An increasing number of vehicles on roadways has made traffic safety a serious challenge for transportation engineers. For the mitigation of traffic safety concerns, a variety of active traffic control measures, such as the variable speed limit (VSL), have been intensively investigated and deployed. VSL is usually adopted to advise drivers of a lower speed limit that is more appropriate to a congested traffic condition and takes advantage of the homogeneous traffic flow effect. However, in earlier studies, because of the absence of traffic state prediction, the impact of applied VSL control was not quantitatively analyzed. In this study, a model predictive control framework was adopted for predicting and assessing future traffic states. Taking into consideration the impact of VSL control, the study used a macroscopic traffic flow model. The collision probabilities of the predicted traffic states were assessed with a precursor-based collision prediction model to determine the optimized control signal. With this design, the proposed algorithm controller provided a robust method for determining the VSL control plan to optimize safety performance over a traffic network. The proposed control algorithm was evaluated with a simulation study based on field data that was conducted to reproduce a major ring road in Edmonton, Alberta, Canada. The proposed algorithm was used to implement VSL control on the studied 11-km freeway stretch. The proposed algorithm control scenario was then compared with the uncontrolled scenario. The evaluation proved that the proposed VSL control algorithm could effectively reduce the probability for collisions in a congested traffic network without significantly compromising mobility.

VSL control provides drivers with an appropriate operating speed, one lower than the posted static speed limit, in response to dynamic road conditions. The posted speed limit on highways suggests the standard operating speed for road users in ideal conditions. However, during adverse traffic conditions, such as excessive demand or reduced roadway capacity (such as with construction), the posted speed limit may not be the optimal operating speed (1). Through field implementations and simulations, earlier studies reported that by enhancing the speed homogeneity effects, VSL improves traffic flow in terms of safety (1–3) and, potentially, mobility (4, 5). A statistical crash probability model is usually used to assess the safety benefits of a VSL control. Abdel-Aty et al. developed a crash probability model for formulating incident likelihood by examining traffic state measurements of the previous 15 min (6). This real-time crash probability model was later adopted to evaluate the performance of a VSL control (4, 7). Hellinga and Michael designed a control algorithm for implementing VSL using decision trees (8). From the analysis of a crash probability model, Hellinga and Michael concluded that VSL reduces crash probability.

However, in most of these works (4, 8), the crash probability model was adopted only as the measure of effectiveness (MOE) that evaluates system performance after VSL implementation. In these studies the VSL control algorithm did not consider the future crash risk. (The previous algorithms did not quantitatively evaluate the VSL impact to choose the control plan that leads to minimized safety risks.) To overcome this problem, this study proposes a VSL control algorithm with traffic state predictions based on a safety assessment feature. The designed control strategy aims at optimizing network safety performance according to prevailing and predicted traffic conditions. The VSL impact on traffic flow was taken into consideration during prediction, and then a real-time crash probability model was adopted for determining the most appropriate control plan with the most desirable network safety performance.

The remainder of this paper is organized as follows. A literature review of existing VSL control strategies and crash probability evaluation efforts is first presented. Then the proposed VSL control algorithm with the crash probability prediction model is presented, followed by a field-data-based VISSIM simulation study that reproduces real-world traffic conditions and implements the proposed control algorithm. Then the VSL-controlled network performance is compared with the baseline condition (uncontrolled case) in an evaluation of the efficiency of the proposed control algorithm.
LITERATURE REVIEW

In Europe, a field VSL control study was implemented as early as the 1990s. Van den Hoogen and Smulders implemented VSL in the Netherlands (9). In Finland, Rämä investigated driver behaviors on a highway under weather-controlled VSL (3). These studies focused on implementing the VSL control as a measure for improving the speed homogenization effect and to mitigate the speed differences among individual vehicles for safety benefits. Later, field implementations continued in North America. In Washington State, 25 VSL signs were installed on both directions of I-90 (10). The VSL advised drivers to reduce traveling speed through construction zones. In Missouri, a VSL system was deployed along the I-270/I-255 corridor in Saint Louis (11). The report concluded that although no significant collision benefit was found, the number of crashes was noticeably reduced.

Some studies used a crash probability model to quantitatively examine the safety benefits of VSL control. A major approach to establishing these crash probability models is to use traffic state variables (speed, volume, etc.) before a collision as the model’s input variables. Such models are referred to as precursor-based collision prediction models. To formulate the incident probability, a log-linear crash probability model was developed by Lee et al. (12). By analyzing loop detector data, Lee et al. identified the coefficient of variation in flow speed and density as the two most significant collision precursors. In another study, Lee et al. found that the speed difference between upstream and downstream traffic had a significant impact on traffic safety (13). Lee et al. also suggested adopting a real-time crash probability model as the evaluation tool for examining the proposed VSL control strategy’s efficiency (14). The designed control strategy lowered the speed limit; the adopted model found that the crash probability is higher than the predefined threshold. Similarly, this study identified as the critical indicators the traffic state variables 5 to 10 min before the incident. Another study conducted by Lee et al. proposed a VSL control strategy to change the speed limit that was based on the evaluation results from the adopted crash probability model (15). On the basis of the evaluation of a simulation study, the authors reported a potential collision reduction of 5% to 17%.

A statistical crash probability model was first developed by Abdel-Aty et al. (6). The traffic state variables, taken 30 min before an incident, were divided into six 5-min periods and evaluated by their relationship with incident probability. The authors reported that traffic state variables within 15 min before incident occurrence are the most statistically significant variables related to the crash. This real-time crash probability model was later adopted as the MOE that evaluates the performance of VSL used to mitigate the risk of rear-end incidents (1, 4). Hellenga and Michael designed an algorithm to implement VSL control using decision trees (8). On the basis of the evaluation of a crash probability model, they concluded that VSL reduces crash probability.

Much work has been done to involve a real-time crash probability model in VSL control applications. However, in the existing literature, the crash probability model was adopted only to assess crash likelihood in current traffic conditions. The reviewed control strategies quantitatively analyze neither the impact of the selected VSL control inputs on traffic dynamics nor the correlated traffic safety performance. Moreover, most of these VSL control algorithms determine the control input (VSL value to be advised) according to predefined thresholds (on traffic state variables or measured crash probability). Because the traffic flow dynamic is a complex stimulation and response system, it is arbitrary to assume that simply lower-
The following notation is used in the paper:

- \( k \) = current time step,
- \( N_p \) = prediction horizon,
- \( x(k) \) = traffic state variable vector (flow, speed, occupancy) at time step \( k \),
- \( u(k) \) = candidate control plan vector at time step \( k \),
- \( x(k + 1|u(k)) \) = model-predicted traffic state variables at time step \( k + 1 \) [given the control input (advised VSL value), \( u(k) \) is implemented],
- \( P(x(k + 1|u(k))) \) = model-predicted incident probability at time step \( k + 1 \) [given the control input, \( u(k) \) is implemented], and
- \( u^*(k) \) = optimized control input for time step \( k \).

In the proposed framework, the entire network runs on a rolling horizon system. The current time step is denoted as \( k \), and the consecutive time step is denoted as \( k + 1, k + 2, \ldots \), respectively.

As illustrated in Figure 1, previous studies took the traffic variables before the current time step \( k \) to assess traffic safety risks \((18)\). Typically, the traffic state variables of previous time steps (e.g., \( k - 1, k - 2, \ldots, k - 10 \)) are brought into the safety assessment model to measure safety risk and then are used to determine whether a lower speed limit should be advised. However, a main drawback of this approach is that the impact of the VSL control (advised VSL value) is not quantitatively evaluated. Therefore, the proposed control algorithm includes traffic state prediction for evaluating the impact of the applied VSL control. At the current time step \( k \), for every candidate control input (VSL value), the future traffic state variables (time step \( k + 1, k + 2, \ldots, k + N_p \)) were predicted. Along with the traffic state variables in the previous time steps, the predicted traffic state variables were evaluated with the collision probability model (Figure 2). The control input that leads to an optimal safety performance will be adopted and applied in the traffic network.

The control procedures of the proposed algorithm are demonstrated in Figure 2. As shown in the figure, the designed algorithm controller takes the traffic state variables on the current time step \( x(k) \) as the input to determine the optimized control input \( u^*(k) \). The controller of the designed algorithm includes three major...
components: the traffic state prediction model, the collision probability prediction model, and the optimization module. The traffic state prediction model takes into consideration both the current traffic state \(x(k)\) and the candidate control plan \(u(k)\) when predicting the traffic state for the consecutive time step, denoted as \(x(k+1|u(k))\). \(x(k+2|u(k)), \ldots, x(k+N_0|u(k))\). Along with the traffic state measurement in previous time steps, the predicted traffic state variables were assessed by the collision probability prediction model. On the basis of the safety performance measured by the model, the optimization module selected the optimized control input \(u^*(k)\) with the optimal safety performance. After applying the selected control input \(u^*(k)\) to the traffic network, the updated traffic state variables were sent to the controller again for optimizing the control signal for the next time step. The proposed control algorithm quantitatively optimized the VSL control input and eliminated the uncertainty brought about by the impact of the applied control. The details of the controller design are described in the next section.

In the proposed control algorithm, a macroscopic traffic flow model was adopted to predict traffic states. The macroscopic traffic flow model divides a freeway into discrete links to analyze their spatial–temporal aggregated characteristics. Here \(m\) represents the index of the links, and \(k\) represents the index of the continuous time steps. The model of Lu et al. was adopted in the proposed control algorithm \((19)\). The model takes the current traffic state variable \(x(k)\) and control plan \(u(k)\) as the inputs to predict traffic conditions. The Lu et al. model is a simplified version of the METANET model: the fundamental diagram assumption in the original model is replaced by direct advising of the control variable in the VSL \((u_m(k))\). The model is composed of the following equations:

\[
\rho_m(k+1) = \rho_m(k) + \frac{T}{L_m\lambda_m}[q_{m-1}(k) - q_m(k) + q_{m+1} - q_{m+2}]
\]

(1)

\[
v_m(k+1) = v_m(k) + \frac{T}{\tau}[u_m(k) - v_m(k)] + \frac{T}{L_m}v_m(k)(v_{m-1}(k) - v_{m+1}(k))
\]

\[-\frac{\mu T}{\tau L_m}(\rho_m(k) - \rho_m(k) + \kappa)
\]

(2)

where:

- \(v_m(k), q_m(k), \rho_m(k)\) = current link speed, flow rate, and density of link \(m\), respectively;
- \(T\) = length of the time step;
- \(L_m, \lambda_m\) = length and number of lanes in link \(m\), respectively;
- \(q_{m}, q_{m+1}\) = flow rate at on- or off-ramps, respectively;
- \(u_m(k)\) = advised VSL value at link \(m\); and
- \(\mu, \kappa\) = model parameters.

Equation 1 is the flow conservation equation, which is similar to both the Lu et al. model and the original METANET model. Equation 2 is the speed prediction model, which incorporates the VSL control. The future link speed is predicted on the basis of the advised VSL value and the traffic states of the adjacent links. To modify the current link speed, the link speed is predicted with three terms: the relaxation term, the convection term, and the anticipation term. The relaxation term reflects the impact of the VSL control applied to the link speed. The convection term expresses the speed convection effect: the downstream link will take the link speed from the upstream link with delays. The anticipation term reflects the phenomenon by which the link speed is affected by driver anticipation of travel speed according to downstream traffic density.

### Collision Probability Prediction Model

The predicted traffic state variables, along with the previous traffic state variables, were evaluated with the safety assessment model. A precursor-based collision prediction model, following the methodology presented in earlier work \((3)\), was adopted. A similar case-control logistic regression technique was adopted for modeling traffic incidents. In the model, case referred to a collision, and control referred to a no-collision event. The dependent variables of the model were designed as a binary variable (collision versus no collision). The traffic characteristics (speed, occupancy, and flow) before a collision event, and a corresponding no-collision event, were considered as the explanatory variables of the model.

The traffic state variables 30 min before the incident were selected and divided into six 5-min time slices. Index 1 is the 5-min slice right before a collision occurs. Two years of collision data, which include 46 collisions at the experimental site, were used to conduct the model. After calibration, the probability of \(x\) \([\Pr(x)]\) as a collision was computed with the following equation:

\[
P(x) = \frac{\exp(\text{constant} - b_1 SV_2 - b_2 AO_1 + b_3 \log SS_2)}{1 + \exp(\text{constant} - b_1 SV_2 - b_2 AO_1 + b_3 \log SS_2)}
\]

(3)

where:

- \(SV_2\) = standard deviation of volume in past 5 to 10 min,
- \(AO_1\) = average occupancy in 0 to 5 min before incident, and
- \(SS_2\) = standard deviation of speed 5 to 10 min before incident.

The calibrated values of the constant and the coefficients \(b_1\), \(b_2\), and \(b_3\) are \(-1.207, 3.149, 4.028, \) and \(-3.694\), respectively. Detailed descriptions of the model are available elsewhere \((5)\).

### VSL Control Optimization

As shown in Figure 2, the optimization module in the proposed algorithm controller uses the evaluation results from the collision probability prediction model to determine the optimized VSL control input. The optimization minimizes the overall safety risk in the examined prediction horizon \(N_0\) (10 min in this study). The optimization process is a problem of minimizing the objective function \(J\):

\[
J(x) = \sum_{j=1}^{N_0} \sum_{m} P_{m,j}(x)
\]

(4)

where \(M\) is the set of all links.

As shown in Equation 4, the objective function measures the summation of incident probability over all the \(m\) analyzed links, as well as the entire prediction horizon (from time step \(k + 1\) to \(N_0 - 1\)). The collision probabilities were evaluated at every link and at all time steps within the prediction horizon \((P_{m,j}(x))\) and separately for each feasible control input. The average overall collision probability was then used to determine the optimal VSL control input.

In consideration of safety and limitations of field operations, several constraints must be applied to the optimization problem:

\[
u_m(k) \in (30, 40, \ldots, 80 \text{ km/h})
\]

(5)

\[|u_m(k) - u_m(k)| \leq 20 \text{ km/h}
\]

(6)

\[|u_m(k) - u_m(k-1)| \leq 10 \text{ km/h}
\]

(7)
Of the listed constraints, Equation 5 narrows the selections of the candidate VSL values to between 30 and 80 km/h. The upper boundary was set to 80 km/h to match the static speed limit of the studied area. The lower boundary was set to 30 km/h because drivers rarely follow a speed limit that is lower than 30 km/h. Furthermore, to improve the clarity of a VSL control message, the advised speed limits were selected only from multiples of 10 km/h. Constraint 2 in Equation 6 was established to prevent an abrupt speed limit change between two successive links. The difference in speed limits between two adjacent links was limited to less than 20 km/h. Constraint 3 in Equation 7 was established to prevent an abrupt speed limit change between two consecutive time steps at the same link. The difference in speed limits between two successive time steps was limited to less than 10 km/h.

For optimizing the control plan, several optimization techniques could be considered. For applying the designed control algorithm over a large network with multiple VSL locations, a standard nonlinear optimization method could be adopted, such as a genetic algorithm or sequential quadratic programming. However, in this study only four VSLs were deployed. Furthermore, the selection of the candidate VSL control signal was limited by the applied constraints. Thus, it was unnecessary to adopt a sophisticated optimization method in the controller. Alternatively, the control algorithm simply traverses all the candidate control inputs to determine the optimal control input, and the time consumed for optimization is still acceptable for online applications (less than 1 min).

EXPERIMENTAL DESIGN

A field data–based simulation study was conducted to evaluate the effectiveness of the proposed control algorithm. For implementing the proposed control algorithm, an 11-km freeway stretch was selected from Whitemud Drive, a major congestion-prone highway that serves as the inner ring road of Edmonton, Alberta, Canada (Figure 3).

The westbound direction of this freeway stretch, which consists of three lanes for most of the segments, was reproduced in the microscopic traffic simulation software VISSIM. The annual average daily traffic of the selected highway is greater than 40,000 vehicles, which causes daily recurrent traffic congestion during peak hours. The operating speed could be lower than 50 km/h for more than 70% of the workday peak hours. On this stretch, the traffic is monitored by more than 30 loop detectors, which report traffic state measurements at 60-s intervals. A complete morning peak demand profile (from 6:00 to 9:00 a.m.) was input into VISSIM to reproduce the real-world traffic demand. In VISSIM, virtual loop detectors were placed at the middle of each link, as well as where the actual loop detectors are located on Whitemud Drive. To accurately reproduce the congested real-world traffic condition and driver behaviors, the simulation parameters, such as driving behavior parameters and link characteristics, were adjusted so that the data collected by the virtual loop detectors closely matched the actual loop detector data.

After careful calibration, the simulation site was considered the baseline test bed; on the baseline test bed, the proposed VSL control algorithm was implemented so its impact on traffic flow could be evaluated. From the analysis and results of the loop detector data, two bottlenecks were identified in the studied area; these are indicated in Figure 3. In this study, the VSL with the proposed control algorithm was implemented at four locations: before and after each of the two recognized bottlenecks. The VISSIM model was coded through the COM interface to facilitate the proposed active VSL control algorithm.

ANALYSIS OF RESULTS

For the evaluation of the proposed control algorithm, the traffic network performance without VSL control was considered the baseline condition. The VSL-controlled traffic network performance was compared with the baseline condition for both safety and mobility.

![Figure 3: Site of application study, Whitemud Drive (NW = northwest; r = on-ramp; S = off-ramp; L = link; q0 = inbound demand).]
For quantitatively evaluating the performance of the proposed control algorithm, three MOEs were selected: TTT, TTD, and collision probability. The first half hour of the study period was considered the warm-up period of the simulation, and it was excluded from the comparisons. TTT measures the total travel time of all vehicles on the studied network during the experiment, which was formulated by Equation 8:

$$\text{TTT} = T \ast L_u \ast \sum_{m \epsilon} \rho_u(k)$$  \hspace{1cm} (8)

where $\rho_u(k)$ and $q_u(k)$ are the link density and flow rate, respectively, in $x^u(k) \epsilon u(k)$.

Equation 8 measures TTT over all the $m$ links throughout the study period. A smaller TTT indicates that the vehicles were able to go through the studied network in less time. The result was aggregated at 1-min intervals. TTD measures the total travel distance of all the vehicles within the network, formulated as Equation 9:

$$\text{TTD} = T \ast L_u \ast \sum_{m \epsilon} q_u(k)$$  \hspace{1cm} (9)

Similar to TTT, TTD examines the effectiveness of VSL on the networkwide traffic flow. TTD measures the traffic flow efficiency according to the discharge flow rate. A larger TTD indicates better network mobility performance with more efficient traffic flow.

The first two MOEs were selected to measure networkwide mobility performance, but collision probability was selected to measure the networkwide safety performance. Equation 3 can be used to measure collision probability for each link at each time step. The average overall collision probability was recorded for comparison.

Global MOE comparisons for the study period are summarized in Table 1 and demonstrate the overall VSL system performance. As shown in the table, the proposed VSL control algorithm produces a significantly lowered collision probability. For the two identified bottlenecks, the network has the highest safety risks, collision probability was significantly reduced from 36% to 23%, which is a 35% relative reduction. This was achieved by quantitative analysis of the impact of the VSL control on traffic flow dynamics. Under the proposed control, improving network safety performance does not lead to compromises in mobility performance. The comparisons of TTT show that the proposed control algorithm decreased TTT by approximately 6%. According to Equation 8, the control algorithm managed to restrain the traffic flow density as an effect of lowering the collision probability. This contributes to mobility improvements, as the experienced delay was reduced (indicated by the reduced TTT). A slight increase was observed in the TTD calculation (0.9%) because in the adopted collision probability model, the increased flow rate does not necessarily go against better safety performance. Thus, while optimizing the traffic network, flow throughput is not tightly restricted by the control algorithm except when preventing the overcritical density. Therefore, when the flow density and demand decreased after the peak hour, a higher discharge volume was encouraged by the algorithm to enable a more efficient traffic flow, which is beneficial to both safety and mobility. A detailed trend of comparison results is illustrated in Figure 4.

Figure 4a demonstrates the measured amount of TTT for both scenarios, aggregated at 1-min levels. Figure 4b demonstrates the evaluation result of collision probability for both scenarios. In the figure, the dashed line shows the changes in network traffic conditions. In the uncontrolled scenario, the traffic became increasingly congested after 7:30 a.m. (the measured TTT increase). The measured TTT reached its peak at approximately 8:30 a.m. and then started to decline as the demand decreased. In the scenario with the proposed VSL control, the traffic flow characteristic pattern (solid line) was significantly changed. In the controlled scenario, since the traffic was not congested, the proposed control algorithm was not activated before 7:00 a.m. Thus, the two measured TTT profiles are on top of each other. At approximately 7:20 a.m., benefitting from the designed traffic state prediction feature, the proposed control algorithm was able to anticipate the forthcoming congestions and thereby activate the control.

To sustain a more stable traffic flow and to prevent any abrupt flow speed changes (safety risks) caused by the traffic breakdown, the speed limits were lowered at the VSL locations placed ahead of the identified bottlenecks. The proposed control algorithm engaged this control action to take advantage of the speed homogeneity effect: with the speed limit lowered, the differences of the travel speed between individual vehicles were mitigated to enhance network safety performance. Figure 4b shows that, as a consequence of the lowered travel speed, the increase of collision probability between 7:30 and 8:00 a.m. in the controlled scenario (solid line) is smoother than the uncontrolled condition (dashed line). As a compromise, Figure 4a shows that the TTT in the solid line went higher than the uncontrolled scenario after 7:30 a.m. Furthermore, in the controlled scenario, the network reached its capacity earlier than the uncontrolled scenario. This caused both the measured TTT and the collision probability to appear higher in the VSL controlled scenario during its peak period (around 8:00 a.m.).

However, benefitting from the speed homogeneity effects enhanced in the VSL control scenario, the peak demand was also discharged earlier than the uncontrolled scenario. Figure 4, a and b, shows that in the VSL control scenario, the traffic flow recovered from the congestion earlier than the uncontrolled scenario, at just after 8:30 a.m. This occurred because, in the adopted safety assessment model, the increased traffic volume does not go against better safety performance. Therefore, the control algorithm encourages more discharge flow by gradually raising the speed limit once the demand on the network decreases. Second, the homogeneous traffic flow enabled by the applied VSL control increases the throughput of the network.

### Table 1: Comparison of Overall Network Performance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bottleneck Crash Probability (%)</th>
<th>Overall Crash Probability (%)</th>
<th>TTT (vehicle hours)</th>
<th>TTD (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncontrolled</td>
<td>36.2</td>
<td>17.8</td>
<td>3,281.4</td>
<td>187,814.3</td>
</tr>
<tr>
<td>Proposed VSL control</td>
<td>23.4</td>
<td>14.2</td>
<td>3,089.0</td>
<td>189,598.4</td>
</tr>
<tr>
<td>Relative change compared with uncontrolled case (%)</td>
<td>−35.4</td>
<td>−19.8</td>
<td>−5.9</td>
<td>0.9</td>
</tr>
</tbody>
</table>

*Crash probability was measured at two identified bottlenecks.
FIGURE 4  Comparison results for (a) total travel time and (b) network overall collision probability.
(proved by the increased TTD shown in Table 1) to allow the peak demand to discharge faster.

Analysis of the evaluation results proves that the application of the proposed VSL control algorithm can not only effectively reduce the collision probability on a congested traffic network but also improve traffic safety performance without significant compromises in mobility.

CONCLUSIONS AND FUTURE WORK

This paper proposed an algorithm that optimizes the VSL control signal by quantitatively predicting and assessing network safety performance. The proposed control algorithm design processed a traffic state prediction feature and a precursor-based collision prediction model. Before implementation, the candidate VSL control input was analyzed against the current traffic condition so future traffic states could be predicted. The associated safety performance (collision probability) was measured on the basis of the predicted control results. The VSL control plan that leads to the least network-wide collision probability was selected for implementation. Different from earlier studies, the proposed control algorithm introduces traffic state prediction into safety-oriented active traffic control applications and avoids the uncertainty of the impact of the implemented control.

A field data–based simulation study evaluated the efficiency of the proposed control algorithm. The proposed algorithm was implemented to perform VSL control over an 11-km congested highway stretch. The control algorithm successfully predicted the forthcoming traffic breakdown and lowered the speed limit to restrain collision probability. The speed limit was gradually raised during the congestion recovery phase to encourage a more efficient and safer traffic flow. The proposed VSL control algorithm effectively reduces collision probability on a congested traffic network, and no significant mobility compromise was observed.

The proposed algorithm reduces the number of congestion-related collisions by predicting traffic states and providing a dynamic and safe VSL control. If the proposed algorithm and control are adopted by traffic safety authorities, collision probability may decrease and roads will be safer for all users. The Whitemud Drive corridor evaluated in this paper has been equipped with appropriate VSL signs and the dynamic control system. Future studies will evaluate the proposed VSL control algorithm in real-world implementations.

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