

Bayesian Constrained Optimization of IEEE 802.11 VANET for Safety Applications

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Abstract—IEEE 801.11p/bd based Vehicular Ad Hoc Networks (VANETs) have been introduced to improve road safety that involves message broadcasts with low transmission latency and high reliability. Different safety-critical applications of VANETs have different quality of service (QoS) requirements under dynamic vehicular environments. A set of dynamically adaptive parameters for the communication networks is essential to obtain the best channel efficacy constrained on that the QoS requirements are satisfied. However, the complexity and high computation consumption of simulation models for safety applications make direct parameter optimization inaccessible. This paper proposes a real-time optimization scheme for VANET safety applications based on a Bayesian constrained optimization algorithm. The scheme consists of a Bayesian Optimization algorithm and an analytical model for IEEE 802.11 VANET channel access. The Bayesian Optimization generates surrogate functions with lower computational costs based on the sampling points obtained from the analytical model or measurement observations, incorporates QoS requirements as the optimization constraints, and iterates to find the optimal parameters for the best channel usage. Experiments results on Python demonstrate that compared with other non-gradient optimization algorithms, Bayesian Optimization can converge to the optimal parameters solutions for IEEE 802.11 driven VANETs efficiently and accurately.

Keywords— *Optimization, Bayesian Optimization, Ad hoc networks, Quality of Service, Safety*

I. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) are a technology that allows vehicles to interact with each other over communication networks while in motion. One of the underlying protocols for VANETs is IEEE 802.11 p/bd. This paper will focus on the quality of service (QoS) of VANETs and specific safety applications under the IEEE 802.11 standards. With the help of a series of new technologies such as low-density parity checking (LDPC), error correction coding, dual carrier modulation (DCM), adaptive transmission schemes, multiple input multiple outputs (MIMO), and higher speed modulation and coding schemes (MCS) with high channel bandwidth, IEEE 802.11 systems have been recently upgraded, which makes it an excellent candidate for driving VANET for safety applications. Since different safety applications require different QoS and vehicular communication environments change very frequently, delivering safety messages with fixed communication parameters could cause poor QoS or low channel efficiency. This problem has research value because the communication parameters of current IEEE802.11-driven

VANETs cannot be adjusted with dynamic changes in the vehicular communication environment such as vehicle density, channel shadowing/fading characteristics, and current safety application type.

The objective of this paper is to use an efficient optimization method to quickly search the optimal combination of communication parameters of VANETs that achieve the best channel occupation usage with constrained on QoS requirements. Facing this problem, some valuable studies have been proposed [1] [2]. However, the optimization schemes proposed in these studies can only adjust one or two parameters, while being computationally expensive and not having the real-time optimization capability needed in real vehicle operations. A recent paper [3] proposes a deep neural network-based optimization algorithm for VANET safety applications and achieves multi-parameter tuning in reasonable computation time. Although this method has some practical application value, it poses two drawbacks. First, the neural network model adopted for the optimization uses a structure and learning algorithms for classification. So, this optimization-seeking scheme is competent for discrete parameters with well-defined intervals but cannot be applied to continuous parameters. Second, the reliability required in the optimization is assumed to be at most 99%. But it is not sure if the optimization method is effective for some safety-critical applications with higher QoS requirements (say, $\xi > 99.9\%$).

Based on the previous problems and the shortcomings of the existing schemes, this paper proposes a model-based Bayesian Optimization of IEEE 802.11 VANETs for safety applications. First, Given the ease and tractability of analytical models, the proposed scheme generates mapping data from communication parameters to QoS of the safety services for VANETs by running the analytical model for SINR-based IEEE 802.11 p/bd ad hoc networks [4]. The parameters of the network involved in the optimization include information transmission rate, Modulation and Coding Schemes (MCS) index, the number of message repetitions and communication transmission power. Meanwhile, the considered QoS metrics include Channel Busy Rate, Packet Reception Probability, and Packet Transmission Delay. Then, a Bayesian Optimization algorithm with a method incorporating QoS requirements constraints are deployed and tailored for the purpose of dynamically adjusting the network communication parameters to reach the lowest channel occupation constrained on QoS assurance. Compared with the existing

optimization methods for VANETs, the main contributions of this paper are: 1) The proposed scheme provides a general optimization framework combining Bayesian Optimization algorithm and the fast analytical model for complex communication networks that cannot be optimized by gradient type optimization algorithms. 2) Constraints on the QoS requirements can be incorporated into the process of Bayesian optimization. Also, the optimization-searching method can be used for multiple non-discrete parameters such as node transmitting power P_t , etc. 3) The algorithm under Bayesian Optimization can converge quickly with satisfactory precision, thus facilitating real-time optimization of the VANETs networks. The paper is organized as follows. Section II gives a brief overview of IEEE 802.11 based VANETs for safety services and the analytical model. Section III describes the Bayesian Optimization scheme and an implementation method of incorporating constraints. Section IV shows the numerical results of the proposed scheme and discusses them. Conclusions are presented in Section V.

II. SYSTEM MODEL FOR VANET SAFETY SERVICES

A. Description of 802.11 based VANET for BSM Services

IEEE 802.11-driven VANET improves vehicle driving safety by disseminating real-time messages or safety-related information. The communication system includes, but is not limited, high data rate transmissions with Orthogonal frequency-division multiplexing (OFDM) and advanced coding methods in physical layer, a higher spectral efficiency in MAC layer with an enhanced distributed channel access (EDCA) approach, and an adaptive retransmission scheme that adjusts the number of retransmissions based on the dynamic occupancy of the channel. These designs can significantly improve the reliability of safety messaging and ensure high QoS to maintain data exchange between high-speed vehicles and vehicles' roadside infrastructure.

In the U.S., the safety information disseminated by VANETs consists of two main types: basic safety messages (BSMs) and event-driven safety messages (ESMs). BSMs keep drivers informed of the status of nearby vehicles by periodically broadcasting basic safety messages. At the same time, ESMs are messages broadcast in some emergency situations, such as traffic accidents. This paper will focus on optimizing communication network parameters for BSM safety services.

B. Stochastic Model for Bayesian Optimization

In our optimization scheme, immediate mapping from the parameters to the QoS metrics is needed and derived from a developed analytical model. The analytical model used in this paper is obtained with some modifications on the SINR-based model [5] for IEEE 802.11 broadcast ad hoc networks. The safety application scenario in a one-dimensional highway is considered in the model. In this highway wireless IEEE 802.11 driven broadcast VANET, safety message (BSM) messages with transmission time T will be transmitted periodically by each vehicle to other vehicles within a certain range. Given the message transmission rate λ , the vehicle

density β , and other fixed communication parameters such as the 802.11 backoff window size W_0 , the MCS index k , the node transmission power P_t , and the carrier sensing range r_E , the analytical model starts with the analysis of IEEE 802.11 channel access to evaluate the transmission probability.

The IEEE 802.11 broadcast channel access behavior in this analytical model is described by an SMPA (semi-Markov process with absorbing states) model. The transmission probability of the hidden terminal can be obtained by solving the SMPA model. In addition, the signal-to-noise ratio (SINR) distribution at each receiver in the VANET is a crucial component considered in the model. Considering the node distribution, the distance d_s between transmitter and receiver, and the mobility of the vehicle, the SINR distribution can be derived as:

$$\begin{aligned} F_{SINR|d_s}(\theta) &= Pr(SINR < \theta|d_s) \\ &= 1 - (1 - P_{sh}(d_s))(1 - P_{hc}(d_s))(1 - P_{cc}(d_s))(1 - P(Y \leq \theta|d_s)) \end{aligned} \quad (1)$$

where $P_{sh}(d_s)$ represents the probability of a hidden terminal that at least one transmission from both sides of the hidden interference region occurs. $P_{hc}(d_s)$ is the probability of at least two simultaneous transmissions from nodes on both sides of the hidden terminal region; $P_{cc}(d_s)$ is the probability that at least one simultaneous collision occurs; $P(Y \leq \theta|d_s)$ is the distribution of the signal-to-noise ratio (SNR) at the receiver.

Based on the above settings and formulas, we can analyze the QoS of a safety application. The three main QoSs are Packet (Message) Reception Probability (PRP), Packet Transmission Delay (ED), and Channel Busy Rate (CBR).

First, the Packet (Message) Reception Probability (PRP) is defined as the probability that the receiver will successfully decode a packet from a source node that has a distance d_s from the receiver. PRP can be derived as

$$PRP(d_s) = (1 - \int_0^\infty PLR(s)f_{SINR|d_s}(s)ds)(1 - \int_0^{R_{th}} f_{P_r|d_s}(x)dx) \quad (2)$$

where R_{th} is the received power threshold and PLR is the probability that a packet is incorrectly received as a function of the bit error rate (BER).

Second, the packet transmission delay ED is the average time taken by a packet from its generation to its successful reception by other nodes in the communication range. The formula for ED is

$$ED = E[D_q] + N_{rp}E[S] \quad (3)$$

where $E[D_q]$ is the average queuing delay and $E[S]$ is the average channel service time.

Third, the channel busy ratio CBR is a percentage which indicates how busy the channel is at a certain time. The formula for CBR is

$$\begin{aligned} CBR &= 100\% \times \frac{\text{Duration Channel indicated as busy}}{\text{Channel observation interval}} \\ &= 2r_E\beta T\lambda \left(1 - \frac{P_{dc}}{2} - \frac{P_{dh}}{4}\right) \end{aligned} \quad (4)$$

where P_{dc} is the probability that at least one more transmission occurs within the carrier sensing range in the channel, and P_{dh} is the probability that at least two hidden terminal transmissions are overlapping.

III. STRUCTURE AND IMPLEMENTATION OF THE BAYESIAN OPTIMIZATION WITH CONSTRAINTS

A. Objective and Formulation of Optimization Problem

This paper aims to achieve dynamic and real-time tuning of the parameters of the VANETs communication network. In contrast to previous approaches, we wanted to introduce continuous variables in the optimization process of this paper instead of being limited to only discrete integer parameters in our previous approaches [3]. Bayesian Optimization methods are chosen to meet this requirement and achieve stable and reliable optimization.

Consider an IEEE 802.11 driven wireless ad hoc network where each node transmits messages regularly to its one-hop neighbor(s). Each node in the transmitter's ROI receives the messages according to immediately measured SINRs. Denote S_p as a set of cross-layer communication adjustable parameters $S_p = \{P_t, k, \lambda, N_{rp}\}$, where P_t is the node transmission power, k is the MCS index, λ the message generation rate, the vehicle density β , and N_{rp} is the number of message repetitions in one transmission. Then, the optimization problem can be formulated as follows. Given a mapping from the communication parameters to QoS, search through the parameter set to find the best combination set so that the channel usage reaches to its minimum under the constraints that both the reliability and transmission delay meet the requirements for the given safety application, which can be expressed as

$$\begin{aligned} & \min_{S_p} CBR \\ & \text{subject to } PRP(ROI, S_p) \geq \xi_p, ED \leq \xi_d, S_p \in S_{cp} \end{aligned}$$

where ROI is a region of interest for the safety application, S_{cp} is a possible value set of the parameters, ξ_p and ξ_d are the requirements of PRP and ED for the given application, respectively.

B. Bayesian Optimization with Constraints

The Bayesian Optimization method is a conventional optimization method if a function to be optimized becomes gradient evaluation-difficult or when the evaluation process takes a long time or requires a lot of human or monetary resources. If a conventional grid or random search is used directly to find optimal solutions to such gradient evaluation-difficult functions, the time consumed would be enormous. Therefore, Bayesian Optimization is considered a more efficient approach for finding the optimal value.

Similar to grid search and random search, the framework of Bayesian Optimization can be described as the following expression:

$$x^* = \underset{x \in X}{\operatorname{argmin}} f(x) \quad (5)$$

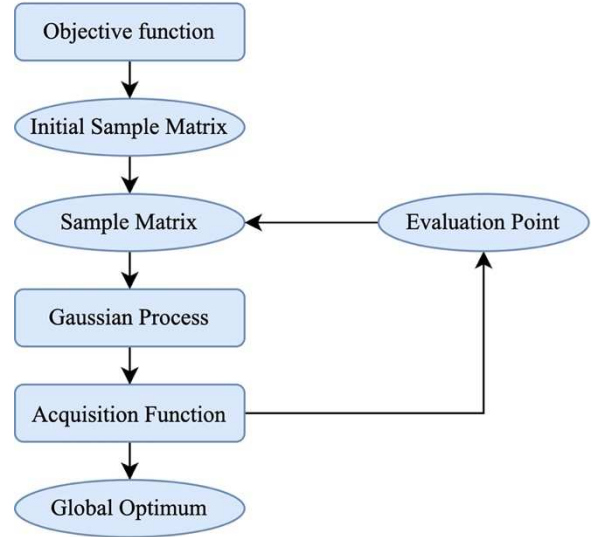


Figure 1. Constrained Bayesian Optimization Flow Chart

where the $x \in \mathbb{R}^d$. Typically, the d , namely the dimensions of the optimization objective, should ideally be less than 20 so the Bayesian Optimization can be conducted successfully [5].

The centerpiece of Bayesian Optimization is the use of a Gaussian Process ($\mathcal{GP}$) to fit the gradient evaluation-difficult function and to find the predicted value of the input x by the fitted function. A complete Bayesian Optimization consists of two main components: Acquisition Function and Surrogate Function. And the gradient evaluation-difficult function will be treated as a black box function during the optimization process. Only a small number of samples will be randomly sampled from the black box function. After obtaining the samples, the surrogate function in the optimization algorithm will use a Gaussian process to generate a probability distribution with mean μ and covariance kernel k . This computationally convenient probability distribution will be used as an alternative to the function to reduce the time required for optimization.

The role of the acquisition function is to find the point at which the optimal value is most likely to exist at each iteration. Some choices of acquisition algorithms include Probability of Improvement [7], Expected Improvement [8], and Upper Confidence Bound [9]. Considering the constraints that will be introduced in the optimization, we choose the Probability Improvement (PI) algorithm for optimal point acquisition. First, let x_c^* in Eq. (5) be the optimal value in the current optimization search process, namely:

$$x_c^* = \underset{x \in X_c}{\operatorname{argmin}} f(x) \quad (6)$$

where the X_c is the current data sets, including the initial samples and all the evaluated acquisition points.

According to Kushner [7], improvement to incorporate constraints can be defined as the reduction of the value of the function represented by the probe point compared to the current optimal value. Thus, the acquisition function can be

described as finding the point that maximizes the *improvement* (I) among a large number of candidate points (X_{ca}) in each iteration, namely:

$$I(x) = \operatorname{argmax}_{x \in X_{ca}} \{0, f(x_c^*) - f(x)\} \quad (7)$$

Afterward, this improvement will use the mean μ and covariance kernels σ from the $\mathcal{GP}$ to calculate the final PI. The formula is shown as follows:

$$PI(x) = \Phi\left(\frac{\mu_c^* - \mu(x)}{\sigma(x) + \xi}\right) \quad (8)$$

where the Φ is the Cumulative Distribution Function (CDF), and μ_c^* is the $f(x_c^*)$ or current optimal value in form of $\mathcal{GP}$ prediction. Note that ξ represents a very small number. In our program, the value is equal to 10^{-9} . Its purpose is to prevent the denominator from being zero and thus causing the program to report an error.

Figure 1 exhibits the entire process of the proposed constrained Bayesian Optimization. After running, the structure shows that the Acquisition Function will find an Evaluation Point, which is the optimal value of the $\mathcal{GP}$ response in the current sample set. This Evaluation Point is added to the sample set, and the $\mathcal{GP}$ generates a new Surrogate Function in the next iteration. The Acquisition Function will find another evaluation point based on this new $\mathcal{GP}$ Surrogate Function. After a certain number of iterations, the algorithm will find a result close enough to the real optimal solution.

The above algorithm structure embodies the overall framework of Bayesian Optimization. But it is not complete because the qualification of the objective function is not yet reflected in the algorithm. There are two difficulties in implementing the constraints. First, it is computationally difficult to compute the constraints on the VANETs network; second, if the constraints cannot be introduced in the optimization process, the final result is likely to be a local optimal that does not meet the constraints. This constrained Surrogate Function will use the $\mathcal{GP}$ to fit the qualification of each candidate, that is, whether they satisfy the constraints or not. This process is almost identical to the Acquisition Function described above. The only difference is that the sampled object is changed to the objective function for constraint results. After sampling and $\mathcal{GP}$ calculation, the $PI_{constrain}$ of the constraints will be obtained from Eq. (5). The magnitude of $PI_{constrain}$ represents the probability magnitude that the target sampling point meets the qualifying condition. Therefore, the equation for the target PI_{final} containing constrained information is expressed as follows:

$$PI_{final}(x) = PI(x)PI_{constrain}(x) \quad (9)$$

In this paper, we will optimize the VANETs communication parameters $\{\gamma, k, \lambda, N_{rp}\}$. Unlike the previous study, the backoff window size W_0 , which has a relatively small impact on the communication results, will be set to a fixed value of 1024 [3]. Meanwhile, a new tunable parameter γ is introduced, which is a coefficient indicating the power

Algorithm 1 Analytical Model Function

Input: ($\gamma, k, \lambda, N_{rp}$)

Output: (CBR, Constrain Result)

- 1: **Initialization:** Read the inputs
 - 2: Compute CBR, PRP, ED by analytical model
 - 3: **if** $PRP \geq \xi_p$ and $ED \leq \xi_d$:
 - 4: **then** Constrain Result = 1
 - 5: **else:**
 - 6: **then** Constrain Result = 0
 - 7: **Return** (CBR, Constrain Result)
-

Algorithm 2 Bayesian Optimization Procedure

- 1: Define the ranges for the parameter γ, k, λ , and N_{rp}
 - 2: Generate some initial parameter sets
 - 3: Put initial sets to Analytical Model and find results
 - 4: Fit Gaussian process ($\mathcal{GP}$) regression model for both CBRs and Constrain Results
 - 5: **for** i in range(250):
 - 6: Compute the $\mathcal{GP}$ predictions to find the current optimal CBR in the prior parameter sets
 - 7: Generate a list of random parameter sets
 - 8: Compute a list of μ and σ of this new sets by $\mathcal{GP}$
 - 9: Compute the PI for both CBRs and Constrains
 - 10: Multiply these two PI to obtain the valid PI
 - 11: Find the maximum PI and its parameter set
 - 12: Compute the actual CBR and Constrain of this parameter set by the Analytical model
 - 13: Add this parameter set into the prior parameter sets
 - 13: Find the minimum from the constrained CBR list
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magnitude of each node in the communication network. P_t is γP_{nr} , where P_{nr} is a nominal reference transmission power. In contrast to the other discrete integer parameters k, λ , and N_{rp} , the value of γ is a continuous variable.

C. Implementation of Bayesian Optimization Algorithm

The entire VANETs communication parameter constrained Bayesian Optimization algorithm consists of two parts. Algorithm 1 represents the objective function in Bayesian Optimization and is an analytical model of IEEE 802.11 VANETs. By entering the given four communication network parameters, the function will return the Channel Busy Rate (CBR) and the judgment result of the qualification condition. For Constrain, any combination of parameters that fail to satisfy $PRP \geq \xi_p$ and $ED \leq \xi_d$ is judged to be unqualified. In the algorithm, the failed Constrain result will be marked as 0, and the passed will be marked as 1. The purpose of this is that when calculating the $PI_{constrain}$ in Eq. (9), the PI evaluation point that does not meet the constraints will have a small $PI_{constrain}$ value. This will ensure that the final optimal value found will meet the constraints. Unlike Gardner et al., who compute $\mathcal{GP}$ s for each constraint condition, our approach merges the two qualifying conditions, PRP and ED, by outputting results that simultaneously meet the requirements through the analytical model [10]. In this way, only one additional $\mathcal{GP}$ for the constraints is needed in Bayesian Optimization, significantly reducing the optimization time.

Algorithm 2 is the main body of Bayesian Optimization. The program will randomly generate several sets of parameters $\{\gamma, k, \lambda, Nrp\}$ to sample a small range of the analytic model. Given the computational complexity of the model, in our experiments, we set the initial number of samples to 5. These initial sampling points will include the size of the CBRs and the results of the judgments on the constraints. Subsequently, two $\mathcal{GP}$ models will be fitted to the CBRs and constrain results, respectively. These two $\mathcal{GP}$ models will replace the computationally complex analytical model for the optimization search. According to the characteristics of $\mathcal{GP}$, the initial Surrogate Function will only be fitted with high accuracy around the sampling points. To approach the actual optimal solution, the Surrogate Function needs a new sampling point to update its model. This sampling point should be the optimal solution in the current Surrogate Function. Thus, the algorithm will find the set of parameters that minimizes the $PI_{constrain}$ in Eq. (9) and bring this set of parameters into the analysis function to obtain the evaluation point for updating the $\mathcal{GP}$ model. After a certain number of iterations, the optimal solution found on the $\mathcal{GP}$ model will be very close to the actual optimal solution, which indicates the success of the optimization.

IV. NUMERICAL RESULTS AND DISCUSSIONS

In order to test the effectiveness of the program, a slow vehicle warning (SVW) safety application was selected as the test standard. The communication network parameters for VANET in our experiments are listed in TABLE I. The QoS required for the SVW safety application is listed in TABLE II below. In these communication parameters, the communication transmission power is a continuous variable taking values in the range of 0 to 10. We will search via the Bayesian Optimization and find the communication parameter set that minimizes the channel busy rate (CBR).

We set Node density to 0.2 or 0.3 nodes/m, and Bandwidth to 20 or 120MHz. And we used the other data from Table I to perform restricted Bayesian search experiments. The two experimental results are shown in the following graphs. The experimental run times and optimized communication parameters are obtained in TABLE III. For different Bands and densities, 200 iterations are performed for each optimization search. By looking at the graphs we can see that the optimization object CBR converges quickly at the beginning. The discrete points in the graph represent the communication network parameters found by the Bayesian acquisition function after each iteration, and the parameters are brought into the analysis function to calculate the obtained CBR values. Since the predictions of the restricted Bayesian Optimization are not completely accurate, the set of parameters generated during the iterations may not satisfy the restrictions. In the discrete points, the solid blue dots represent the parameters of the communication network validated by the analytical model, while the blue cross symbols represent the CBRs that are predicted by the Bayesian network but actually do not satisfy the constraints after validation by the analytical model. This means that the

TABLE I Communication parameter settings

Parameters	Values	Parameters	Values
Average sensing range rE	500 m	Packet generation rate λ	2~40 packets/s
Slot time t_s	13 μs	No. of subcarriers	52
Preamble duration	4 μs	Bandwidth BW	10~160 MHz
AIFS	64 μs	Packet length PL	1600 bytes
CW W_0	2~1024	Node trans. power P_t	0~10
Symbol duration t_{sy}	1~8 μs	MCS index k	6~10
Coding rate r	$\frac{3}{4}, \frac{5}{6}$	Packet Rep. no. Nrp	1~10
MAC header	64 bits	Node density β	0.1~0.3 v/m

TABLE II QoS Requirements for SVW safety applications

Safety Apps	SVW
ROI (d_{ROI})	100 m
Tolerance Delay time ξ_d	0.01 s
APP probability requirement (ξ_p)	99.9%

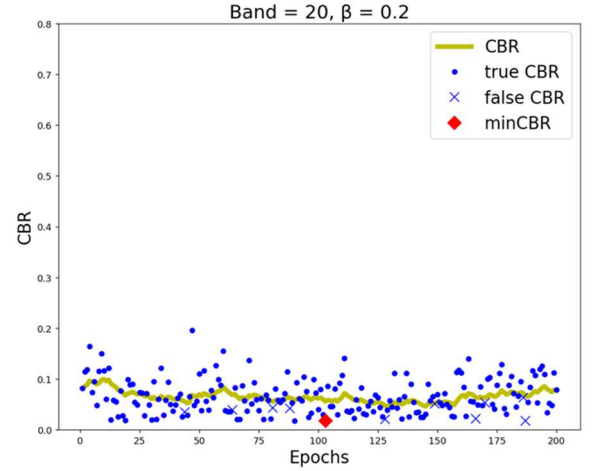


Figure 2. Optimization convergence curve; Bandwidth = 20 MHz, $\beta = 0.2$ nodes/m

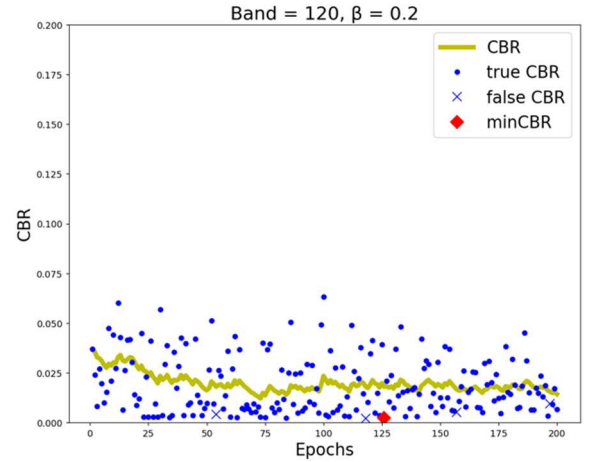


Figure 3. Optimization convergence curve; Bandwidth = 120 MHz, $\beta = 0.2$ nodes/m

TABLE III Comparison of optimization algorithms

Density	0.2 nodes/m		0.3 nodes/m		0.2 nodes/m	
Bandwidth	20 MHz		20 MHz		120 MHz	
	Bayesian	Grid	Bayesian	Grid	Bayesian	Grid
time	85s	574.39s	90s	572.74s	85s	657.87s
min CBR	0.0175	0.0168	0.0272	0.0263	0.0022	0.0021
γ	2.644	6.8	3.367	8.9	2.202	0.9
k	8	8	8	10	10	10
λ	1	1	1	1	1	1
Nrp	1	1	1	1	1	1
PRP	0.9993	0.999	0.9990	0.9990	0.9997	0.9992
ED	0.00043	0.0004	0.00046	0.0004	5.6E-05	6.0E-05

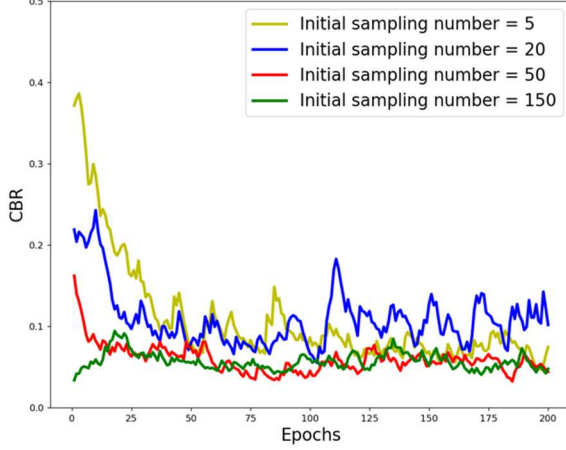


Figure 4. Relationship between the initial sampling number and convergence speed

restricted Bayesian model achieves the prediction of the validity of the communication parameters while collecting the optimal values.

In TABLE III, we compare Bayesian Optimization with the Grid search algorithm which is a traditional parametric optimization method [11]. It samples all discrete parameter (k, λ, Nrp) values in their intervals. We use uniform sampling for the continuous variable γ with a step size of 0.1. Then, four parameters are then combined and used for optimization. Experimental results show that our Bayesian Optimization algorithm can find an optimal solution close to the grid search but in a much shorter time (less than 100 seconds for Bayesian Optimization vs. more than 500 seconds for Grid optimization. This reflects the superiority of our algorithm in terms of optimization efficiency. In other words, the proposed Bayesian Optimization algorithm is more suitable for real time optimization of vehicular communication systems.

In our experiments, we found that the initial number of samples for analyzing the model has a crucial impact on the optimization results. In the beginning, only five samples were collected for the initial fit of the $\mathcal{GP}$ model, which resulted in a low success rate under the short running time requirement. Subsequently, we increased the initial number of sampling points, and the results showed that the success rate of the optimization within the specified time was greatly improved. We believe this is because sufficient sampling points allow the $\mathcal{GP}$ model to fit the analysis function adequately at the

beginning. As Figure 4 shows, as the initial number of samples increases, the function converges more quickly to the vicinity of the optimal value, improving the optimization-seeking accuracy. As a result, the Acquisition Function can more accurately find candidates for the optimal value during the iterative process.

V. CONCLUSIONS

In this paper, an approach to finding optimal parameters of IEEE 802.11 vehicular communication networks using Constrained Bayesian Optimization is presented. The advantage of the method is the inclusion of continuously varying values in the parameter objective of the optimization search, which enhances the practical usefulness of the scheme. Another contribution of the proposed approach is to incorporate the constraints of the VANET applications into the Bayesian search process and still maintain the stability and effectiveness of the scheme. Compared with other non-gradient searching algorithms, this scheme can stably converge to the optimal solution in real time. This core algorithm of the scheme could also be applied to any optimization problem with high computation complexity and requiring constraints in the future.

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