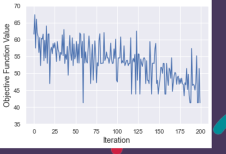

Market Penetration Rate Optimization for Mobility Benefits of Connected Vehicles: A Bayesian Optimization Approach

C2SMARTER
CONNECTED COMMUNITIES WITH SMART MOBILITY TO EQUITABLY REDUCE CONGESTION

Paper 24-06484

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Abstract

The benefits of connected vehicle (CV) technologies largely rely on the market penetration rate (MPR) of CVs and connected infrastructure. However, the predominant assumption that higher market penetration will always result in greater benefits in a transportation system is questionable in some cases even if we do not consider the deployment cost of CVs. 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 road network. The proposed methodology is tested in the I-210 E (in California) simulation network 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.

Data and Experimental Design

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. There are 8 on-ramps and 6 off-ramps along this freeway segment. Each on-ramp is regulated by the demand-capacity strategy. The traffic flow data related to the study area are collected from the PeMS website, which consists of: 1) 5-min flow through the mainline, on-ramps and off-ramps, and 2) 5-min speed data at the mainline.

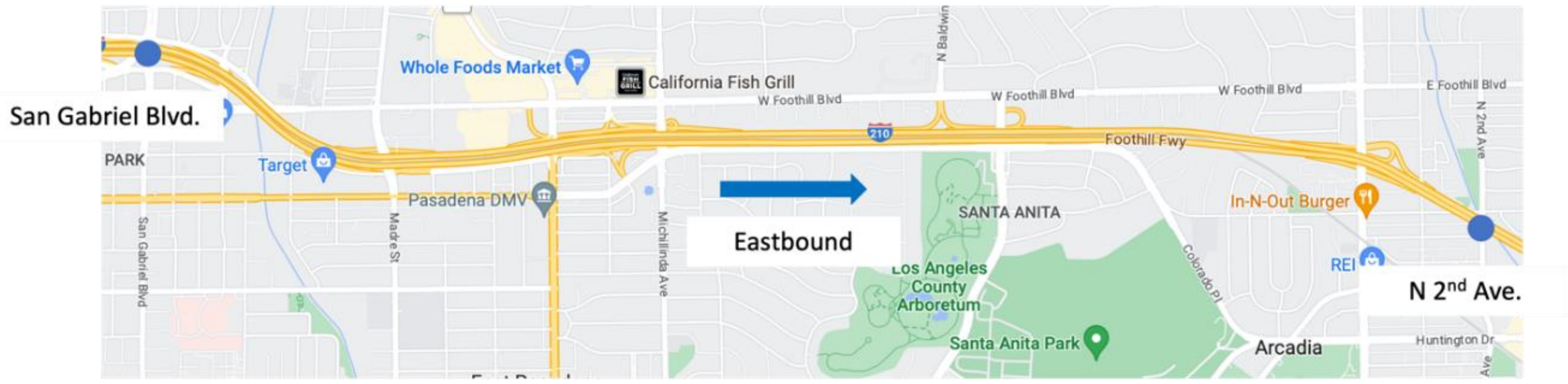
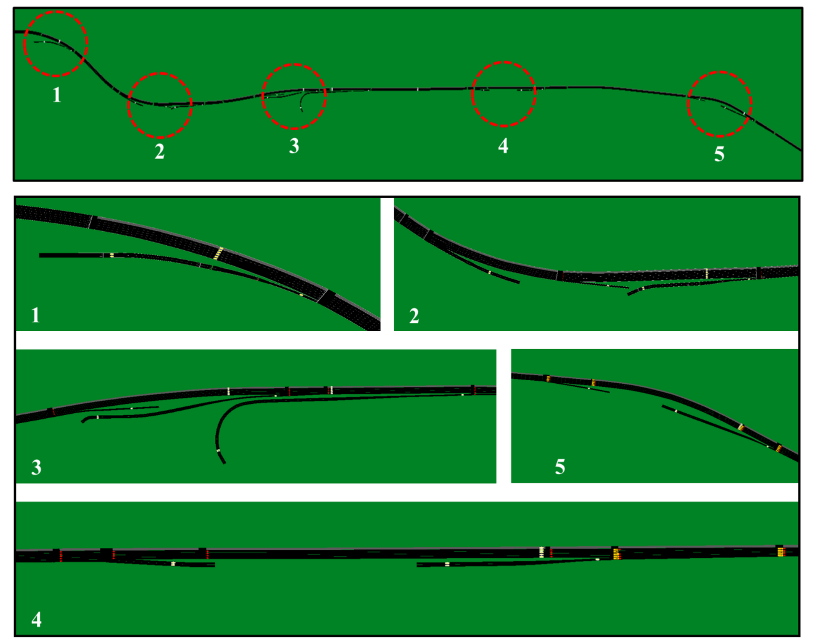
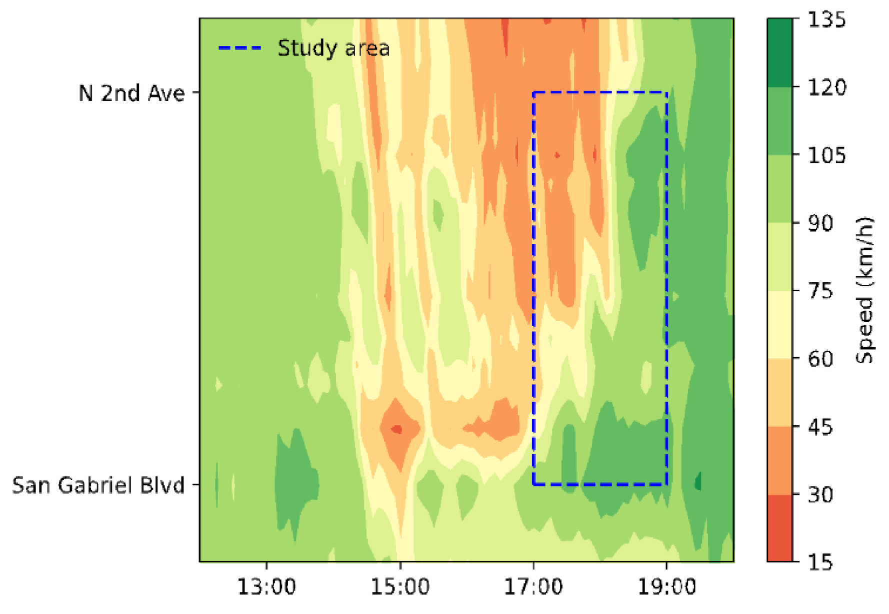


Illustration of the I-210 E study area

I-210 Network in SUMO



Congestion Pattern of I-210



Objective Function of the Optimization Problem

Two performance measures are selected to quantify the mobility benefits of the CV technology for the I-210 E network: the average total travel time on the mainline and the average queue length of on-ramps. 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:

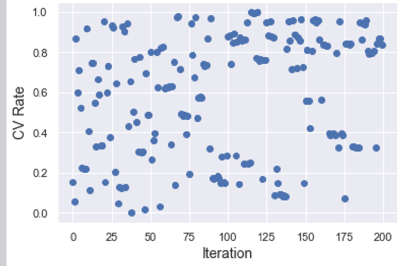
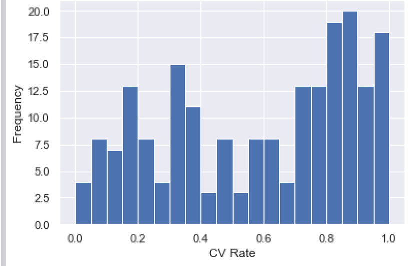
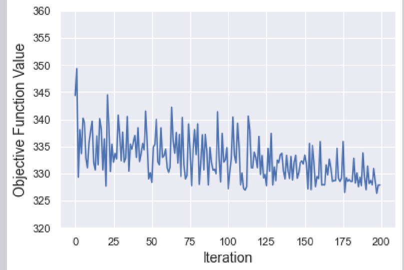
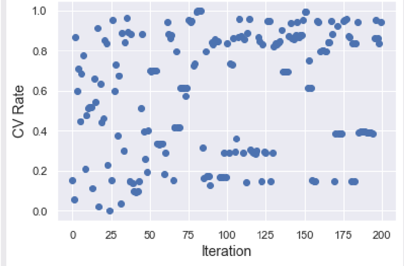
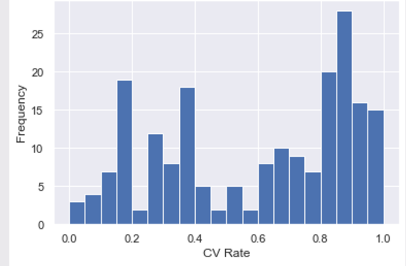
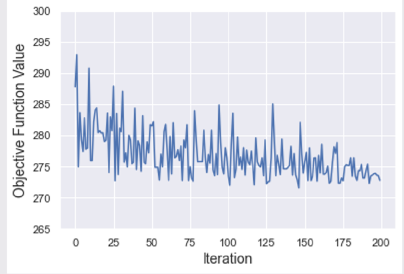
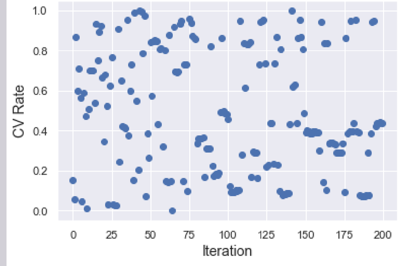
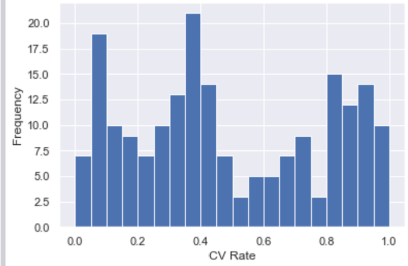
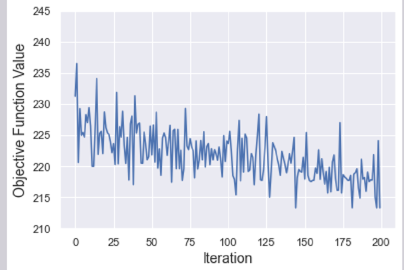
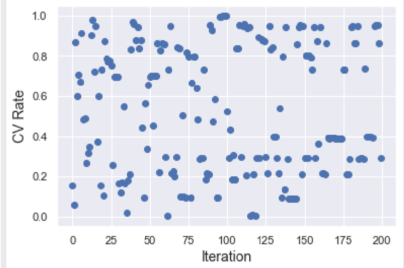
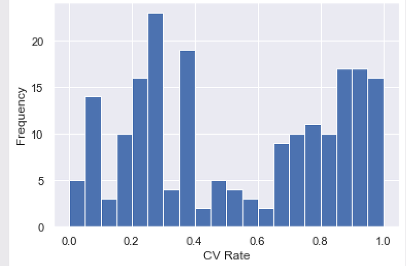
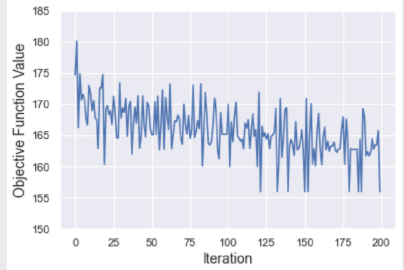
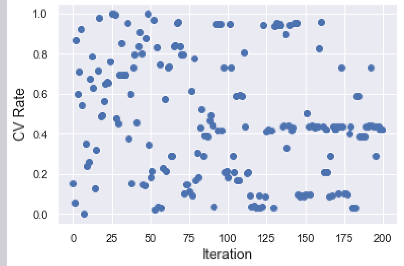
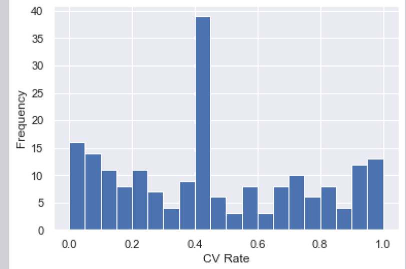
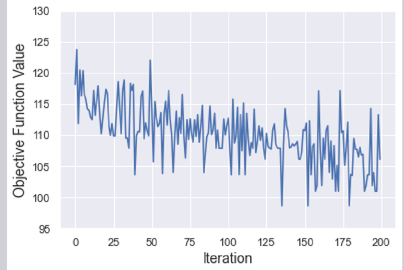
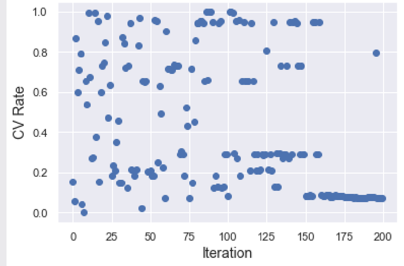
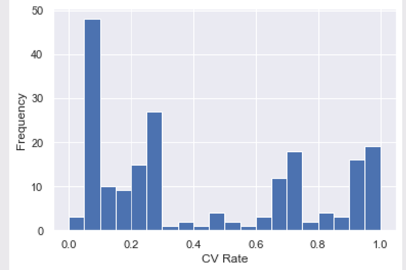
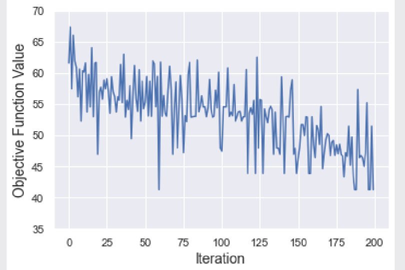
$$\min \quad L(R_{CV}) = w_1 \cdot T + w_2 \cdot Q$$
$$s.t. \quad 0 \le R_{CV} \le 1$$

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

Conclusions

1) 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.
2) The results of (1,0) and (0,1) scenarios show 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.
3) 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.

Optimization Results of Different Weights 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%
$(0.8, 0.2)$				87%
$(0.6, 0.4)$				44%
$(0.4, 0.6)$				29%
$(0.2, 0.8)$				44%
$(0, 1)$				7%

Acknowledgement

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