Constrained Bayesian Optimization of VANET Safety Messaging Using Deep Learning Neural Networks

Aidan Samuel Wright, Sandeep John Philip, and Xiaomin Ma,
School of Engineering, Oral Roberts University, Tulsa, OK 74171, USA
Emails: aidan_w@oru.edu, sandeepjohnphilip@oru.edu, xma@oru.edu

***Abstract*—Bayesian optimization has been used for the global optimization of communication parameters of Vehicular Ad Hoc Networks (VANETs) for safety applications with stringent quality of service (QoS) requirements. However, the effectiveness of the methodology relies on an accurate analytic model for querying a distribution over functions, which is not practical. Furthermore, incorporating QoS requirements as constraints into the search process is cumbersome, time-consuming, and even unreliable. In this paper, we present a new approach to the constrained Bayesian optimization of IEEE 801.11 based VANETs for safety messaging with the help of deep learning neural networks (DLNNs). First, we design and train a DLNN using data collected from the analytic models or channel measurements to approximate a mapping from the search parameter space to the QoS metrics. The QoS constraints are naturally incorporated into the DLNN through sorting out data pairs that cannot meet the QoS requirements. Then, the Bayesian optimization is conducted to find the optimal communication parameters for the best channel usage On the condition that all QoS requirements are met. To assure the convergence and stability of the optimization process, a new shaking algorithm is proposed in the event that the optimized parameters do not meet the QoS requirements due to possible generalization errors in the DLNN. Accordingly, experiments are carried out on a Google Colab platform where the impact of DLNN structure, data sampling rate, and other optimization parameters are investigated. In comparison to other optimization approaches, utilizing a DLNN in the Bayesian optimization process is more efficient and flexible.**

Keywords— Bayesian Optimization, Vehicular Ad hoc networks, Deep Learning Neural Networks, Quality of Service, Safety

I. Introduction

Road safety of vehicles and autonomous vehicles can be potentially improved by deployment of Vehicular Ad Hoc Networks (VANETs) through which vehicles are able to communicate with each other and be aware of other vehicles and road conditions via exchanging safety related messages. IEEE 802.11 based communication system with recently upgraded technologies such as higher speed modulation and coding schemes (MCS), high channel bandwidth, etc., is one of two candidates for Vehicle to Everything (V2X) safety applications. Since the vehicular communication environments and traffic change very frequently, and the different safety applications require different quality of service (QoS) requirements, delivering safety messages with fixed communication parameters could cause poor QoS or low channel efficiency. It is natural to come up optimization schemes to dynamically adjust communication parameters for high efficiency of channel usages based on the observation of communication channels and road traffic.

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. Since vehicular communication systems are very complex systems that cannot be characterized by simple models, it is hard to apply many existing gradient based optimization algorithms to find the best solutions within a reasonable time duration. Bayesian optimization is an effective approach for non-gradient model-based global optimization of random black-box functions [3], which allows balanced extrapolation and interpolation in the search process. Recently, a Bayesian optimization scheme was proposed to optimize the parameters of IEEE 802.11 based VANET in real-time for vehicular safety applications [4]. However, the optimization scheme needs to run the analytic model in each iteration of the optimization, and the constraint incorporation process via the introduction of the probability magnitude that the target sampling point meets the QoS requirements is very time consuming and potentially unreliable.

To overcome the shortcomings of the existing schemes, this paper proposes a new constrained Bayesian optimization of IEEE 801.11 based VANETs for safety messaging with the help of deep learning neural networks (DLNNs). First, a DLNN is introduced and configured to realize a mapping from the communication parameter space which covers the parameters of the network information transmission rate, MCS index, the number of message repetitions and communication transmission power to QoS metrics including Channel Busy Rate, Packet Reception Probability, and Packet Transmission Delay. All data collected from either the analytic models or real channel measurement are sorted out to meet the QoS requirements. In other words, the DLNN is trained by constrained data. Then, the DLNN trained function replaces the optimization objective function and is involved into the Bayesian optimization algorithm to search the parameter set that minimizes the channel usage or maximizes the channel efficiency. The parallelism and generalization capabilities of DLNNs help improve the accuracy and speed of the search. To assure the convergence and stability of the optimization process, a new shaking algorithm is proposed in case the optimized parameters cannot meet the QoS requirements due to possible generalization errors of DLNN.

Compared with the previous Bayesian optimization methods for VANETs, the main contributions of this paper are: 1) The proposed scheme introduces a DLNN as an alternative of the objective function in the Bayesian Optimization algorithm. This new approach makes incorporating constraints into the optimization easier and more efficient. 2) The new shaking algorithm is designed to further assure the robustness of the DLNN based Bayesian algorithms 3) The algorithm of new Bayesian Optimization is implemented and compared with other optimization algorithms in terms of convergence speed, optimization precision, and optimization reliability that will facilitate real-time optimization of the VANETs.

The paper is organized as follows. Section II gives a brief overview of IEEE 802.11 based VANETs for safety messaging and optimization problem formulation. Section III describes the new DLNN based Bayesian Optimization scheme and how it is implemented. 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 802.11based VANET for BSM Services

VANETs powered by the IEEE 802.11 communication system are utilized to deliver safety services via one-hop or multi-hop broadcasting, which disseminate real-time traffic information or safety-related messages. The PHY layer of the communication system utilizes Orthogonal Frequency Division Multiplexing (OFDM) operating in the licensed 5.9 GHz frequency band with bandwidths ranging from 5 MHz to 160 MHz. The introduction of Low-Density Parity Check (LDPC) error-correction coding in the PHY layer provides a sensitivity gain of 2~3 dB and increased spectral efficiency compared to the Binary Convolutional Code (BCC) for channel coding. The system with channel tracking using midamble symbols sustains higher-rate MCS up to 256-QAM (MCS index k=8) and 1024-QAM (MCS index k=10) with 52 data subcarriers. The implementation of new multi-user multiple-input and multiple-output (MU-MIMO) and Dual Carrier Modulation (DCM) is anticipated to provide a diversity gain of approximately 3dB, resulting in an extension of the safety range. In the MAC layer, the channel access protocol adopts an enhanced distributed channel access (EDCA) method with carrier sense multiple access with collision avoidance (CSMA/CA). To improve the reliability of safety messaging, in view of the high transmission rate and high channel bandwidth, IEEE 802.11bd adopts an adaptive retransmission scheme where the number of retransmissions N_{rp} (1~3) is dynamically changed with the measured occupancy of the channel.

The use of advanced high data-rate communication technologies in IEEE 802.11 driven VANETs has the potential to support numerous safety services in both human driving and autonomous driving, which were previously uncertain due to their high QoS requirements.

Our research in this paper focuses on Basic Safety Messages (BSMs) services. BSMs are broadcasted by each vehicle in the VANETs regularly to keep drivers alert about the status of nearby vehicles. It is evident that these safety-critical services are time-sensitive and necessitate high reliability. The corresponding QoS requirements are listed in [5]. Interferences from transmissions of other nodes, high mobility of vehicles, unfavorable multi-path fading/shadowing channels, and channel additive noise are the primary factors that deteriorate the QoS of BSM broadcast in VANETs.

B. System Model and Metrics for Bayesian Optimization

To facilitate the optimization of IEEE 802.11 VANET for safety messaging, we need to have a good understanding of the communication system and channels. Mathematically, given a communication parameter set S_p and a QoS set, an immediate mapping from the parameters to the QoS metrics $QoS=f(S_p)$ is needed, which can be derived from either the analytical model for IEEE 802.11 broadcast ad hoc networks [5], the simulation model [6], or real-time measurements. For the BSM related safety services, $S_p=\{P_t, k, \lambda, N_{rp}\}$, 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. QoS={*PRP*, *ED*, *CBR*}, where the three main QoSs: *PRP*, *ED*), and *CBR* are defined as follows.

First, the Packet 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.

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.

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:

$$CBR = 100\% \times \frac{Duration\ Channel\ indicated\ as\ busy}{Channel\ observation\ interval} \tag{1}$$

In this paper, we assume that the above mapping is known and derived. For detailed understanding of the communication systems for safety applications and derivation or data collection of the mapping, please refer to the related references [5] [6]

III. Structure and Implementation of the Bayyesian Optimization with Constraints Using DLNN

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. Bayesian Optimization methods are chosen to meet this requirement and achieve stable and reliable optimization.

Consider a VANET where each node is equipped with IEEE 802.11 OFDM communication capability and transmits safety related BSM messages regularly to its one-hop neighbor(s) in broadcast mode. The safety messages are received by all nodes within the transmitter's Region of Interest (ROI) based on the signal-to-interference and noise ratios (SINRs) measured in real-time. the primary factors that impact the QoS of the network are interferences and multi-path fading/shadowing, which can be characterized by cumulative density function (CDF) of SINR: $F_{SINR|d}(\theta)$ as a function of SINR threshold θ at a given distance d and probability density function (PDF) of node receiving power P_{rx}: $f_{P_{rx}|d}(x)$.

As the communication environments and safety applications in VANETs are subject to constant change, a fixed communication parameter configuration may result in inadequate QoS or ineffective use of communication resources. An optimization platform combining Bayesian optimization and a meticulously configured DLNN is proposed to adaptively adjust the communication network parameters for sufficient and efficient use of the communication resources. 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. These parameter values are dropped in a value range set S_{cp} due to their physical limitation and nature of the parameters.

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

$$\min_{S_p} CBR$$

$$\text{subject to } PRP(RoI, S_p) \geq \xi_p, ED \leq \xi_{d,} S_p \in S_{cp}. \quad (2)$$

B. Structure and Implementation of Constrained Bayesian Optimization with DLNN

The Bayesian Optimization is a conventional optimization method when the function to be optimized becomes gradient evaluation-difficult or when the evaluation process takes a long time or a lot of human and monetary resources. The framework of Bayesian Optimization in the context of can be formulated as the following expression:

$$x^* = \underset{x \in S_{cp}}{argmin}\, f(x) \quad (3)$$

where the $x = S_p \in \mathbb{R}^d$. x^* is the optimal set of S_p. 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. Complete Bayesian Optimization consists of two main components: Acquisition Function and Surrogate Function. After obtaining the samples, the surrogate function in the optimization algorithm will use a Gaussian process to generate a probability distribution. This computationally convenient probability distribution will be used as an alternative to the function to reduce the time required for

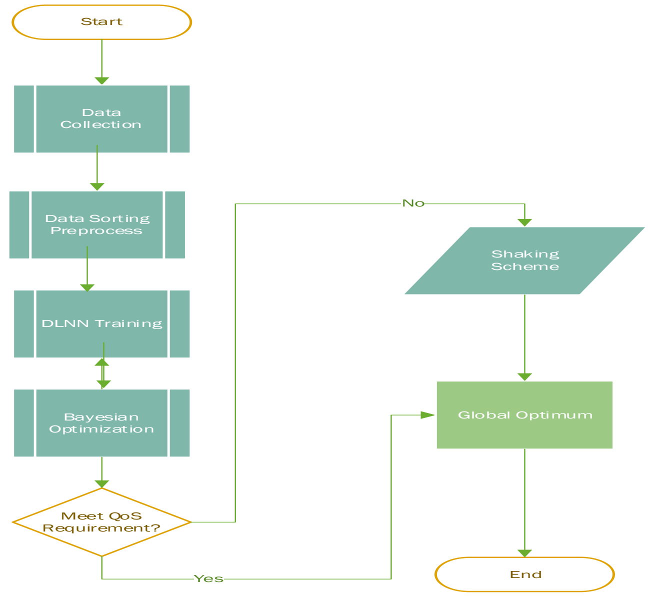

Figure 1 Flowchart of DLNN based Constrained Bayesian Optimization

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.

Figure 1 exhibits the entire process of the proposed constrained Bayesian Optimization. First, the sampled objective function $f(x)=CBR(S_p)$ needs to be specified at each iteration. Next, the inequity constraints in Eq. (2) are required to be incorporated into the Bayesian optimization process. Although there were several approaches [5], [9] to change surrogate function to implement constraint in acquisition function, they added more computation load and risk of low reliability of searching. In this paper, we propose to replace the analytical model with a DLNN for the mapping $f(x)$. There are three reasons for making this change. First, the constraints can be naturally incorporated into $f(x)$ if the DLNN is trained with the data where the lowest CBR surely meets the QoS requirements. In this way, manipulation and change of internal structure of Bayesian algorithm can be avoided. Second, with parallel and generalization capability of DLNN, the scale of data sampling and generation can be reduced for the same searching precision. Therefore, the searching process can be sped up. Third, the DLNN can be potentially retrained to adapt to the changes of wireless channels and vehicular traffic environments.

To build a framework of DLNN-driven Bayesian Optimization, data pairs for training the DLNN are collected and sampled from running analytic models, simulations, or real-time measurements. Then, the collected data is sorted to keep the data pairs that meet the QoS requirements, thus shaping a new standardized training data set $\{CBR, S_p\}|QoS{>}QoS_{req}$ & $\{CBR{=}1, S_p\}|QoS{\leq}QoS_{req}$. To speed up the searching process, the data pairs can be further sorted to only keep the data pairs where relatively smaller CBRs are observed. The data is used to train a DLNN to accomplish the following mapping:

$$CBR = f_L(S_p) \quad (4)$$

Once the DLNN training is completed, the trained DLNN $f_L(x)$ is used to replace $f(x)$ in Eq. (3). The Bayesian algorithm is called to set up Gaussian surrogate function and acquisition function to find the optimal point x^*. Since the DLNN approximates $f(x)$, there is the rare possibility that the optimized x^* set leads to a situation where the QoS constraints are not satisfied due to possible mapping errors or a low sampling rate. To deal with the possible situation and assure the robustness of the optimization, a shaking algorithm is proposed in case that x^* fails to meet the QoS requirements. The basic idea of the shaking algorithm is to alter the values in the set x^* within small range according to physical meaning of the respective parameters. Then, test the alternative parameter values using the original model to see which ones satisfy the QoS requirements. If there is more than one set meeting the requirements, the one with the minimum CBR is selected. If there is no one set meeting the QoS requirements, extend the shaking ranges and repeat the shaking algorithm until a viable set is found.

C. Implementation of Bayesian Optimization Algorithm

In this paper, the VANETs communication parameters to be optimized $\{P_t, k, \lambda, Nrp\}$ is converted to $\{\gamma, k, \lambda, Nrp\}$, where a tunable parameter γ is a coefficient indicating the power magnitude of each transmitting node in the communication network. $P_t = \gamma P_{nr}$, 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.

The entire VANETs communication parameter constrained Bayesian Optimization algorithm is composed of two sub algorithms. Algorithm 1 runs system models to generate data pairs and DLNN training for objective function mapping and QoS function mapping. By entering the given four communication network parameters, the functions will return the Channel Busy Rate (CBR) and the judgment result of the qualification condition. Algorithm 2 conducts the constrained Bayesian optimization.

As demonstrated in the pseudo code for Algorithm 1, the analytical model or other accepts communication and network parameters, along with channel fading and shadowing characteristics, which are represented as $f_{P_{rx}|d}(x)$ (which can be acquired from theoretical equation for typical vehicular communication channel or measured and statistically summarized from real channel measurements). Going through the adjustable parameters in their possible value ranges, the model is run to produce a set of mapping data: $\{S_p, QoS\}$. As the data set is being generated, a data preprocessing scheme is applied to shape a new standardized training data set $\{CBR, S_p\}|QoS>QoS_{req}$ & $\{CBR=1, S_p\}|QoS \le QoS_{req}$. To assure fast convergency of the learning and to maintain balance between accuracy and generalization capability of the DLNN model, we elaborate on and come up with an effective DLNN configuration that fits our optimization structure well. Based on the principle that deeper and wider neural networks with random initialized weights and enough distance between training patterns can be trained with high precision and generalize better, we carefully configure a DLNN model using Google Tensorflow as a regression model with four inputs and one output. Three hidden layers with 64, 128, and 32 neurons in each individual layer, respectively. In the DLNN, ReLU is selected for the layers. The ADAM optimizer is selected as the training optimizer of the DLNN; The Mean Absolute Error (MAE) function is chosen for the loss function in the training process. In addition, the preprocessing schemes described previously can assure satisfactory distance between the training samples. All weights in the DLNN are initialized with random numbers generated from Gaussian distribution with mean 0 and variance 0.0001. Furthermore, L_2 regularization and Dropout strategies are introduced to overcome overfitting while keeping sufficient precision in the meantime.

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

Algorithm 1 Data Generation and DLNN Training

Initialization: variables range of γ, k, λ, Nrp
for parameters in ranges S_p and r_{CS}, β **do**
  input S_p, r_{CS}, β, and W_0 into the **QoS generator model**; and
  execute the model to derive *PRP*, *ED*, *CBR*
  return the results as **mapping data**
end for
generate mapping data: $\{PRP, ED, CBR\}=f(\gamma, k, \lambda, Nrp)$
preprocess and **standardize** data$\{CBR|\ QoS>QoS_{req}, S_p\}$
regroup and split into the training data and valid data
build DLNN and **train** by following parameters**:**
define inputs=$\{\gamma, k, \lambda, Nrp\}$, output=$\{CBR\}$
  x = layers.GaussianNoise(0.001)(inputs)
  x = layers.Dense(64, activation= 'relu', kernel_regularizer=tf.keras.regularizers.L2(0.001))(inputs)
  x = layers.Dense(128, activation='relu')(x)
  x = layers.Dense(32, activation='relu')(x)
  outputs= layers.Dense(1)(x)
compile model with optimizer=ADAM, Loss=MAE with L2 regularizer, Metrics=accuracy
train model with **data**, epochs=150, batch size=250;
return DLNN $f_L(S_p)$ **model** from training
searching the **minimum *CBR*** from **training data** as a local minimum

Algorithm 2 DLNN based Bayesian Optimization Procedure

Define the ranges for the parameter γ, k, λ, and *Nrp*
Generate some initial parameter sets S_p
Run DLNN model $f_L(S_p)$ with initial sets and find results
Fit Gaussian process ($\mathcal{GP}$) regression model for *CBR*s
for *i* **in** range(250):
    Compute the $\mathcal{GP}$ predictions to find the current optimal CBR in the prior parameter sets
    Generate a list of random parameter sets
    Compute the acquisition function
    Find the minimum CBR and its parameter set
    Compute the actual CBR and parameter set by running a general model $CBR = f_L(x^*)$
    Add this parameter set into the prior parameter sets
Find the minimum from the CBR list and corresponding parameter set x^*
end for
If ($f(x^*) < QoS_{req}$) **do**
decide shaking ranges of 4 parameters: δ_1, δ_2, δ_3, δ_4
for j=1 to 4
compute {QoS, CBR} $= f(x_j^* \pm \delta_j, x_i\ (i = 1{,}4\ and\ i \neq j))$
end for
find minimum *CBR* and parameter set x'^* such that $f(x'^*) > QoS_{req}$
otherwise extend the shaking range, redo shaking and checking
end do
find the true global optimal solution to *CBR*

Surrogate Function. Thus, the algorithm will find the set of parameters 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 proposed scheme and compare it with the previous optimization approaches, the same communication network parameters for VANET with the same slow vehicle warning (SVW) safety application are selected and then run the program in a Google Colab platform. For keeping this paper self-contained, the communication network parameters in our experiments and the QoS requirements for the SVW safety application are listed in TABLE I and TABLE II, respectively. Among the communication parameters to be optimized, the communication transmission power is a continuous variable taking values in the range of 0 to 10. The other parameters: k, λ, and N_{rp} are integers. The searching program via the DLNN and Bayesian Optimization will be called to find the communication parameter set that minimizes the channel busy rate (CBR).

Figure 2 shows the convergence of the deep learning neural network for function mapping $f(x)=CBR(S_p)$. The training data is provided by running the stochastic model. 25 percent of the data generated from the model is used for the purpose of validation. From Figure 2, we can see that both the loss values and the validation error values decrease consistently as the training process continues. After 500 epochs, the average loss value is 0.0052 and the average validation error is 0.0055, which indicates that the neural network has successfully learned the function mapping $f(S_p)$ with sufficient accuracy and generalization capability.

To show the advantages of the proposed optimization scheme, three typical optimization algorithms for searching the optimal parameters are compared: the proposed combination of deep learning neural network and Bayesian optimization algorithm, the constrained optimization scheme in [5], and a traditional grid search algorithm [10]. We set node density to 0.2 or 0.3 nodes/m, and Bandwidth to 20 or 120MHz. The three experimental results with the optimization run times are shown in TABLE III. For different values of bandwidth and density, 200 iterations are

TABLE I Communication parameter settings

Parameters	Values	Parameters	Values
Average sensing range r_E	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*	¾, 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 (ξp)	99.9%

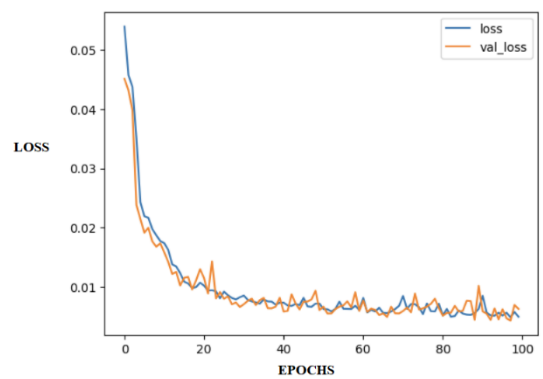

Figure 2. Training loss and validation loss of the neural network model used to replace the function $f(S_p)$.

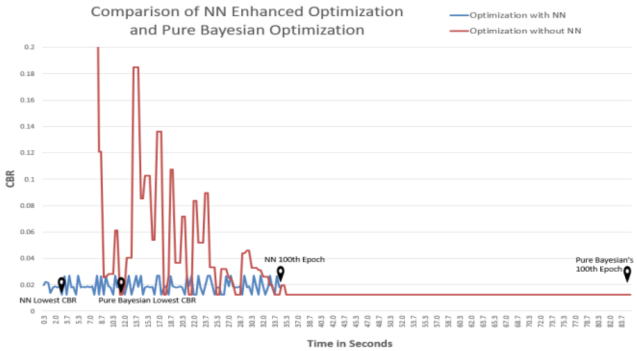

Figure 3. Pure Bayesian optimization (red) compared with neural network enhanced Bayesian optimization (blue)

performed for each optimization search. The experimental results in TABLE III show that our deep learning-based optimization algorithm can find an optimal solution close to the grid search in most cases but in a much shorter time compared with other two optimization algorithms (less than 50 seconds for the proposed optimization scheme vs. less than 100 seconds for restricted Bayesian Optimization vs. more than 500 seconds for the Grid optimization), which reflects the superiority of our optimization scheme in terms of optimization efficiency. In other words, the proposed deep learning-based Bayesian Optimization algorithm is more suitable for real time optimization of vehicular communication systems.

In Figure 3, the Bayesian optimization process is run for 100 iterations, one is the restricted Bayesian optimization using the QOS function (outlined in red) [5], and the other is our proposed deep learning-based Bayesian optimization using the neural network that replaces the QOS function (outlined in blue). As made apparent by the graph, the Bayesian optimization function can run much faster when it calls the neural network as opposed to calling the QOS function. The reason for the observation is that the neural network with high mapping accuracy and generalization capability in the Bayesian model achieves the prediction of the validity of the communication parameters while collecting the optimal values under given constraints.

V. CONCLUSIONS

In this paper, a new approach to find optimal parameters of IEEE 802.11 vehicular communication networks using constrained deep learning-based Bayesian Optimization is proposed and implemented. The main advantages of the method are the inclusion of constraints in the optimization via training a DLNN with generalization capability to replace the mapping function for Bayesian optimization and the design of the shaking scheme for robust optimization. The data for the function learning could be collected from analytic models or real-time measurements, which are carefully preprocessed using normalization and manual CBR sorting to facilitate fast and efficient optimization process. The numerical experiments show the effectiveness and adaptability of the optimization scheme under various network configurations and scales. Compared with other similar search algorithms, this scheme can stably converge to the optimal solution in real time. This core thread of the scheme could be generalized and applied to many optimization problems which require the use of constraints and those with high computation complexity in the future.

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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		
	Neural Network	Bayesian	Grid	Neural Network	Bayesian	Grid	Neural Network	Bayesian	Grid
time	40s	85s	574.39s	45s	90s	572.74s	45s	85s	657.87s
min CBR	0.0168	0.0175	0.0168	0.02635	0.0272	0.0263	0.0022	0.0022	0.0021
γ	6.8	2.644	6.8	9	3.367	8.9	1.14	2.202	0.9
k	10	8	8	10	8	10	10	10	10
λ	1	1	1	1	1	1	1	1	1
Nrp	1	1	1	1	1	1	1	1	1
PRP	0.9991	0.9993	0.999	0.999	0.9990	0.9990	0.9997	0.9997	0.9992
ED	0.0004	0.00043	0.0004	0.0004	0.00046	0.0004	5.5E-05	5.6E-05	6.0E-05