Market Penetration Rate Optimization for Mobility Benefits of Connected Vehicles: A Bayesian Optimization Approach

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ABASTRACT

The advancements of connected vehicle (CV) technologies promise significant safety, mobility, and environmental benefits for the future transportation systems. These benefits will largely rely on the market penetration rate (MPR) of CVs and connected infrastructure. However, higher market penetration is not guaranteed to result in greater benefits in a transportation system in some cases even if we do not consider the deployment cost of CVs. Therefore, understanding the optimal CV MPR to achieve the best system benefits is informative and can provide some guidance for transportation agencies to use appropriate incentives or other policies to potentially impact the speed of CV adoption. Instead of using the traditional incremental method, this paper proposed a simulation-based approach combined with Bayesian Optimization to determine the optimal CV MPR that achieves the highest performance benefits for a freeway segment. The proposed methodology is tested in the I-210 E (in California) simulation freeway segment built and calibrated in SUMO simulation software as a case study. The weighted sum of the average total travel time on the mainline and the average queue length of on-ramps is formulated as the objective function to optimize the CV MPR. Different weight combinations are tested as different scenarios. The optimization results of these scenarios show that when the weight of total travel time is high, the optimal CV MPR tends to be high. On the contrary, when the weight of queue length increases, higher CV MPRs may not guarantee higher benefits for the traffic system. The globally optimal CV MPR can be as low as 3%. The case study also confirms the effectiveness of optimizing the CV MPR based on microsimulation and Bayesian Optimization.

Keywords: Connected vehicle, Market penetration, Traffic simulation, Bayesian Optimization

INTRODUCTION

The connected vehicle (CV) technology is a mobile platform that enables a new way of data exchange among vehicles and between vehicles, pedestrians, and infrastructure (*1*). The past few decades have witnessed the great advancement of the CV technology in both real-world testing, deployment and the research field (*2*). By enabling vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-pedestrian communications, the CV technologies promise significant safety, mobility, and environmental benefits for the future transportation systems with wider adoption and new advancements (*3, 4*). These benefits will largely rely on the market penetration rate (MPR) of CVs and connected infrastructure. However, like many other novel technologies, the adoption of CV technology is a gradual process. Before being fully deployed in the real world, the CV technologies need to be tested and evaluated in a controlled environment.

However, in the near-term, the low market penetration rates of CVs and the limited, non-uniform availability of CV data make it challenging for researchers to fully understand the impacts of CV technologies. Even with some data from an actual CV pilot, the level of data that can be observed or field measured may be insufficient to reach detailed conclusions about the efficiency and benefits of the CV technology adoption (*5*). Therefore, microscopic traffic simulation has drawn considerable attention for the performance evaluation of CV technologies, which can provide a controlled environment that eliminates the impacts of confounding factors. The TRB National Cooperative Highway Research Program (NCHRP) Research Report 997 (*6*) suggests state and local transportation agencies to take early advantages of CV data, such as Basic Safety Message (BSM) data, including the emulated BSMs that can be derived from simulation models to reduce costs, improve accuracy, and add new mobility and safety measures to their systems management capabilities. Other examples include Haas and Friedrich (*7)* who used a micro-simulation model in SUMO to test the autonomous connected platoons application of logistics vehicles and demonstrated the impact of varying platoon numbers and sizes on the travel time. So et al. (*8)* used VISSIM to create an integrated simulation environment to assess the safety impact of the CV-based driver warning systems. The evaluation results showed that the V2V/V2I communication delays can degrade the effectiveness of driver warnings, and the driver warnings under ideal conditions can effectively reduce traffic conflicts. Huang et al. (*9*) developed a novel simulation test bed and adopted it to test the mobility and environmental benefits of the intelligent intersection control application. The study demonstrated the utility of using the simulation test bed in the design and evaluation of CV applications.

The microscopic traffic simulation is also powerful when considering different levels of MPRs. There are many studies in the literature that evaluate the benefits of CV technologies by testing different levels of CV MPRs. However, most of these studies only tested a few values of MPRs using the incremental method instead of regarding the CV MPR as a continuous variable, hence failed to fully evaluate the impacts of market penetration of CVs. This paper will show that in some cases higher market penetration is not guaranteed to result in greater benefits in a transportation system, even if we do not consider the deployment cost of CVs. Besides, the traditional incremental approach may miss the actual "optimal" point as most studies only tested a limited number of scenarios, and sometimes they can be very sparse like 10%, 25%,50%, etc. Therefore, regarding the CV MPR as a continuous variable, assessing the impacts of MPR on transportation system performance can be viewed as a global optimization problem.

This paper aims to provide a methodology to determine the optimal MPR that achieves the highest performance benefits in a freeway segment. The proposed methodology is a simulation-based approach combined with the Bayesian Optimization algorithm. Compared with the traditional incremental method, the proposed methodology considers the CV MPR as a continuous variable and can search for the optimum globally. Bayesian Optimization is a powerful global optimization technique and has been successfully applied to tackle transportation problems in recent years (*10-12*). The derivative-free feature of Bayesian Optimization makes it attractive for black-box functions which are very common in the transportation field. The proposed methodology is tested on a freeway segment with ramp metering strategies. By evaluating the total travel time and on-ramp queue length of the freeway segment, an optimal MPR of CVs can be obtained. The results show that the deployment of CV combined with ramp metering strategies as shown in the case study in this paper can be optimized considering the system performance benefits, and the simulation-based approach combined with the Bayesian Optimization algorithm is powerful for such problems.

LITERATURE REVIEW

As transportation technology evolves, there are three new kinds of vehicles being introduced into the automobile market with respect to vehicle automation namely, automated vehicle (AV), connected vehicle (CV), and connected and automated vehicle (CAV). It is important to understand the difference between the three terms. According to the definitions of the U.S. Department of Transportation (DOT), CVs are vehicles "using wireless exchange of data to allow vehicles to communicate between one another and with the roadway infrastructure", AVs are vehicles that "use information from cameras, radar, lidar (image sensing), Global Positioning System (GPS), odometry, and computer vision to detect their surroundings, and can take control over some, or all, human driving tasks such as steering, accelerating, and braking with little to no human input", and CAV technology is a broad term that combines both CV and AV technology (*13*). In literature, CV technologies are usually studied along with CAVs. There are two main topics on CV and CAV technologies regarding the market penetration rates. The first one focuses on the adoption of the CAVs and aims to predict the market penetration based on expert knowledge, adoption experience of other technologies, or analytical modeling. For example, a group of experts from the Institute of Electrical and Electronics Engineers (IEEE) suggest that about 75% of all vehicles will be CAVs by 2040 (*14*). Lavasani et al. developed a generalized Bass diffusion model for predicting autonomous vehicle (AV) technology adoption on the basis of data from earlier technologies such as Internet and cell phones (*15*). Laidlaw et al. applied probit models to the data obtained from a survey in the Greater Toronto and Hamilton Area, and found that land use, age, price, and information about CAVs are the main predictors of adoption (*16*). There are also a number of studies using discrete choice modeling (*17, 18*). However, the traditional discrete choice models suffer from the problematic assumption of "rational expectations" when dealing with a radical innovation such as CAV. Therefore, more advanced models which incorporated peer effects have gained more power for discrete choice analysis of CAV technologies (*19, 20*). Talebian and Mishra (*14*) proposed a long-term forecasting model by coupling the theory of Diffusion of Innovation (DOI) with agent-based simulation modeling (ABSM). The proposed model is capable of predicting the CAV adoption at a disaggregate level. There are also other studies using the simulation approach to predict the adoption of CAVs. For example, Bansal and Kockelman (*21*) developed a micro-simulation model to forecast long-term adoption of CAVs in the US. Multiple discreate choice models are used in a Monte Carlo simulation to emulate decisions such as buying or selling a car, purchasing a used or new car, adding connectivity and automation features, etc.

The second topic focuses on the improvements of CAV technologies to road networks and aims to investigate the mobility, safety, or environmental benefits. For example, Lioris et al. found that Cooperative Adaptive Cruise Control (CACC) could have the ability to double or triple the flow rate of vehicle traffic by simply reducing vehicle headway (*22*). Levin and Boyles proposed that dynamically reversing a lane of traffic depending on the predominant direction of traffic using the CAV technology can effectively reduce road congestion (*23*). There are also a number of studies using the simulation approach to investigate how the CAV technology can help road traffic merge more effectively. The predicted potential improvements in merging flow can be as high as 61 percent (*24, 25*). Lee and Park (*26*), Mostafizi et al. (*27*) investigated the impacts of CAV technologies on travel time reduction and the experimental results showed that the travel times can be reduced by up to 33%. Han et al. (*28*), Chakravarthy et al. (*29*) considers the safety improvements as a key advantage of the CAV adoption due to the technology's ability to reduce the risk of traffic conflicts and collisions. The environmental benefits analysis also draws a lot of attention in the literature. Based on factors such as market penetration and the amount of traffic, the reduction of fuel consumption can be as significant as 33% (*28, 30*).

The motivation and scope of this paper falls into the second topic, investigating the mobility benefits of CV technologies. The relationship between the benefits and the market penetration of CV technologies has drawn attention to various aspects. For example, Ansariyar and Tahmasebi (*31*) tested different CV MPRs in an incremental manner, and found that as MPR of CVs increases, the total delay time decreases by an average of 14% and the fuel consumption decreases by an average of 56%, respectively, compared to the base scenario with zero CV market penetration. Rakha et al. (*32*) investigated the environmental impact of a Connected Energy-Efficient Dynamic Routing (C-EEDR) application and achieved fuel savings of 15.2 percent and 11.7 percent at 75 percent and 100 percent market penetration rates, respectively. Ahn et al. (*33*) evaluated the system-wide delay and throughput of Multi-Modal Intelligent Traffic Signal Systems (MMITSS) at different volume capacity ratios (V/C) and CV technology penetration rates (e.g., for V/C = 0.5, system-wide benefits are 13.9%, 17.3%, and 16.2% for 25, 50, 75 percent CV MPRs, respectively; for V/C = 0.85, system-wide benefits are 11.5%, 20.0%, and 20.6% for 25, 50, 75 percent CV MPRs, respectively). Ishak et al. (*34*) evaluates the effectiveness of three CV safety applications, namely: Blind Spot Warning (BSW), Forward Collision Warning (FCW), and Do Not Pass Warning (DNPW) applications at different MPRs using a driving simulator test bed that allows vehicles to communicate and transmit warning messages within the virtual environment. The tested CV MPRs include zero MP (no CV communication), low MP (25 percent), medium MP (50 percent) and high MP (75 percent). It was found that the safety benefits of CV MPRs on different applications are also different, and higher levels of CV MP can make the warning system distracting for drivers in some cases, resulting in worse safety benefits compared with lower MPRs. These studies confirmed that different MPRs can result in different levels of traffic performance benefits, and there should be an optimal CV MPR that can achieve the highest traffic system benefits, which is not necessarily as high as 100 percent in every possible deployment scenario.

Although such an optimal value of CV MPR is essentially a theoretical value since a transportation agency typically has little control over the MPR of CVs, understanding at what level the CV technologies will be beneficial can help transportation agencies understand the long-term effects of CVs and drive their decision-making process and investments (*35*). The transportation agencies can also influence the market penetration of CVs to a certain degree through operational strategies like tolling and lane restriction. In previous studies, the researchers have tested different MPRs to understand 14 different safety and mobility measures of CV-based ramp metering (*36, 37*), some of which may have conflicting benefits due to the trade-off between safety and mobility. Vasudevan et al. (*6*) highlighted the need to identify the "best" elbow point of MPR for conducting safety analysis using CV data. The purpose of this study is to explore the impacts of CV market penetration on traffic system benefits, and to propose a methodology to determine the optimal CV MPR that achieves the highest performance benefits in a freeway segment. The proposed methodology first formulates the benefit evaluation as an optimization problem, then utilizes Bayesian Optimization to search for the global optimum.

Bayesian Optimization is a kind of response surface method which attempts to build a global response surface, commonly using techniques such as Kriging or Gaussian process regression (*38*). It also has properties of direct search methods. As described by Hooke and Jeeves (*39*), direct search methods refer to the sequential examination of trial solutions involving the comparison of each trial solution with the "best" obtained up to that time together with a strategy for determining (as a function of earlier results) what the next trial solution will be. Bayesian Optimization is also a type of derivative-free optimization technique, which makes it an attractive method for tackling complex transportation optimization problems without a closed form objective function. For most complex and realistic transportation optimization problems, the objective function is a black-box function, and the gradient information is not readily available. In these cases, we can still use Bayesian Optimization to search for the global optimum because it does not rely on the gradient information. In recent years, Bayesian Optimization, in combination with Gaussian process, has become an attractive method for tackling transportation problems. For example, Chen et al. used it for toll optimization (*40*). Schultz and Sokolov adopted it for OD matrix calibration (*10*). Sha et al. applied Bayesian Optimization for microsimulation calibration (*11*). Tay and Osorio applied the method to a high-dimensional traffic signal control problem and confirms the capability of Bayesian Optimization to solve high-dimensional transportation optimization problems (*12*). In this paper, the optimization problem is a 1-D problem. The only variable is the CV MPR. Bayesian Optimization should be very efficient to solve the problem. It should be noted that, however, the proposed Bayesian Optimization based methodology is scalable to deal with optimization problems with higher dimensions. The capability and efficiency of Bayesian Optimization on high-dimensional problems have been documented by several studies in the literature (*11, 12*).

METHODOLOGY

Similar to other optimization processes, Bayesian Optimization also aims to find the minimum of a function $f(x)$, which can even be a black-box function, on some bounded set Ξ, which is a subset of P^D. What makes Bayesian Optimization different from other optimization algorithms is that it constructs a probabilistic model for $f(x)$ and then exploits this model to make decisions about where in Ξ to evaluate the function in next steps. The essential philosophy of Bayesian Optimization is to use all available information about $f(x)$ from previous evaluations, but not simply rely on local gradient and Hessian approximations. This makes the algorithm able to find the minimum of difficult non-convex functions with relatively few evaluations, at the cost of performing more computation to determine the next point in Ξ to try.

Two major choices must be made when performing Bayesian Optimization. The first one is to select a prior over functions that will express assumptions about the function being optimized. Gaussian process (GP) prior is the most widely used one due to its flexibility and tractability. The second one is to choose an acquisition function, which is used to construct a utility function from the model posterior and allows us to determine the next point to evaluate. There are several popular choices of acquisition function. In this paper, the expected improvement (EI) acquisition function is adopted and introduced below.

Gaussian Process

Gaussian process (GP) is an extension of multivariate Gaussian distribution to infinite-dimensional variables, and as such, can be considered a distribution over functions with continuous domains (*41*). Suppose we have collected a finite set of points $x_1, \ldots, x_k \in \mathrm{P}^D$, and the corresponding function's values at these points $f(x_1), \ldots, f(x_k)$. Whenever we have a quantity that is unknown in Bayesian statistics, we can assume that it is drawn at random from some prior probability distribution. Gaussian process takes this prior being a multivariate Gaussian distribution, with a particular mean vector and covariance matrix. The mean vector is constructed by evaluating a mean function μ_0 at each x_i, while the covariance matrix is constructed by evaluating a covariance function or kernel Σ_0 at each pair of points x_i and x_j. The kernel is chosen so that points x_i and x_j that are closer in the input space have a larger positive correlation, encoding the belief that they should have more similar function values than points that are far apart. The kernel should also guarantee a positive semi-definite covariance matrix, regardless of the collection of points chosen. Then the resulting prior distribution of vector $[f(x_1), \ldots, f(x_k)]$ is:

$$f(x_{1:k}) \sim N\ (\mu_0(x_{1:k}),\ \Sigma_0(x_{1:k}, x_{1:k})) \qquad (1)$$

The elegant marginalization properties of Gaussian distribution allow computing marginals and conditionals in closed form, which makes Gaussian process the most commonly used prior over functions when performing Bayesian Optimization (*42*). A detailed overview of Gaussian process can be found in (*38*).

Expected Improvement Acquisition Function

Now the unknown function $f(x)$ is assumed to be drawn from a Gaussian process prior, and the observations are of the form $\Delta = \{x_n, y_n\}_{n=1}^{k}$, where $y_n \sim N\ (f(x_n), \nu)$ and ν is the variance of noise introduced into the function observations. This prior and these observations induce a posterior over functions (*42*). Even though the unknown function $f(x)$ can be approximated from this posterior, it could still be expensive to evaluate the function itself in practical problems. Therefore, we may want to optimize a cheaper proxy function instead. The acquisition function, denoted by $\alpha : \Xi \rightarrow \mathrm{P}^+$, is such a cheaper function which determines what point in Ξ, a bounded subset of P^D, should be evaluated next. This is achieved via a proxy optimization $x_{next} = \mathrm{argmax}_{\mathbf{x}}\ \alpha(\mathbf{x})$, where $\mathbf{x}$ is the vector of points in Ξ, and x_{next} is the next evaluated point determined by the acquisition function. In general, the acquisition function depends on previous observations as well as GP hyperparameters θ. This dependency can be denoted as $\alpha(\mathbf{x};\ \theta, D)$. The acquisition functions balance the needs of exploration and exploitation considering what it already knows about the unknown function from the observations.

The EI acquisition function tries to maximize the expected improvement over the current best value (*43*). If the new evaluation is made at x, the observation will be $f(x)$. After this new evaluation, the best value will be either $f(x)$ (if $f(x) < f(x_{best})$) or $f(x_{best})$ (if $f(x) \geq f(x_{best})$). The improvement of the best value after this new evaluation is then $f(x_{best}) - f(x)$ if this quantity is positive, or 0 otherwise. This can be denoted more compactly as $[f(x_{best}) - f(x)]^+$, where $a^+ = \max(a, 0)$ indicates the positive part. $f(x)$ remains unknown until the new evaluation is performed. However, the expected value of this improvement can be calculated and we can choose x to maximize it. So EI for any point x is defined as:

$$\mathrm{EI}(x) := \mathrm{E}_n\left[[f(x_{best}) - f(x)]^+\right] \tag{2}$$

The right part indicates the expectation taken under the posterior distribution given evaluations of $f(x)$ at $x_1, \ldots, x_n$. EI can be evaluated using integration by parts, hence EI acquisition function also has a closed form under GP prior, which is:

$$\alpha_{EI}(\mathbf{x};\ \theta, D) = \sigma(\mathbf{x};\ \theta, D)(\gamma(\mathbf{x})\Phi(\gamma(\mathbf{x})) + N\ (\gamma(\mathbf{x});\ 0, 1)) \tag{3}$$

$$\gamma(\mathbf{x}) = \frac{f(x_{best}) - \mu(\mathbf{x};\ \theta, D)}{\sigma(\mathbf{x};\ \theta, D)} \tag{4}$$

where $\mu(\mathbf{x};\ \theta, D)$, $\sigma^2(\mathbf{x};\ \theta, D)$, and $\Phi(\cdot)$ are defined the same as above.

The EI acquisition function is the most commonly used one among the different acquisition functions proposed so far, as it has been shown to be better-behaved than the others such as the probability of improvement (PI) and the GP upper confidence bound (UCB). The PI acquisition function can get stuck in local optima and fail to explore globally, while the GP UCB one is somewhat complicated and cannot be interpreted as computing a natural expected utility function (*43*). A package built in Python, named *bayesian-optimization*, will be used to implement the Bayesian Optimization algorithm for CV MPR optimization problem. This package was developed for the constrained global optimization problem with GP and EI (*41*). The implemented optimization algorithm will be tested in the following case study.

DATA AND SIMULATION MODEL

The case study considers a stretch of Interstate 210 Eastbound (I-210 E) between San Gabriel Boulevard and N 2nd Avenue, up to 6.6 km (**Error! Reference source not found.**). There are 6 on-ramps and 5 off-ramps along this freeway segment. Each on-ramp is regulated by the demand-capacity strategy (*44*). The traffic flow data related to the study area are collected from the PeMS website (*45*), which consists of: 1) 5-min flow through the mainline, on-ramps and off-ramps, and 2) 5-min speed data at the mainline.

The base simulation model is developed and calibrated in SUMO, an open-source microscopic road traffic simulation package short for "Simulation of Urban MObility" (*46*). The practical ramp metering strategies (*47-49*) are implemented via the SUMO APIs. The speed limit is also added at the downstream end of the I-210 E segment as a boundary condition based on real traffic speed data. The simulation model developed in SUMO is shown in **Error! Reference source not found.**. Then the base model is calibrated to produce satisfactory operational measures following the calibration framework suggested by FHWA (*50*). The calibrated model also reproduces the congestion pattern of the selected representative day as shown in **Error! Reference source not found.**.

The calibration process of the I-210 E simulation model follows the flowchart as shown in **Error! Reference source not found.**. Firstly, two distinct operational conditions during the peak period, namely, few incidents scenario and many incidents scenario, are identified using clustering analysis. Then a representative day is selected for each scenario based on the distance to the cluster centroid. The traffic data collected on the representative day are used as the calibration target for the simulation model to reproduce the real-world traffic condition. In this case study, the few incidents scenario simulation model is adopted. Traffic flow and speed are selected as the performance measures to quantify the simulation error. SPSA algorithm (*51*) is used to implement an automatic calibration framework to update key simulation parameters until the discrepancy between the simulation output and the observed data satisfies a predefined criterion (*52*). The root mean square percentage errors (RMSPEs) of traffic flow and speed for the calibrated model are 6.7% and 14.0% respectively. The stochastic simulation outputs are also validated against the multiple days' observed data using variation envelopes and four acceptability criteria suggested by the FHWA Guidelines (*50*). The validation results confirm the consistency between the simulation outputs and the real-world traffic conditions.

The well calibrated I-210 E simulation model is then used to optimize the CV MPR to achieve the greatest mobility benefits. The ramp metering strategy of the I-210 E freeway segment works through the CV technology. The modeling framework of this V2I application is illustrated in **Error! Reference source not found.**. Firstly, the BSM emulator is applied to mimic the generation of BSMs (*37*). Then the BSMs are converted into 1) CV flows into the on-ramps, 2) CV flows out of the on-ramps, and 3) CV counts at the on-ramps (*37*). Induction loops are also exploited to collect total flows into and out of the on-ramps. With this information, it is possible to obtain the CV rates at the on-ramp entrances and exits. The average value of these two CV rates is used to approximate the real-time CV rate over the on-ramp. Then the vehicle counts at the on-ramp can be estimated via dividing the CV counts by the average CV rate (*37*). As for the ramp metering, the algorithm takes the mainline occupancy and the estimated on-ramp queue length as inputs, then attempts to stabilize the mainline occupancy around the critical value to reduce mainline congestion and to avoid overlength queues. For detailed information of the implementation of the ramp metering strategy in SUMO and the calibration of the simulation model, please refer to (*37*).

By controlling the on-ramp vehicles to merge into the mainline, the mobility of mainline vehicles can be improved. In a conventional way, the control of on-ramp vehicles is based on limited (and often inaccurate) queue information detected from the fixed location sensors. These sensors are usually installed at the beginning and end of an on-ramp, and the metering control based on the queue length is only triggered when a vehicle on the ramp reaches the fixed sensor at the ramp's end. In a CV environment, the ramp queue length is estimated based on the actual location of CVs on the on-ramp. Under a low CV MPR, the metering control system tends to overestimate ramp queue lengths based on limited CV information to avoid congestion spillback, and thus misleads the ramp controllers to release more vehicles to the mainline, resulting in relatively shorter on-ramp queues. This in turn reduces the mainline mobility performance. However, as the CV MPR increases, the queue length estimation becomes more accurate and robust, which avoids over-reaction in the metering control. As a result, more ramp vehicles are kept in the queue, leading to relatively longer average on-ramp queues, which in turn improves the mainline mobility performance. If the queue keeps increasing, it is likely to cause congestion spillback and impact the upstream traffic. Therefore, increasing the CV MPR all the way up to 100% may not guarantee the highest mobility benefits for the whole segment. Therefore, two system wide performance measures are selected to quantify the mobility benefits of the CV technology for the I-210 E segment: the average total travel time on the mainline and the average queue length of on-ramps. By considering both measures in determining the optimal CV MPR, the trade-off between mainline and on-ramp performance can be examined. The optimal CV MPR should lower the mainline travel time as much as possible while maintaining feasible queues for on-ramps. The objective function for the optimization problem is formulated as a weighted sum of the two performance measures:

$$\min \quad L(R_{CV}) = \omega_1 \cdot T + \omega_2 \cdot Q \tag{5}$$

$$\text{s.t.} \quad 0 \leq R_{CV} \leq 1 \tag{6}$$

where R_{CV} represents the CV MPR, $L(R_{CV})$ is the optimization objective function depending on the CV MPR, T, Q are average total travel time on mainline (s), average queue length of on-ramps (veh), respectively, and w_1, w_2 are weights of T, Q, respectively. In practice, the average total travel time and the average queue length are firstly scaled to the same magnitude, then assigned weights to calculate the objective function value.

When applying the proposed methodology to optimize Equation (5), Bayesian Optimization is performed for 200 iterations in this study, of which 20 are initial samples to build a prior distribution for $L(R_{CV})$, and 180 are explored samples to update the posterior distribution. For each sample point, the I-210 E simulation model needs to be run once using the determined CV MPR. As the number of explored samples grows, the posterior distribution improves, and the algorithm becomes more certain of which regions of the parameter space are worth exploring and which are not, thus the explored samples are closer to the global optimum. With the help of the EI acquisition function, the next explored sample can always be determined quickly during the optimization process. Therefore, the Bayesian Optimization based methodology is efficient to solve Equation (5). In this case study, different combinations of (w_1, w_2) in $L(R_{CV})$ are tested. The optimization results are discussed in the next section.

RESULTS AND ANALYSIS

Error! Reference source not found. shows the optimization process of CV MPR using Bayesian Optimization for different weight combinations of T and Q. Each row belongs to a combination of weight scenario. For each scenario, Bayesian Optimization is performed for 200 iterations, which includes 200 simulation runs with a different random seed for each iteration. Due to the stochasticity of the Bayesian Optimization algorithm, the input parameters of the simulation model at different iterations can be similar or even the same, thus the varying random seeds of different iterations can account for the stochasticity of the simulation model in the optimization process. In **Error! Reference source not found.**, the first column shows the weights of T and Q respectively. The second column shows the sampled value of CV MPR with respect to the number of iterations. The third column shows the distribution of the sampled values of CV MPR using histograms. The fourth column shows the objective function values with respect to the number of iterations. And the last column presents the optimal CV MPR obtained by the Bayesian Optimization.

From the fourth column of **Error! Reference source not found.**, an overall downward trend of the objective function values can be observed for all tested scenarios, despite of the fluctuations due to the stochasticity of the simulation model and Bayesian Optimization algorithm. The figures in the second column show a tendency of the sampled values to be concentrated around the optimal CV MPR, which can be further confirmed by the distributions of sampled values presented in the third column. For the first three scenarios ($(w_1, w_2)=(1,0)$, $(0.9, 0.1)$, $(0.8, 0.2)$), the majority of the sampled values of CV MPR show a tendency to concentrate between 0.8 and 1 as the number of iterations grows, which means the optimal CV MPR is very likely to lie in this area. The results shown in the last column also confirm the correctness of this trend since the optimal CV MPRs are 87%, 86%, and 87% for the first three scenarios respectively. The total travel time measurement has a relatively high weight for these three scenarios. So the optimal CV MPR is more likely to be high, which makes the optimization algorithm search larger values more for the global optimum as the iteration number grows.

When the weight of the total travel time measurement becomes lower compared with the first three scenarios, the effect of the queue length measurement becomes more dominant for scenarios $(w_1, w_2)=(0.7, 0.3)$, $(0.6, 0.4)$, $(0.5, 0.5)$, $(0.4, 0.6)$, $(0.3, 0.7)$, $(0.2, 0.8)$. As mentioned before, higher CV MPRs will increase the accuracy of queue estimation, resulting in relatively longer average on-ramp queues and increase the objective function values. Therefore, the optimal CV MPR is less likely to be high compared with the first three scenarios. This is reflected in the figures in the second and third columns, where the tendency of concentrating sampled CV MPRs to higher values as the iteration number grows is no longer obvious. Instead, there are other concentrated areas (about 0.4, and 0.1) shown in the figures, indicating that there is some possibility that the global optimum moves from the higher values to these lower values. The optimal CV MPRs shown in the last column are consistent with this change of trend. The optimal CV MPRs are either 29% or 44% for these six scenarios, none of which is higher than 50%. In practice, if we keep increasing the CV MPR, the negative effect of on-ramp queues will become more and more dominant, and in turn counteract the benefits of CV deployment.

When the weight of queue length grows even higher ($(w_1, w_2)=(0.1, 0.9)$, $(0, 1)$), the on-ramp queue length becomes the only impacting measurement for CV MPR optimization. In such cases, the optimization algorithm tends to minimize the average queue length of on-ramps by relaxing the ramp control strategy. Therefore, the sampled values of CV MPR are concentrating to the lower value area as the iteration number increases as shown in the figures of the second and third columns. The converged optimal CV MPRs are 3% and 7% for the two scenarios respectively, both lower than 10%.

For comparison, the same optimization problems of all the test scenarios shown in **Error! Reference source not found.** are also conducted using the incremental method. **Error! Reference source not found.** shows the optimization results of CV MPR using the incremental method with 10% as the increment. As can be seen from **Error! Reference source not found.**, most of the optimal MPR results obtained from the incremental method lie between 70% and 100% with two exceptions of 10%. Such high optimal CV MPR results are consistent with the results of Bayesian Optimization for the first three scenarios ($(w_1, w_2)=(1, 0)$, $(0.9, 0.1)$, $(0.8, 0.2)$), although the exact numbers are not the same. This indicates the limitation of the incremental method to search for the optimal CV MPR globally. And this limitation is more obvious for other test scenarios, where the optimization results are very different between the incremental method and Bayesian Optimization. The only exception is the scenario $(w_1, w_2)=(0.1, 0.9)$, where the results are both at a relatively low MPR for both methods. While the incremental method fails to test more sample MPRs within the 10% increment, it is possible that the true optimum is missed and an inferior result is reported. On the contrary, Bayesian Optimization can search for such samples and obtain the best results under different testing scenarios with good efficiency. For more complicated scenarios, the differences between these two approaches are expected to be more significant.

Comparing the results of $(1, 0)$ and $(0, 1)$ scenarios using Bayesian Optimization, we can see that the two different operational measurements lead to opposite outcomes concerning the CV adoption, indicating that the selection of performance measures and the definition of objective functions are important for the CV MPR optimization problem. In practice, an appropriate objective function should include careful assignment of weights for different performance measures so that the optimization process can achieve convincible results. For this case study, the weights combinations between $(0.7, 0.3)$ and $(0.2, 0.8)$ make more sense since they do not result in too high or too low values of the optimal CV MPR rate.

It can be seen from the optimization results that Bayesian Optimization works well under different scenarios. Compared with the traditional incremental method and other derivative-based methods, Bayesian Optimization is capable of searching for the optimum globally and efficiently. Considering the stochastic nature of the microscopic simulation models, the high efficiency of Bayesian Optimization can help mitigate the impact of simulation stochasticity by performing more sample runs, which makes it attractive for more complex optimization problems with a higher dimension of variables.

CONCLUSIONS AND FUTURE WORK

This study proposed a simulation-based approach combined with Bayesian Optimization to determine the optimal CV MPR that achieves the highest performance benefits for a freeway segment. The proposed methodology is tested in the I-210 E simulation model built in SUMO as a case study. In the I-210 E, California freeway segment, the ramp metering strategy works through the CV technology to control the on-ramp vehicles merging into the mainline, hence the mobility of mainline vehicles can be improved. In the meantime, however, the queues of the on-ramps will become longer. To quantify the performance benefits of the CV technology, two system wide performance measures are selected: the average total travel time on the mainline and the average queue length of on-ramps. The objective function for the optimization problem is formulated as a weighted sum of these two performance measures. By testing different weights combinations as different scenarios, the optimization problem is solved for each scenario using the proposed methodology. The optimization results show that when the weight of total travel time is high, the optimal CV MPR tends to be high. On the contrary, when the weight of queue length increases, higher CV MPRs may not guarantee higher benefits for the traffic system. And the globally optimal CV MPR can be as low as 0.29.

The case study in this paper confirms the effectiveness of the proposed optimization methodology for CV MPR based on microsimulation and Bayesian Optimization. Compared with the traditional incremental method and other derivative-based methods, Bayesian Optimization is advantageous due to its global optimization nature and high efficiency. Besides, the findings from the optimization results in this study can provide some insight for the future deployment of CV technologies. Higher market penetration is not guaranteed to result in greater benefits in a transportation system in some cases, even if the deployment cost of CVs is not considered. When considering a single performance measure, the relationship between the CV MPR and the given performance measure is typically a monotonic function (*31, 33, 34*). However, assessing multiple performance measures simultaneously reveals that the interaction among them can disrupt this monotone relationship. As a result, the relationship between the CV MPR and the aggregated objective function may not be a monotonously increasing function. It is crucial to understand this complexity and identify the optimal CV MPR that maximizes system benefits by solving a specific optimization problem, as demonstrated in the case study of this paper. It should be noted, however, that the findings summarized in this paper are based on a single case study and further investigation involving other decision variables at different levels is needed. For example, the objective function of the optimization problem can take safety and environmental effects of CV technologies into account as well. The impact of CV MPR under scenarios with different traffic volumes can also be investigated. The stochasticity of the simulation model will affect the optimization results, too. How to account for the simulation stochasticity during the optimization process is also worth exploring. These factors can impact the complexity of the optimization problem and the optimization framework. The proposed Bayesian Optimization approach is expected to retain its power for such problems because it provides a more systematic methodology than the incremental approach. This will be the future direction of our research.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Kaan Ozbay, Di Sha; data collection and experimental design: Di Sha, Yu Tang, Kaan Ozbay; analysis of results: Di Sha, Yu Tang, Kaan Ozbay; draft manuscript preparation: Di Sha, Jingqin Gao, Kaan Ozbay, Yu Tang, Fan Zuo. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF INTEREST

The authors do not have any conflicts of interest to declare.

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FIGURE 1. Illustration of the I-210 E study area

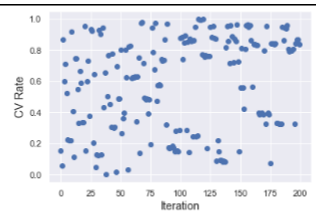
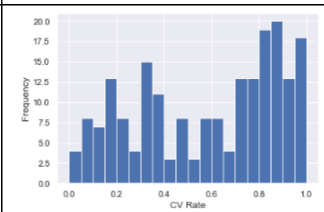
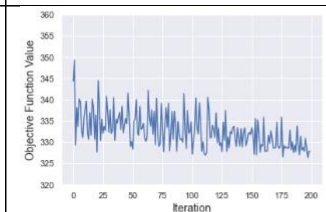
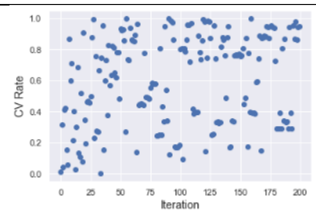
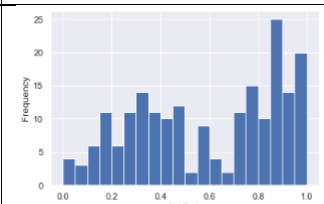
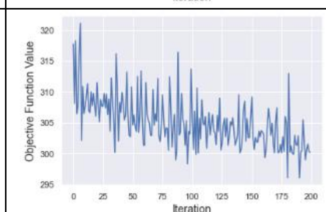
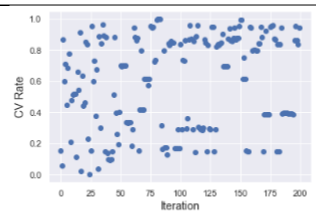
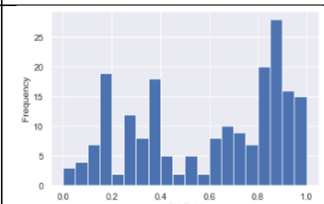
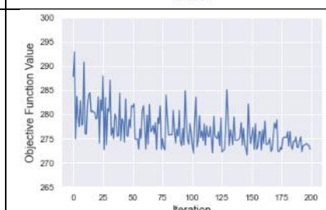
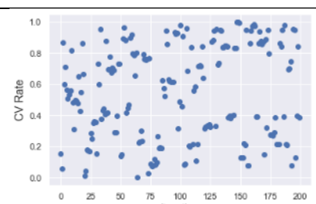
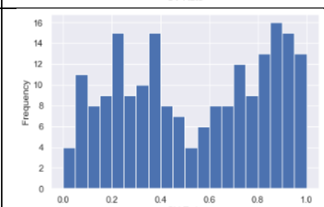
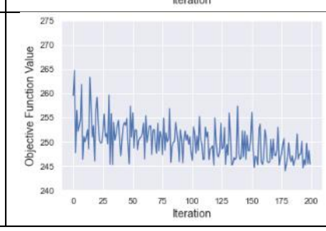
FIGURE 2. Simulation segment of I-210 E developed in SUMO

FIGURE 3. Congestion pattern of I-210 E segment on the selected representative day

FIGURE 4. Flowchart of the calibration process of the I-210 E simulation model

FIGURE 5. Framework of ramp metering modeling of the I-210 E simulation model in SUMO

TABLE 1. Optimization results of CV MPR using different weights (w_1, w_2) combinations

Weights (w_1, w_2)	Sampled value of CV MPR vs. Iteration	Histogram of sampled CV MPR	Objective function value vs. Iteration	Optimal CV MPR
$(1, 0)$				87%
$(0.9, 0.1)$				86%
$(0.8, 0.2)$				87%
$(0.7, 0.3)$				29%

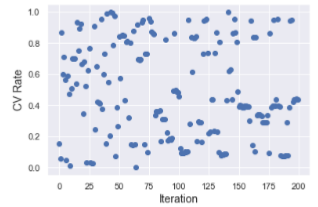
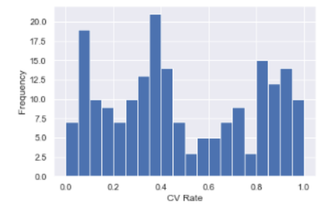
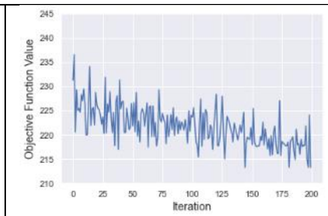
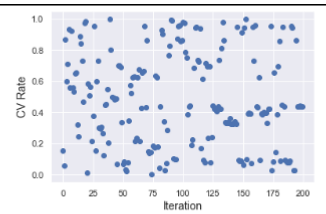
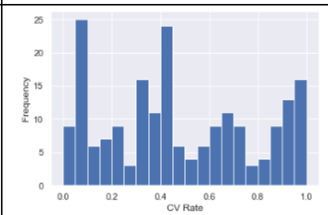
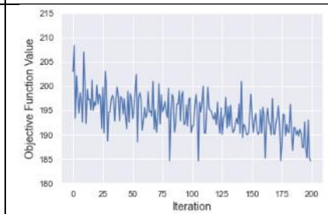
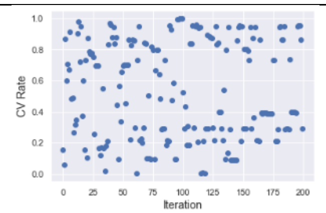
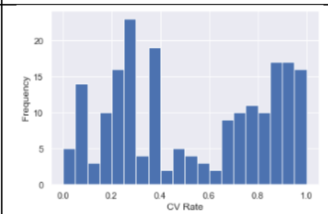
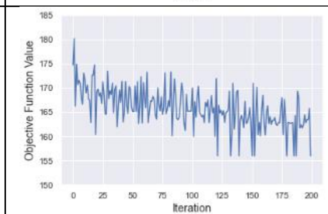
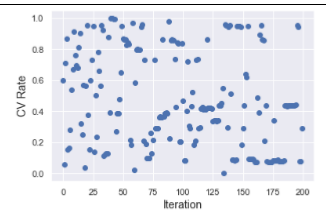
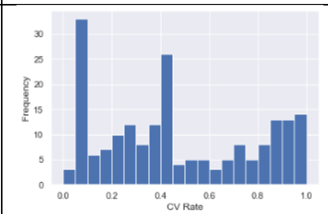
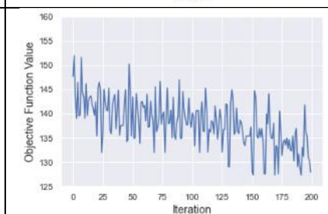
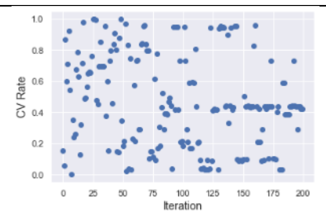
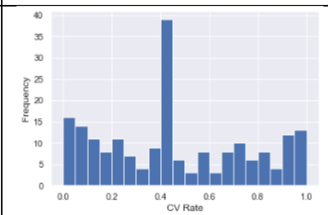
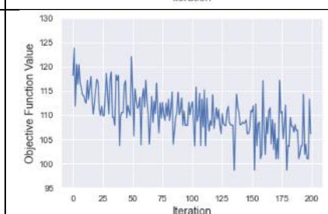
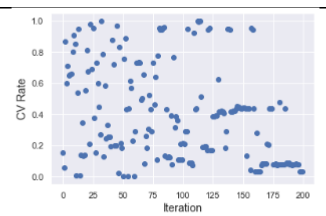
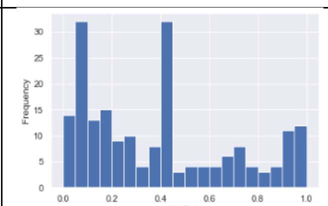
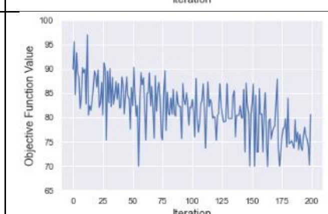
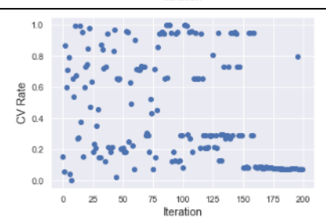
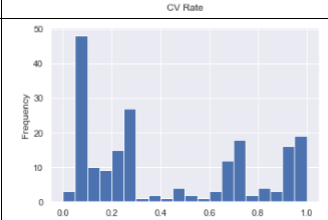
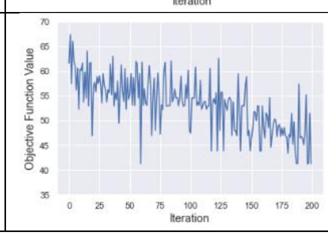
(0.6, 0.4)				44%
(0.5, 0.5)				44%
(0.4, 0.6)				29%
(0.3, 0.7)				44%
(0.2, 0.8)				44%
(0.1, 0.9)				3%
(0, 1)				7%

TABLE 2. Optimization results of CV MPR using incremental methods and comparison against the results of Bayesian Optimization

CV MPR	0	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	Optimal MPR	Optimal MPR from BO
Weights $(1, 0)$	335.8	333.5	332.7	335.5	340.0	340.3	338.9	335.9	328.4	332.9	331.1	80%	87%
Weights $(0.9, 0.1)$	308.3	306.9	307.7	307.0	303.7	307.7	311.2	306.5	305.3	306.3	303.4	100%	86%
Weights $(0.8, 0.2)$	280.8	278.4	277.2	275.7	281.7	283.1	283.5	274.9	273.8	279.4	275.8	80%	87%
Weights $(0.7, 0.3)$	253.2	250.7	249.6	252.3	252.1	252.5	256.5	247.4	251.5	251.7	248.1	70%	29%
Weights $(0.6, 0.4)$	225.7	222.6	227.0	222.6	225.4	224.9	229.3	220.0	224.6	225.6	220.5	70%	44%
Weights $(0.5, 0.5)$	198.2	192.2	197.8	194.6	197.4	197.3	202.1	192.5	197.8	198.3	192.8	10%	44%
Weights $(0.4, 0.6)$	165.9	166.7	167.2	168.2	169.3	170.0	174.9	165.1	170.9	170.6	165.2	70%	29%
Weights $(0.3, 0.7)$	143.2	138.8	143.2	140.7	140.6	142.1	144.9	146.1	144.0	143.4	137.5	100%	44%
Weights $(0.2, 0.8)$	115.7	112.3	113.5	113.3	112.1	111.9	120.5	110.2	117.1	114.3	109.9	100%	44%
Weights $(0.1, 0.9)$	88.2	82.0	85.0	85.9	84.4	86.4	93.3	89.2	90.2	89.1	82.2	10%	3%
Weights $(0, 1)$	60.6	57.3	58.7	58.6	55.8	54.6	66.1	62.0	55.2	61.8	54.6	100%	7%