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Comparison of Visible Light Communication Data Results to Random Search Particle Swarm Optimization Method

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Abstract: The number of studies on communication systems has increased more than ever before. Visible Light Communication (VLC) studies, one of the popular fields of study, are being further researched regarding its ability to illuminate communication and the support structure of radio communication. Visible Light Communication, designed as a strengthening structure for radio communication, has shown that it can provide sufficient performance capability in the laboratory environment without the need for radio communication. Studies focus on the location of transceivers, positioning in mobile communications, coordinate estimation and hardware resource consumption. Optimization is a common theme of studies. Optimization improvements needed in all areas of communication in current studies have been made through the experimental set data, and an important infrastructure has been provided. In the study, the data set is examined with metaheuristic algorithms. It aims to bring popularity to optimization studies with the study on visible light communication systems still in the development stage. The study is based on comparing the experimental set results developed for Visible Light Communication with Particle Swarm Optimization (PSO). With the experimental set running on Layer I, the communication performance results were obtained with the number of data preparation repetitions, payload, optical filters, distance, the ambient light, and different LEDs. The dataset, consisting of 4,200 samples and 7 attributes, was determined and analyzed by PSO as parameters affecting performance. As a result of the study in which VLC was analyzed with a metaheuristic algorithm using a Nested Cross-Validation approach, the model achieved a Coefficient of Determination (R^2) of 0.826, indicating a strong predictive capability. It was found that the amount of data payload was the most effective component in communication performance, as expected. Among the results, the communication performance designed independently from the effect of ambient light interference is affected, albeit to a small extent; LEDs used as transmitters did not affect the communication performance as much as expected.

Görünür Işık Haberleşme Veri Sonuçlarının Random Search Parçacık Sürü Optimizasyonu Yöntemi ile Karşılaştırılması

Anahtar Kelimeler
Parçacık Sürü Optimizasyonu,
Görünür Işık Haberleşme,
Performans Değerlendirmesi

Öz: İletişim sistemleri üzerine yapılan çalışmaların sayısı her zamankinden daha fazla artmıştır. Popüler çalışma alanlarından biri olan Görünür Işık Haberleşme (VLC) çalışmaları, aydınlatma yeteneği ve radyo iletişiminin destekleyici yapısı bağlamında daha detaylı bir şekilde araştırılmaktadır. Radyo iletişimi için güçlendirici bir yapı olarak tasarlanan Görünür Işık Haberleşme, radyo iletişimine ihtiyaç duymadan laboratuvar ortamında yeterli performans kapasitesi sağlayabildiğini göstermiştir. Çalışmalar alıcı-vericilerin konumu, mobil iletişimde konumlandırma, koordinat tahmini ve donanım kaynak tüketimi üzerine odaklanmaktadır. Optimizasyon, bu çalışmaların ortak bir temasıdır. Mevcut araştırmalarda iletişimin tüm alanlarında ihtiyaç duyulan optimizasyon

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iyileştirmeleri deneysel set verileri aracılığıyla gerçekleştirilmiş ve önemli bir altyapı sağlanmıştır. Bu çalışmada, elde edilen veri seti meta-sezgisel algoritmalar ile incelenmektedir. Halen geliştirme aşamasında olan görünür ışık haberleşme sistemleri üzerine yapılan bu araştırma ile optimizasyon çalışmalarına popülerlik kazandırılması amaçlanmaktadır. Çalışma, Görünür Işık Haberleşme için geliştirilen deneysel set sonuçlarının Parçacık Sürüsü Optimizasyonu (PSO) ile kıyaslanmasına dayanmaktadır. Fiziksel Katmanda (Layer I) çalışan deneysel set ile iletişim performans sonuçları; veri hazırlama tekrar sayısı, veri yükü (payload), optik filtreler, mesafe, ortam ışığı ve farklı LED'ler kullanılarak elde edilmiştir. 4.200 örnek ve 7 öznitelikten oluşan veri seti, performansı etkileyen parametreler olarak PSO tarafından belirlenmiş ve analiz edilmiştir. VLC'nin İç içe Çapraz Doğrulama (Nested Cross-Validation) yaklaşımı kullanılarak meta-sezgisel bir algoritma ile analiz edildiği bu çalışmanın sonucunda model; güçlü bir tahmin yeteneğine işaret eden 0.826'lık bir Belirlilik Katsayısı (R^2) elde etmiştir. Beklendiği üzere, iletişim performansındaki en etkili bileşenin veri yükü miktarı olduğu tespit edilmiştir. Elde edilen sonuçlar arasında; ortam ışığı girişiminin etkisinden bağımsız olarak tasarlanan iletişim performansının az da olsa etkilendiği, verici olarak kullanılan LED'lerin ise iletişim performansını beklendiği kadar etkilemediği görülmüştür.

1. Introduction

One of the optical wireless communications systems (OWS), Visible Light Communication (VLC), is a communications technology designed to support communication on a radio frequency band. In communication, data transmission between two or more points is done using transmitters running between 370 and 780 nm wavelengths, the light band the eye can see. Communication structure works using the presence-absence representation of light. VLC is currently using LED lamp technology from the solid-state lighting group as it requires fast switching. It has distinguishing features such as long-lasting use, low power consumption, fast switching, and low cost, which are sought after in today's communications systems.

Visible Light Communications began with the Visible Light Communications Consortium (VLCC), created between Japanese companies in 2003 [1]. The Visible Light ID System Standard in 2007 and the Visible Light Communication System Standard in 2008 are the national standards published [2]. Japan Electronics and Information Technology Industries Association (JEITA) has accepted these standards as JEITA CP-1221 and JEITA CP-1222. Visible Light Communication physical and media access layers were standardized in 2011 by the IEEE 802.15.7 Task Group (IEEE, 2012). This standard, which specifies the properties of the MAC and PHY layers, marked a turning point in promoting visible light communication in Wireless Personal Area Networks (WPAN).

Table 1. PHY operating modes.

Physical Layer	Modulation	Optical Clock Frequency	Data Rates
PHY I	OOK/VPPM	200/400 kHz	11.67-266.6
PHY II	OOK/VPPM	≤120 MHz	1.25-96 Mb/s
PHY III	CSK	12/24 MHz	12-96 Mb/s

The communication infrastructure determined as the IEEE 802.15.7 standard offers necessary recommendations for providing an effective ambient access protocol, which is an essential problem of optical communication. It also offers recommendations for human health and eye comfort specific to this standard. The role of lighting needs in today's working environments is great in proposing this structure. The capabilities of visible light communication come to the forefront for environments that cannot be illuminated with natural light, areas with high-security requirements, and for places where lighting is mandatory. Meanwhile, the communication infrastructure also has the advantages of not allowing magnetic emissions and being unaffected by such emissions. The theoretical bandwidth is unlimited, which gives hope for the future.

The IEEE standard defines the physical layer in three different ways. The aim is to create structures suitable for different needs and to ensure the operational performance of the structure. Figure 1 presents a physical layer platform designed to create structures for different needs, guaranteeing the structure's operational performance, and work independently of ambient light.

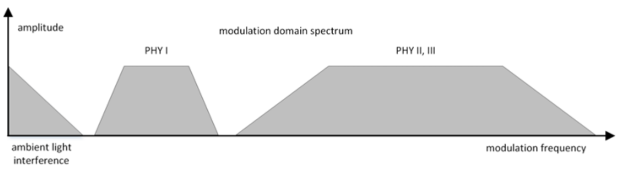

Figure 1. Modulation-Domain spectrum [1]

PHY I used in the study allows the creation of acceptable systems for basic needs even though data communication rates are lower than today's communication rates (between 11-266kb/s). The structure can support the existing communication infrastructure with physical layer 1. The subtypes of Layers 2 and 3 that can increase up to 96 Mbps suggest competing performance values for today's communication infrastructure. Table 1 shows the performances of the VLC protocol layers.

The VLC areas that can meet today's communication systems performance requirements can be listed as follows:

- Aviation [2],
- Clock Calibration [3],
- Communication and Assistance in Natural Disasters [4],
- Hospitals [5],
- Human Perception [6],
- Indoor Location Determination [7], [8],
- Internet of Things (IoT) [9],
- Internet of Things with Light (IOL) as a New Structure [10],
- Mobile Interaction [11],
- Museums [12],
- New Generation Cellular Networks [13],
- Next-Generation High-Speed Cellular Networks [14],
- Security in Defense Systems [4],
- Smart Lighting [15],
- Toy to Toy Communication [16],
- Underwater Communication [17],
- Wi-Fi Spectrum Support [18].

The experiment setup was designed to work on PHY I in the study. Table 2 shows the reference performance of the VLC PHY I layer structure. Figure 2 shows the trial set components designed in accordance with the IEEE 802.15.7 PHY I reference.

Table 2. VLC PHY I Operating Mode

PHY I Operating Modes					
Modulation	RLL Code	Optical Clock Rate	FEC Outer Code (RS)	FEC Inner Code (CC)	Data Rate
OOK	Manchester	200 kHz	(15,7)	1/4	11.67 kb/s
			(15,11)	1/3	24.44 kb/s
			(15,11)	2/3	48.89 kb/s
			(15,11)	none	73.3 kb/s
			none	none	100 kb/s
VPPM	4B6B	400 kHz	(15,2)	none	35.56 kb/s
			(15,4)	none	71.11 kb/s
			(15,7)	none	124.4 kb/s
			none	none	266.6 kb/s

Like other communication structures, the physical layer performs the functions of signal representation, how signals are sent, communication, the inclusion of electronic interface elements, and synchronization. Different in communication, the light-air duo is used as the transmission medium. The Data Link layer, which serves as the MAC layer, has been applied at the kernel level with the TCP/IP layer, while the Application layer has been implemented on the Linux operating system interface.

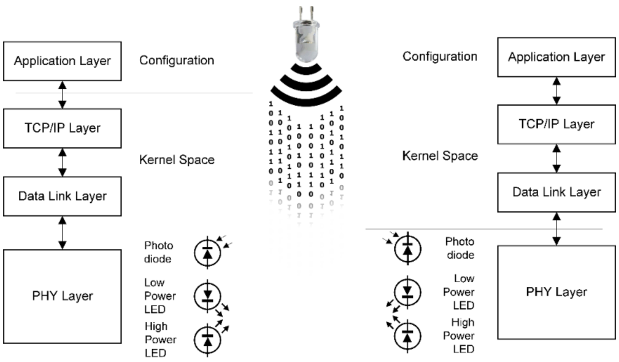

Figure 2. Block diagram of a transceiver

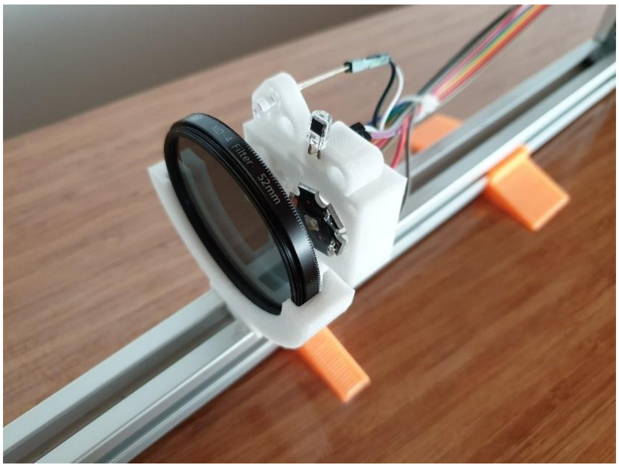

Figure 3. Transceiver

Table 3. Hardware Components

1	L-53SRC-J4	Low-power 5 mm red LED
2	REBEL-STAR-	High-power LED, 3V, 2,7W
3	OPT101	Photodiode together with an
4	BPW46	Photodiode 350-1120 Nm
5	PCB	Communication with BeagleBone

Table 4 provides variables that are selected as experiment variables. For the experiment, ambient light, communication distance, data set preparation frequency, data payload, filter, and LED variables have been selected from variables that affect communication performance.

Table 4. Experiments Variable

Ambient Light	Distance	Data Packet Iteration Times	Payload	Filter	LED
1 lux	30 cm	5	128 kb	No Filter	Low Power
120 lux	50 cm	10	256 kb	Ultraviolet (UV) Filter	High Power
300 lux	100 cm	30	512 kb	Polarizer Filter	
	200 cm	50	768 kb	Neutral-Density (ND) Filter	
	300 cm	60	1024 kb		
	400 cm				
	500 cm				

2. Particle Swarm Optimization

Particle swarm optimization (PSO) is a numerical optimization algorithm introduced by Eberhart and Kennedy in 1995 PSO is a method inspired by the social behavior of animal herds [19]. It was inspired by the successful delivery of food to a flock, even though no animal in the herd knows where food was. In the PSO method, each individual is called a particle, and the group is called a flock. The flock creates a series of random particles and sets the flock's starting position and other parameters. Each particle has the current location information. The speed of particles is updated to begin the cycle for optimal solutions. The speed and position of particles are updated according to the mathematical expression given in Equations 1, and 2.

$$v_{id}(t+1) = \omega . v_{id}(t) + c_1 . \tau_1 . \left(pbest_{id} - x_{id}(t)\right) + c_2 . \tau_2 . \left(gbest_d - x_{id}(t)\right) \qquad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (2)$$

In the mathematical expression, v_{id} shows the velocity of the particle, x_{id} indicates the position of the particle, $pbest$ indicates the best possible solution found by the particle so far, τ_1 and τ_2 indicate randomly generated values between 0 and 1, c_1 and c_2 are learning factors (cognitive and social parameters), ω is the inertia weight, and finally, $gbest$ shows the global best solution found by the swarm.

Due to its success, the model is often favored in visible light communication. In its first paper, pioneered in 2013 by Rui Guan and his colleagues [20] the model was used for single plural uses and positioning predictions of LEDs used for communication. Similarly, although the location of the transceivers, the coordinate estimations for mobile communications, hardware-software resource allocations and energy efficiency are studied, there is no study reporting which hardware component can be effective in what environment and at which software settings.

2.1. Random Forest Algorithm

Random Forest (RF) is a machine-learning algorithm used to develop prediction models. The RF is a popular algorithm developed by Leo Breiman in 2001 The RF algorithm is used for classification and regression problems by creating a random forest that is a decision tree collection. The decision trees selected in the RF algorithm are a subset of the data set. In the RF algorithm, training is performed using different subsets, and the results obtained from each tree are combined to make predictions. As a result, the RF algorithm has a higher accuracy rate than a single decision tree model and prevents overlearning [21].

2.2. Random search algorithm

Random search algorithm is an optimization algorithm used for function optimization. Random entries in the random search algorithms are generated and evaluated. It is updated depending on whether the solution is better than the previous solution. The study used the number of estimators of random forest algorithm, maximum feature, maximum depth, minimum samples split, minimum samples leaf and Bootstrap hyperparameters were used for optimization.

2.3. Other metaheuristics works

In their 2017 study, Cai et al. proposed a new VLC positioning system based on a modified particle swarm optimization (PSO) algorithm. It has been observed that the proposed system can demonstrate high localization accuracy while algorithm complexity has been significantly reduced. Indoor positioning is done within centimeters based on the results [22].

Gözüaçık et al. In their 2021 study, the indoor positioning system with VLC was designed based on a market application. The location data of the data received from the system are obtained according to the signal strength (RSSI), and the shortest distance between the selected stops for the navigation operation was determined using the Floyd-Warshall algorithm. The shortest route was determined using a genetic algorithm for the stops between which the distance is known [23].

When the academic literature related to the study is reviewed, Bastiaens et al., in their study conducted in 2021, used particle swarm optimization (PSO), Gray Wolf Optimizer (GWO), JAYA, Salp Swarm Algorithm (SSA) and Cat Swarm Optimization (CSO) metaheuristics optimization algorithms in order to understand the optimal LED positions of the received signal strength for different configurations and to determine the corresponding positioning error values.

As a result, positioning has been optimized in visible light communication, and cost-effective transmission of centimetrelevel data with photodiode has been achieved [24].

Meng et al., in their work in 2022, proposed a threedimensional (3D) indoor visible light positioning (VLP) system using an improved whale optimization algorithm (IWOA) to reduce the error caused by photodiode optical conversion efficiency. According to the results obtained, it is seen that the 3D positioning average error can effectively reduce the positioning error caused by the photodiode angle [25].

2.4. Method

In the study conducted by Taşdelen and Bekçibaşı [26], the experimental setup consisted of a BeagleBone Black (BBB) board running the Debian operating system with a 3.8 kernel version, which was specifically compiled with the Xenomai real-time development framework. For communication, the UDP protocol was utilized with the iperf command set to report bandwidth and data loss.

The experiment involved systematically altering several variables. Software-controlled variables, including the internal operating frequency, payload size, and the choice of LED used as the transmitter, were changed by a script every 150 measurements. In contrast, variables requiring physical adjustments, such as the filter, communication distance, and ambient light conditions, were modified manually. For each unique configuration, 150 data transfer rate measurements were taken, and these were then averaged into a single value. This process ultimately resulted in a final dataset composed of 7 attributes and 4200 instances [26].

As seen in the structure, the flow diagram is given in Figure 4. To ensure the reliability of the model and prevent data leakage, a rigorous Nested Cross-Validation (Nested CV) pipeline was implemented in Figure 4..

Missing Data Analysis and Imputation (In-Fold Preprocessing):

Missing data analysis was performed on the dataset. To avoid data leakage (using information from the test set to inform the training set), imputation was performed strictly within the training folds of the cross-validation loop.

- Categorical Variables: Missing values were imputed using the mode (most frequent value) of the training data.
- Numerical Variables: Missing values were imputed using the median of the training data.

This "Fold-Internal Pipeline" ensures that the model is never exposed to the statistical properties of the test data during the preprocessing phase.

Feature Selection:

Input attributes were selected via the Binary Particle Swarm Optimization (BPSO) method to reduce processing time and cost while improving model accuracy. This selection was also conducted within the training folds to ensure valid performance estimation. In the method, ambient light (X1), distance (X2), frequency (X3), load (X4), ambient temperature (X5), filter (X6), and LED (X7) are represented as input parameters.

Nested Cross-Validation:

The specified attributes were subjected to a Nested Cross-Validation design:

- Outer Loop (10-Fold): Used to assess the generalized performance of the model (R^2, MAE, RMSE).
- Inner Loop (5-Fold): Used for hyperparameter optimization via Random Search. This structure ensures that the hyperparameters are tuned on a subset of the data that is distinct from the set used to evaluate the final performance, thereby preventing overfitting and providing a conservative, realistic estimate of model accuracy.

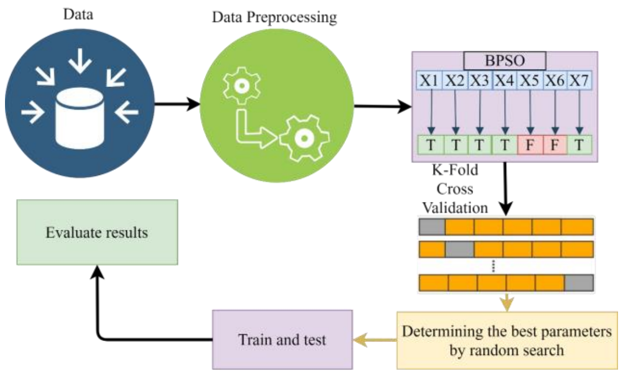

Figure 4. Optimization of random search hyperparameters

After the data preprocessing phase, input attributes are selected via the Binary particle swarm optimization method to reduce the processing time and cost of the data set model and improve the accuracy of the model. Model attributes are determined by accuracy and significance, and the sigmoid purpose function is used. In the method, ambient light (X1), distance (X2), frequency (X3), load (X4), ambient temperature (X5), filter (X6), and LED (X7) are represented as input parameters. "T" value means that its attribute is selected, but an "F" value indicates that the attribute is not selected. The specified attributes are subjected to 10fold K-Fold Cross Validation, overfitting status of the model has been determined. Subsequently, selected attributes are trained using the Random Forest machine learning algorithm. During the training process, the model's hyperparameters are optimized with the Random Search algorithm to improve the accuracy performance of the model. According to the results of hyperparameters, the data set has been retrained to determine the accuracy and importance of the selected parameters.

3. Results

In the study's first phase, the processed data was trained with the Binary Particle Swarm Optimization (BPSO) algorithm to select attributes. The attribute selection obtained by the BPSO method is given in Table 5. The attributes are trained by the Random Forest machine learning algorithm.

Table 5. Attribute Selection Results on Binary Particle Swarm Optimization

Attribute	Using Status
Ambient light	True
Distance	True
Frequency	True
Load	True
Ambient Temperature	False
Filter	False
LED	True

Binary particle swarm optimization algorithm recommended ambient light, distance, frequency, load, and LED attributes for model training, while ambient temperature and filter attributes were not recommended. Consequently, attributes marked "True" were retained, while "False" attributes were removed.

Before performing the model training according to the newly created attributes, the hyperparameters of the Random Forest machine learning algorithm were determined using the Random Search algorithm within the inner loop of the Nested CV. The optimal hyperparameters identified are given in Table 6.

Table 6. Hyperparameter Results from Random Forest Algorithm Using Random Search Algorithm

Hyper parameters	Values	Best values
Number of estimators	[10,20,.....190,200]	40
Maximum Features	['auto', 'sqrt']	Sqrt
Maximum Depth	[10,20,30,.....,110,120]	60
Minimum Samples Split	[2, 6, 10]	10
Minimum Samples Leaf	[1, 3, 4]	3
Bootstrap	[True, False]	false

When Table 6 is examined, the number of estimators parameter was explored from 10 to 200 in steps of 10, with the best value detected at 40. The maximum features parameter was tested with 'auto' and 'sqrt', with 'sqrt' yielding the best result. The maximum depth parameter was increased from 10 to 120 by 10, and the best value was found to be 60.

In the next phase of the study, based on the hyperparameter values determined by the Random Search algorithm, the model was re-trained, and the feature importance was analyzed. Results are shown in Figure 5.

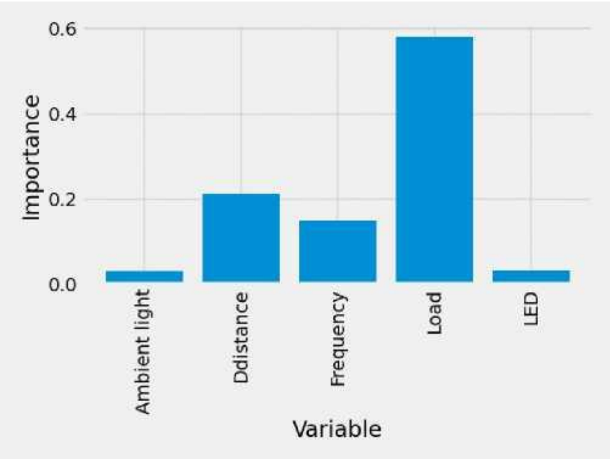

Figure 5. Attributes that Affect Data Transfer Rate According to Random Forest Algorithm

Figure 5 shows that within the 5 attributes used in the study, the attribute that most affects the data transfer rate is load at 58%. The second most effective attribute is distance (22%) and frequency (15%), while LED (3%) and ambient light (2%) parameters have little effect. Although the most effective parameter is the load, distance and frequency combined affect data transfer speed by a total of 37%. In the final phase, the regression performance of the Random Forest model was evaluated using the outer loop of the Nested Cross-Validation. The results are presented in Figure 6.

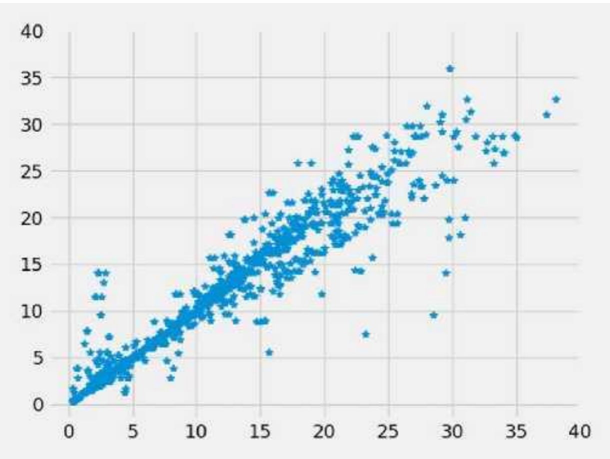

Figure 6. Regression Results from Random Forest Algorithm

Figure 6 illustrates the correlation between the predicted values and the actual values. The model achieved a Coefficient of Determination ( ) of 0.826, indicating that the model explains approximately 82.6% of the variance in the target variable. Furthermore, the Mean Absolute Error (MAE) was calculated as 0.14 Mbps, and the Root Mean Squared Error (RMSE) was 0.21 Mbps. These metrics confirm that the Random Forest algorithm, optimized via Random Search and BPSO, provides a robust prediction of Visible Light Communication performance.

The study contributes to the visible light communication studies in the literature, especially in the optimization fields such as communication positioning, communication energy efficiency, coordinate estimation and efficient use of resources. Visible Light Communication, which has various interferences compared to other communication types, was most affected by the data load according to the optimization model in the study. After the data load changes, the data preparation frequency, where the power of the hardware structure used in the communication is adequate, has emerged as the value that affects the communication the most. As a result of the standards established on not being affected by the interferences, the effect of the lighting in the communication environment on the communication is relatively tiny. Contrary to the expected results, the power of the LED as the transmitter in the communication has a minor effect on the communication.

Declaration of Ethical Code

In this study, we undertake that all the rules required to be followed within the scope of the "Higher Education Institutions Scientific Research and Publication Ethics Directive" are complied with, and that none of the actions stated under the heading "Actions Against Scientific Research and Publication Ethics" are not carried out.

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