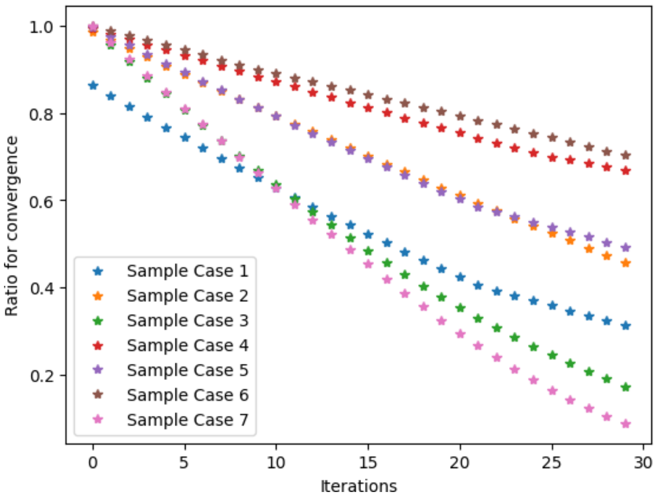

Figure 6: Gradient Descent Convergence Result.

Limitation of Gradient Descent Algorithm: When we observed the differential values of the locations, we found the values to be so small that they could not significantly affect the trajectory value. Thus, it seems like the values are not changing as the iterations progress, so it was tough to reach the solution where it converges with the gradient descent algorithm. However, the advantage of the gradient descent method was that it was faster, and we were not required to solve the equations for every iteration.

III. Machine Learning Algorithm

We collected the data from the 1000 sample points, solved them using the ECOS and Gradient Descent methods, and collected the initial location data, power data, and secrecy rates. Then, we designed a regression that takes the initial power and location values and outputs the secrecy rate.

We find two regression SVR [15] and a machine learning model consisting of one fully connected layer with an SVM optimizer working with MAE of 0.20 and 0.19, respectively.

Since both optimization methods took significant time to converge, using a machine learning model helps us reduce the time for each case and new values. Instead of doing the optimization, we can rely on the machine learning model to get the maximum secrecy rate.

The mean inference time of the linear regression model is 0.0369 s, much less than the two optimization methods' mean convergence time, 32 seconds for the ECOS-SOCP method and 488 seconds for the Gradient Descent method.

Figure 8 shows a flowchart delineating the optimization process for UAV location and power for maximum secrecy rate. The process begins with inputting initial locations and power values, followed by an attempt to optimize using the (ECOS) SOCP method. If SOCP can solve it, the output is an optimized location, power, and maximum secrecy rate. Otherwise, the Gradient Descent method is applied, leading to a similar optimized output. This figure underscores the decision-making process in selecting the appropriate optimization technique based on the problem's solvability by SOCP.

The machine learning pipeline depicted in Figure 7 involves several critical steps, from input data split into training and testing datasets. The data undergoes preprocessing, including normalization, to ensure it's in a suitable format for model building. Afterward, the model is trained and tuned to optimize performance. Once the model is finalized, it is evaluated using metrics such as RMSE, MAE, and R2 to assess its accuracy. The final step in the pipeline is the prediction stage, where the model applies what it has learned to make predictions on new, unseen data.

We have considered 1000 randomized points for the training method, of which 715 could be solved by the ECOS-SOCP method. The rest of the cases were optimized by the Gradient Descent Method; we later proceeded to fit the optimal secrecy rate and the initial power and location into the machine learning pipeline for fast interference for further cases.

In the machine learning pipeline, we have used 20% of the randomly sampled data of 1000 points as a test set, and the rest of the 80% data is used as a train set.

For the Normalization process of Data, we have first min- max scalared the location data ranging from -250 to 250. Later, we have separately min-max scalared the power input data, which runs from 0 to 30. In this way, we got significant features for the training process.

Prediction accuracy is an important aspect when evaluating the performance of the UAV model. The evaluation metric is the performance measure. It shows how much error the UAV model typically makes in its predictions. Here, we'll discuss standard metrics for evaluating the proposed machine learning algorithms. Three metrics are used to test and evaluate the performance of the UAV model: root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R2). These evaluation matrices measure the distance between the vector of predictions y_{pred} and the vector of actual values y_{act}. It was calculated as follows:

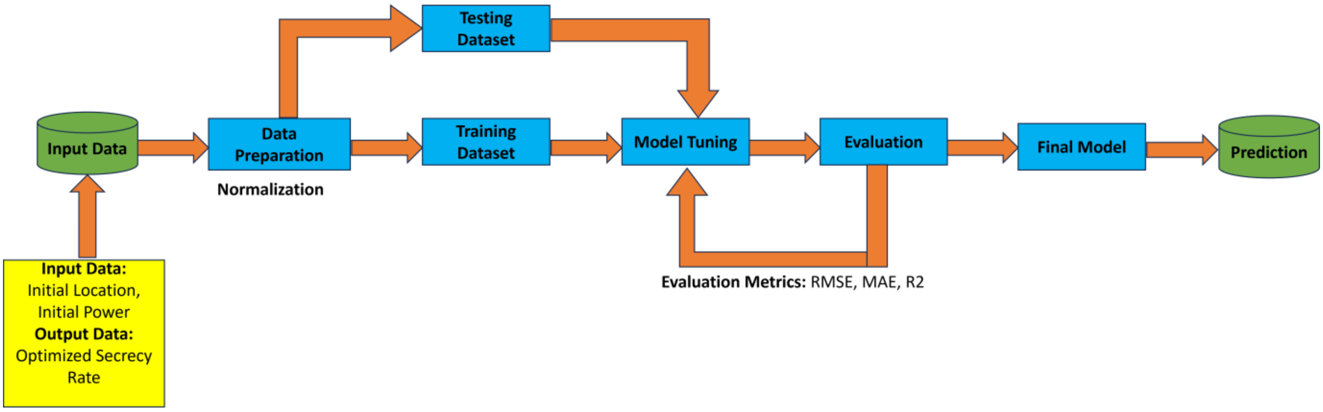

Figure 7: Machine Learning Pipeline.

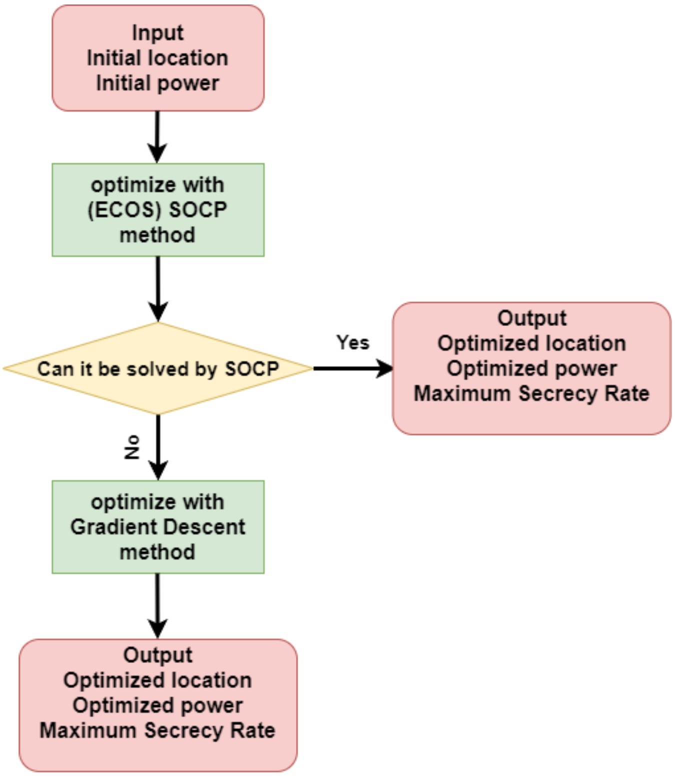

Figure 8: Optimization process for UAV location and power for maximum secrecy rate.

$$RMSE(y_{act}, y_{pred}) = \sqrt{\frac{1}{n_{samples}} \sum (y_{act} - y_{pred})^2} \quad (2)$$

$$MAE(y_{act}, y_{pred}) = \frac{1}{n_{samples}} \sum |y_{act} - y_{pred}| \quad (3)$$

$$R2 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (4)$$

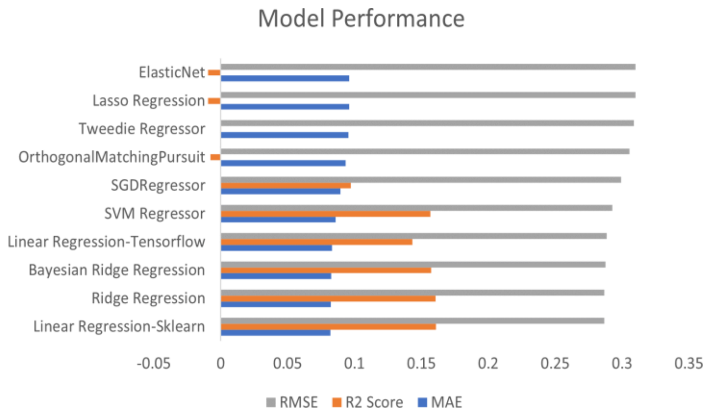

Figure 9: Machine Learning Model Performance.

y_{act} = actual values;
y_{pred} = predicted values;
$n_{samples}$ = is the number of instances in the database;
$R2$ = correlation coefficient;
x_i = values of the x-variable (features input) in a database; $x\_$ = mean of the values of the x-variable (features input) in the database;Type equation here.
y_i = values of the y-variable in a database;
$y\_$ = mean of the values of the y-variable in a database.

Even though the RMSE in the equation is generally the preferred evaluation metric for regression machine learning algorithms, the RMSE is preferred. The evaluation errors are first squared before averaging, which presents a high penalty for significant evaluation errors. We may use other evaluation matrices in some contexts, such as Mean Absolute Error MAE and the correlation coefficient R2. The MAE is a linear evaluation metric in which all the individual differences are weighted equally. It is unsuitable for a database where we must consider the outliers. Our paper [16] presents a novel model for energy-efficient thermal comfort in smart buildings, significantly reducing energy usage while enhancing occupant comfort. Employing machine learning techniques, we accurately predict thermal preferences, contributing to smarter and more sustainable energy management in commercial buildings.

Figure 9 demonstrates the performance of different machine learning models, comparing their accuracy metrics, such as RMSE (Root Mean Square Error), R2 Score, and MAE (Mean Absolute Error). The models include ElasticNet, Lasso Regression, Tweedie Regressor, Orthogonal Matching Pursuit, SGDRegressor, SVM Regressor, Linear Regression implemented with TensorFlow, Bayesian Ridge Regression, Ridge Regression, and a Sklearn version of Linear Regression. Each model's performance is evaluated to determine which has the lowest prediction error and the highest prediction accuracy for the task at hand. The visual representation allows for a clear comparison, highlighting which models perform better according to the respective error and score indicators.

IV. Conclusion

This paper investigated two methods for solving multi-variable optimization problems in UAV networks, focusing on maximizing the secrecy rate. First, we approached the problem with a convex formulation using the ECOS-SOCP method but faced limitations. Consequently, we implemented a gradient descent algorithm with a variable learning rate (dynamic) for greater flexibility. Despite longer optimization times for both methods, we created a machine-learning pipeline. This resulted in the Linear Regression model outperforming others in predicting maximum secrecy rates from the best-performing model among the ten models tested.

Result Statement: This study effectively utilizes convex optimization and gradient descent strategies to improve UAV communication networks' secrecy rates. Additionally, it demonstrates the potential of machine learning algorithms in predicting optimal UAV configurations for secure communications.

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