A Bat Optimized Reliable Elm (Bore) For an Efficient Throughput of Cap-VLC System

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Abstract. Indoor Visible light communication (VLC) is considered one of the most famous communication technologies in today's industrial life, showing importance in data broadcasting and glowing instantly with the cost-effective source of light-emitting diode (LED). This kind of high-speed network's properties is controlled by the source device's shortened bandwidth (LED). Therefore, it is considering highly efficient modulation technique and extreme adaptive demodulation technique for better data rate in visible light communication. Carrier less amplitude-phase (CAP) modulation is an eminent modulation scheme that increases implementation ease and places good position inefficiency. Somehow, the CAP-VLC system's impact is signal jamming, poor sensitivity, scattering, and noise issues. To overrule this problem, it witnesses the implementation of VLC system with CAP modulation using advanced neural network system of High-Speed Feed Forward Neural Network, which works based on the principle of Extreme Learning Machine (ELM). The same is adopted and extended using the BAT algorithm. Along with this, algorithm optimization technique has been integrated to enhance the entire CAP-VLC system's performance. Altogether, it can be named as bat-optimized reliable ELM (BORE). The proposed new learning-based algorithm for CAP-VLC has shown better performance in received power distribution of 90.6% at various modulation indexes, better BER of about 97.6% in the voltage level of 3V, and different distances between transceivers, respectively.

Keywords: Visible Light Communication, Extreme Learning Machine, BAT optimized reliable ELM, Carrier less Amplitude Phase Modulation.

1. Introduction
RF technology is the most welcoming technology earlier stage, which has the spectral limitations that block increasing capacity. One of the disadvantages of RF is electromagnetic interference. Radiofrequency waves have security issues; affect human health by increasing transmitter power. So, here comes the VLC system, a stable and standard technology that overcomes RF technology issues. VLC system has various specifications for its standardization based on its spectrum range, frequency range, non-licensed channel [1]. VLC system has some obstacles like dimming control and flicker in the physical layer. It can be achieved by using different modulation techniques [2]. VLC system can be improved by having a proper tilting angle on the photodiode. The tilting angle changes, power, channel gain, and bit error rate show better [3]. The power competition and nonlinearity impact are
also shown in 16QAM and QPSK [4]. The VLC system is illustrated for light sourcing and sharing information for a huge area of a structured indoor VLC system. Different types of sourcing are employed for a complete communication system [5]. The low-cost and widely spread sources are LEDs and phosphorescent-based filter type blue LEDs used for active communication. Blue light components emitted from chips are changed to yellow, which together form a white spectrum [6]. A joint algorithm of IQ ICA is used in the VLC network to improvise the system capacity and spatial multiplexing gain with sources [7]. The above-discussed demerits can be improved with the help of neural network implementation. The adaptation of SVM parameters detects the spectrum availability and feature separation, which are considered signal strength. This is limited to physical layer protocol identification [8]. Another method used to perform with profiles of PU spectrum is altered K-nearest neighbor supervised network. Manipulation of the spectral hole is augmented using the KNN network. It is not adaptable for huge networks, but it is suitable for small CR networks [9]. NOMA VLC network has been evaluated for a better solution regarding other conventional systems such as ANN, CNN [10].

A new set of the algorithm is surveyed in this paper [11] about GA, PSO and BAT algorithms. These algorithms' working principle is based on the individual evolution, population-based, and metaheuristic approach based on hunting behavior. The BAT algorithm's greatest feature is that it can improve the diversity of the population's solution with the frequency tuning technique's help. Hence it can vary the loudness and pulse emission rate during searching of prey [12].

A fast learning methodology of work has been carried out in this paper that is over-covered by ELM. ELM is a class of neural networks featured for auto-tuning of concealed neurons. Auto tuning leads to instability and time complexity that shows inaccuracy in prediction. In common, ELM has some drawbacks in a continuous flow of data for the system to get a better performance system there may exist a data loss, so to avoid this problem, a newly structured optimization algorithm of the BORE model - Bat Optimized Reliable ELM is introduced in this paper, which is purely based on the learning model, which works based on the noticeable reliable matrix principle with bat optimized reliable ELM. This BAT algorithm overcame the mentioned problems and examined the health care and simulated dataset for data integrity. The results of power distribution and BER versus voltage are shown in the fore coming session.

Further, section II will be showing the literature survey; section III comes out with the proposed model of the system, section IV pumps out with the implementation of BORE, and section V with result & discussion.

2. Literature Survey

Lin Sun et al. [13] utilizes K-nearest neighbor with CAP modulated signal for reduced BER and mitigates nonlinear distortion. It shows that when the K value increases, the BER also increases as it has a limited label in its constellation. However, with K-NN the distance communication is possible with minimum error with CAP modulated signals.

In [14] comes out with a new circulate input weight matrix technique for the ELM-based target work for low complexity with FFTs. It can handle both nonlinearities as well cross-LED interference. The problem in this work is that it requires continuous feeding of input data for its efficient work.

In [15] outperforms the concept of three different stages of sub region implementation of ELM to betterment network positioning accuracy, which performs in the physical layer and the traditional model is affecting both the first-order reflection and the noise.

In [16] committed that the effectiveness of the indoor positioning system of SVM compared with (SLFN) ELM showed a better performance in a fingerprint positioning system. Enhancement of 3D coordinates of the destination point has quickly happened.

In [17] experiment with LED’s power for illumination and satisfied communication. By reducing the total transmission, power optimization can be achieved. So the user association and perfect communication can be done. In [18] showed to reduce the dead zone out from the communication...
area. This author is designing the coverage optimization model to mitigate the CCI (co-channel interference) and maximize communication coverage. To achieve seamless communication about 75%, the author use a Genetic algorithm for LED optimization. In [19] is delivered about the achievement of high data rate by reducing the bandwidth. However, there it shows a major issue on limited bandwidth. They use optimization of DMT-based VLC system for cyclic prefix, clipping range, and several subcarriers. In [20] Optimizing the RSS using a meta-heuristic algorithm to calculate maximum RSS on the NLOS link gives the overall orientation RSS in place, observing for every angle. In [21] integrated two different algorithms to get easy structure and powerful convergence as a well-organized pattern with a high-performance system. The author moves with the BAT-ELM algorithm for better performance.

3. Proposed Methodology
The proposed system, shown in Figure 1, contains different blocks like the VLC system model, feature extraction, ELM demodulation technique, and finally, a result analysis. The test bench created will universally support all learning algorithms and all kinds of optical-related work. This method shows the performance analysis in reduced power distribution which supports both illuminations and transmission of signals.

![Proposed Methodology for the BORE based CAP-VLC system](image)

3.1. Model of the system
A system shown in Figure 2 is a CAP-VLC system model. The data created by the model is modulated under different constellations such as 16, 32, 64, and 256. The modulated output values are being up sampled with three and filtered with size 31 before transmission. The source operated here is LEDs, and the target is PD (photo detector). The light signals transmitted by LED through the wireless medium are received by PD, where the conversions are made between electrical and optical signals. Both at the transmitter and the receiver end, electrical power amplifiers are employed to strengthen the signal. DC bias is then added during transmission to make them all positive signals. The addition of DC biasing may lead to system nonlinearity and also increases in device bandwidth. The complex signals are changed to a real part in the CAP modulation and, CAP supports a single band as a carrier for signal transmission.
Consider a transmitted signal as shown here,[6]

\[ x(t) = \text{Re}\{\cup(t) \ast \rho(t)e^{2\pi f_c t}\}, \quad 0 < t \leq T \]  
---(1)

Where, \( x(t) \) denotes the digital signal, and the rest is all a real part of the complex CAP signal.

Figure 2: CAP-VLC system model

This model examines the training and learning outcomes. Designing a universal test bench and analyzing the simulated dataset will further show the test bench’s experimental outcome. The universal testing unit supports different modulation indexes, different machine learning tools, which can also be enhanced to deep learning tools and all-optical related sources and applications. In this work, two datasets are taken for consideration firstly, simulated dataset and secondly, open online dataset of medical health care. The simulated dataset is utilized here for training and testing.

3.2. Mathematical Background

3.2.1. Received Optical Power Distribution: In the transmitter, the power denotes the energy level irradiated from LED that also shows the signal’s strength, which can be considered \( p\text{_{max}} \) \[ p(t) = M_{\text{per}} \ast p\text{_{max}} \]  
where \( p\text{_{o}} \) represents the LED transmitted power, \( M_{\text{per}} \) denotes the power factor for a different modulation scheme, and \( p\text{_{max}} \) shows the maximum power transmitted.

Considering the received power at photodiode end,[2] \[ r(t) = \sum_{n=0}^{\infty} H(\text{LOS}) \]  
The determination of channel response for LOS (line of sight) is as shown [2] \[ H(\text{LOS}) = A_R (m-1) \theta \cos \cos \phi \]  
where \( A_R \) denotes the area coverage of the receiver detector, \( \delta \) is the distance between a source and a target, \( \theta \) and \( \phi \) are the angle of irradiance and incidence respectively, and \( m \) represents the Lambert radiant index.

Finally, the power received in the system can be calculated as \[ p_r = M_{\text{per}} \ast p\text{_{max}} \sum_{n=0}^{\infty} A_R (m-1) \frac{\theta \cos \cos \phi}{2\pi g^2} \]  

3.3. Extreme Learning Machine

Deep learning neural networks hold their esteemed part in prediction problems. A high-speed feed-forward neural network is more efficient than any other neural network in time cost density. Such a network has a training complexity in updating parameters and concealed neurons. This will increase the training complexity at runtime. Our proposed low complexity neural network algorithm will overcome the problems[21]. Even though the prediction, planning, and speculation are enhanced far-most, this work’s benefits start with designed ELM with spectrum prediction.

A newly proposed neural network consists of three layers: input, output, and hidden layers. The hidden layer consists of random generated hidden nodes that need not be fine-tuned the parameters.
during runtime, making the newly proposed ELM faster than any other algorithm. The mathematical calculations are as shown.

\[ \mathcal{K}(x) = \sum_{i=1}^{\infty} \alpha_i h_i(x) = h(x) \propto \]

\[ \propto = [\propto_1, \propto_2, \ldots, \propto_3]^T \]

where \( \propto \) shows the strength of neurons in the hidden layer, \( x' \) denotes the input vector and \( \propto = [\propto_1, \propto_2, \ldots, \propto_3] \) represents the vector between two parameters, such as hidden neurons to output weights. The output layer is denoted for hidden layer as \( h(x) = [h_1(x), h_2(x), \ldots, h_3(x)] \) were \( \propto \)'s total value in output vector.

The implementation of ELM uses the minimal nonlinear least square methods, which are represented as

\[ \propto' = \propto^* = \propto^T \propto \propto^T = \propto^T (\propto \propto^T)^{-1} \propto \]

where \( \propto^* \) denotes the inverse of \( \propto \) known as Moore-Penrose generalized inverse.

Hence the output function can be written as

\[ \mathcal{K}(x) = h(x) \propto = h(x) \propto^T (\propto^T \propto \propto^T)^{-1} \propto \]

The presence of kernel function can expose the better performance of ELM. Also, the major benefits of ELM are reduced training error and better approximation. Because of the auto-tuning and activation functions, ELM finds good applications in classification and prediction values. The ELM equations and functions are elaborated in [22][23].

The algorithm shown below is the pseudo-code for ELM.

Step 1: Set of data for training (N), activation function, and concealed neurons
Step 2: Proper assignments of parameter values (weights & bias).
Step 3: Mathematical observation for concealed matrix.
Step 4: Analyze the Output Matrix \( \propto \) (update weight) for perfect classification.
Step 5: Predict the values

3.4. BAT Algorithm

The usual BAT algorithm is worked based on the principle of echolocation characteristics of it. A researcher X-S Yang [24], in 2010, framed a set of guidelines which are (i) echolocation is to detect their prey distance (ii) random movement of the bat with the speed of \( V_i \) and its position \( X_i \) with a repetition factor \( F_{\text{min}} \). Until it reaches that prey, it may vary the wavelength, loudness and rate of emitted pulse \( R \) [0 1]. (iii) Loudness may vary in many ways, and it may shifts from \( A_0 \) to \( A_{\text{max}} \).

Calculation of each BAT motion is is associated with speed \( V_i \) and distance \( X_i \) with the ‘n’ known number of iterations in a search place. Using the mentioned rules

\[ F_i = F_{\text{min}} + (F_{\text{max}} - F_{\text{min}}) \propto \]

\[ X_i = X_{i-1} + V_i \]

where \( \propto \) belongs to (0 1), \( (F_{\text{max}}-F_{\text{min}}) \) are minimum & maximum frequency depends on the problem statement. Bat calculation is showing the frequency tuning to give us a combination of investigation and exploration. Once the bat found the prey, the loudness reduces, while the pulse rate expands between \( A_{\text{min}} \) and \( A_{\text{max}} \). Finally, similar to the bat finds its prey; this algorithm shows better results than any other algorithm.

3.5. Drawback of ELM

It has many advantages in its operation, but when it comes to tuning part of weight and bias, it uses more number of concealed layers when compared to other learning algorithms. Due to this optimal tuning problem, accuracy may get affected.

To optimize the parameter tuning, a new bio-advised inspirational BAT algorithm is used. This
improves the classification accuracy. This algorithm is more advantageous with the forthcoming qualities,

- More efficiency than Gn algorithm and other heuristic algorithms.[23]
- More fast and handy workspace [20][21].

This BAT optimized reliable ELM algorithm's motivation says that (i) with the fixed time and varying frequency, it can increase the pulse rate emission until it finds its optimized output. (ii) the option of less power consumption made this algorithm more effective and application-oriented. (iii) the responsivity is also comparatively good. Hence, to overcome the disadvantages, this system moves on to the BORE algorithm.

3.6. BAT Optimization

a) As it has been implementing a learning algorithm into the VLC system, it requires more parameters to be considered. Due to this, stability may get affected, and also complexity increases.
b) To concentrate on the system's stability and maintain accuracy with full efficiency, this needs to pull towards optimization.
c) Optimization has many classifications, GA, PSO, etc., in that BAT has less complexity, time constraint and is easy for implementation in the VLC system.

4. Design and Implementation of BORE

The first and foremost aim of the BORE model is to classify the given dataset. Different types of datasets are used for training and test for accuracy and with the minimum error. BORE model is used to showing its efficiency to extract the original data out from the transmitted data. The new optimization technique of getting accurate and error-free output is BORE. The function of BORE is as shown in Figure 3.

Some stages of the process need to follow, such as segmentation, feature extraction, and optimization (BAT optimized reliable ELM). Here it removes the duplication or the unwanted data, which can increase the accuracy of detection. In images, visual saliency description may be introduced to obtain the subtraction areas in that image. Whereas here in data segmentation, the random data introduced for correlation may get the optimized data with high accuracy extraction. Bore introduces the data analysis, which is considered to be more important for the generated data. BORE uses the bat optimized reliable ELM for better extraction.

The functions of the ELM and BAT algorithms are discussed in greater detail in the preceding section. The ELM's main flaw is that its stowed layer choice is not always optimal, resulting in useless data nodes, lowering detection accuracy. The proposed BORE algorithm optimizes the input weights and bias factors by combining the BAT algorithm with the Extreme Learning machine to develop this flaw.

The most significant advantage of BAT over ELM is that it enhances the global minima in the search path, which is more efficient than traditional algorithms such as GA and PSO. As its fitness function, the suggested BORE customizes accuracy. If the acquired accuracy matches the threshold accuracy, the output parameters are deemed credible; otherwise, the function is exited, and iteration continues until the function values are reached. Table 1 lists all of the parameters that were used in the optimization process.
Figure 3: Flow chart of an implementation of BORN proposed algorithm

Start

Initialize the neurons (BAT)

Initialize the Loudness, Freq, Pulse rate, Velocity

Evaluate the fitness function

Yes

Calculate the best value (neurons)

Calculate the classification Accuracy

If $A_{ac} < A_T$

Yes

Update the loudness, freq, pulse rate, velocity

End

No

No

Start
5. Result and Discussions

5.1. Optical power distribution analysis and evaluation

The room's coverage area (8x8x3 m³) with LEDs placed in specific locations is evenly spaced on the transmitter space. The receiver height is placed apart 3m, considering 1 m as desk height. Placement of LEDs on the ceiling for sourcing are (2,2,2), (2,6,2), (6,2,2) and (6,6,2) as shown in the graph.[2][4]

Table 2 initiates the parameters for the simulation-based on room size, transmitter, and receiver for illumination and communication.

### Table 2: Important Parameters for experimentation - transmitter, and receiver

| Parameter                   | Values                      |
|-----------------------------|-----------------------------|
| Room                        | Room size 8mx8mx3m          |
| Source                      | Number of LEDs 4            |
| LED transmitted power       | 0.2w                        |
| Semi angle half power       | (7.5*π)/180                 |
| Center luminous intensity I₀| 24                          |
| Distance between LED        | 170cm                       |
| Power spectral density N₀   | 10⁻²¹W/cm²                  |
| Receiver                    | Area of detector 7.8E⁻⁷ m²   |
| FoV                         | 120 degrees                 |
| Responsivity                | 0.55 A                      |
| Concentrator refractive index| 1.46                       |
| Filter gain                 | 1                           |
| Data rate                   | 115200                      |

The parameters shown in Table 2 are transmitter and receiver set up for simulation. The simulation result shows that the received power output ranges from 42% to 96% based on the modulation index, the distance between the transceiver, and the detector area. The same parameter value will give us a better BER compared with SNR. However, the purpose of setting up all these parameters is by varying voltage corresponding BER will vary beyond the limit of 3.8e-3 of FEC, which may show better data rate in the future than any other algorithm.
Figure 4: Received Power Distribution for modulation index of 16 CAP

Figure 5: Received Power Distribution for modulation index of 32 CAP

Figure 6: Received Power Distribution for modulation index of 64 CAP
On implementing CAP with IM/DD the receiver power distribution is investigated for different CAP modulation indexes. Better power distribution from the trade-off of transmitted power 0.2W per LED and the test bench is made of 4 LEDs, distance among transmitter, receiver, and coverage area. In this Figure 4, 5, 6 and 7 the received power distribution of different modulation index are shown as 0.61 to 4.8e-5dBm for 16, 3.14 to 15.33e-6 dBm for 32, 1.48 to 4.06e-6 dBm for 64 and 1.6 to 3.64x10^-6 dBm for 256 respectively.

From the above figures, it is obvious that power distribution is high in 32 CAP modulations for lighting and fast communication. In 64 and 256 CAP modulation, it is low. Other modulation index shows very high at the middle and at the corners, and vice versa. This received power level can be used in hospitals for illumination and patient monitoring system and local area networks in industries and offices.

Figure 8: (a) BER for 16 CAP modulation under the distance of 125 cm (b) BER for 16 CAP modulations under distance of 150 cm

Figure 8 (a) modulation index of 16 CAP modulations with the transceiver distance of 125cm has a better BER when run and compared with different machine learning algorithms. Even though the intensity of LED with the variation in voltage of 3V is made, the BER lies between 10^(-6) and 10^(-7) and maintains its position. The better result of BER pulls out from the proposed BORE technique. Similarly, the distance varied for 150 cm marked in Figure 8 (b) with the same 3V, and the BER shown is a little bit lesser than 125 cm.
Figure 9: (a) BER for 32 CAP modulation under distance of 125cm (b) BER for 32 CAP modulation under distance of 150cm

Figure 9 (a) & (b) modulation index of 32 CAP with the transceiver distance of 125cm and 150cm, respectively. The model with 150 cm has a better BER when run and compared with different machine learning algorithms. By increasing the LED's intensity, the variation in voltage of 3V is made, the BER lies between 10 and 7 and 10 and 8, but it requires more power than any other models. The better result of BER pulls out from the proposed BORE technique, which continues further with two more modulations like 64 and 256 CAPs in Figures 10 and 11 (a) & (b), the variation in the distance that also maintains the better BER for the change in voltage and intensity of the LED.

Figure 10: (a) BER for 64 CAP modulations under distance of 125cm (b) BER for 64 CAP modulations under distance of 150cm

Figure 11: (a) BER for 256 CAP modulations under the distance of 125 cm (b) BER for 256 CAP modulations under distance of 150cm
The figures also show the modest relationship and impact on the nonlinearity of the CAP-VLC system. The change in modulation index, increase in the intensity of LED, voltage, and distance for better BER may deliver better data rate and future expansion.

6. Conclusion
When compared to other existing methodologies, the suggested BORE algorithm has found to be more accurate. The proposed algorithms were also evaluated with two neurons to see which ones produced the best outcomes and weight and bias variables that were configured. The bat-optimized extreme learning devices with dependable characteristics are more precise and lead to better outcomes. Finally, in this work, the results show that 32 CAP model systems deliver efficient BER with excess power of about 3.14 e10^-6 dBm to 15.33 e10^-6 dBm. It has achieved 97.6%, and others are below 83.2% of BER with a minimum power level of range between 1.48 e10^-6 dBm and 3.64 e10^-6 dBm. Even though 97.6% accuracy is achieved, the BORE's stability may still be affected by many feature inputs. Hence the best feature selection methodology is needed for future proposed network systems.

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