Promoting safety at railroad crossings by reducing traffic delays

A.G. Hobeika¹, and L. Zhang²
¹Department of Civil and Environmental Engineering
Virginia Tech, Virginia, USA
²Systems Division, ITT Industries Inc. Virginia, USA

Abstract

In this study, an artificial neural network traffic control algorithm has been developed to optimize the traffic delays around highway railroad crossings. The algorithm is divided into two steps. The first step is to design a proper preemption phase plan, and the second step is to find the optimized phase length.

The objective of designing the preemption plan is to maximize the safety at the grade crossing. This can be achieved by designing the preemption plan so that highway traffic will be prevented from queuing on the grade crossing intersection.

The optimized process will use as objective function the traffic delays at the intersections surrounding the grade crossing area. That function will be approximated and represented by neural network. After that function has been developed and trained, mathematical algorithms has been employed to get the optimized length of phases so that total delays can be minimized. This research utilizes the CORSIM simulated traffic network package to conduct its analysis and determine its results.

1 Introduction

Promoting safety at highway rail grade crossing (HRGC) is one of the nation's top priority transportation goals. HRGC safety is the responsibility of both railroad and highway authorities. On the railroad side, the most common safety measures aim at preventing highway vehicles from entering the right of way within a grade crossing during the passage of a train.. For example, traffic signal control and active warning devices (including gates) installed at grade
crossing are considered the highest form of protection, short of grade separation [1]. On the highway side, highway traffic signals are usually interconnected to the railroad track circuits, which preempt the signals to respond to the arrival/departure of a train. It is assumed that the preemption procedure will clear the vehicles on the tracks before the train arrives. However, the preemption could antagonize highway drivers in a congested traffic network and cause them to take unnecessary risks by crossing the tracks to avoid long delays. This will increase the potential of accidents between the vehicles and the train. Also, it is quite common that the highway intersection queue would spill back onto the railroad tracks as well, particularly if the intersection traffic lights are not timed properly.

The question is, can we promote the traffic light preemption while minimizing the traffic delay, in order to increase HRGC safety?

2 Overview of system architecture

The research entitled “Signal Optimization Under Rail Crossing Safety Constraints” (SOURCAO) has two objectives:

- Reduce highway traffic delay
- Promote grade crossing safety

The traffic signal control optimizes not only the current delay, but the forecasted delay in a projected period of time (2 minutes in this research). Promoting safety is also carried by minimizing the “unsafe time”, which is the time a highway vehicle queues on the railroad track when the track is closed for railroad traffic.

2.1 Approaches

The system implementation is divided into two steps, corresponding to the two objectives. The first step is to choose a proper preemption phase sequence; and the second step is to find the optimized phase length for the traffic lights surrounding the railroad crossing.

The first step is to choose a proper preemption phase sequence to promote grade crossing safety. In the proposed system, an inference engine in an Intelligent Agent is designed to prevent the queue from backing onto a grade crossing and spilling back on surrounding intersections.

The optimization process uses the traffic delay at the intersections within the grade crossing vicinity as an objective function. The optimization is implemented into two stages. In the first stage, the delay function is approximated and represented by a multilayer perceptron neural network (off-line training). After the function is trained, an algorithm named Successive Quadratic Programming (SQP) searches the optimized length of the phases so that the total delay in the network can be minimized (on-line). The inference engine takes the on-line detector input and dynamically calculates the de-queuing time constraints according to the detected queue length.
2.2 Methodologies

2.2.1 Intelligent agent
Russel [1] defined the agent as anything that can be viewed as perceiving its environment through sensors and acting upon that environment through efforts. This definition perfectly fits the solution set for the first objective. “A traffic control agent perceives its environment through sensors (surveillance) and acts upon that environment through efforts (choosing sequences and traffic phase lengths).”

In the proposed system, the core mechanism to implement the rule of an intelligent agent is an inference engine. The inference is a simple rule-based deduction procedure. The goal of the agent is to choose the next signal phase, according to current available surveillance detector and grade crossing information.

2.2.2 Neural network
In this research, a multilayer perceptron (MLP) neural network is applied to forecast the network traffic delay. The weights in a three-layer perception neural network are trained to store the traffic patterns so that the delay in the next 2 minutes can be predicted. The network traffic delay forecast can be expressed as:

\[ D = \sum_{m \in M} d_m = \sum_{m \in M} f(X; W, U) \]  

Where:
- \( m \) is the index to a link;
- \( M \) is the collection of surveillance links;
- \( d_m \) is the delay on link \( m \);
- \( W \) is the weight trained from the neural network (off-line training);
- \( U \) is the detector and grade crossing information obtained from on-line;
- \( X \) is control variables or phase length of all traffic signals. In the proposed system, the next three phases are considered to join the optimization. However, only the first phase is implemented and the second phase length is optimized again when the first phase is about to end. The total number of variables in SOURCAO is three times the number of the traffic signals.

2.2.3 Optimization
After the weights in the delay function become stabilized, the optimization process is started. The objective function is subject to the following constraints

\[ x_{\text{min}} \leq x_{ij} \leq x_{\text{max}} \]  
\[ x_1 + x_2 + x_3 \leq 120 \]

Where:
- \( i \) is the number of traffic signals;
- \( j \) is the optimized signal phase number, \( j=1, 2, 3; \)
120 is the time to project the future delay (two minutes in seconds in the proposed system);
\(x_{\text{min}}\) and \(x_{\text{max}}\) are the minimum and maximum green time. The maximum green time is determined dynamically by queue length.

Successive Quadratic Programming [2] is applied to solve the non-liner objective function shown in equation (1) with linear constraints shown in equations (2) and (3).

3 Validation and evaluation

3.1 Introduction

Evaluation is defined as a way to verify whether the system performance meets the stated objectives. In this section, the objective functions and methodologies, including delay model, neural network forecast, inference engine and SQP are validated. In addition, the system performance is evaluated through TSIS/CORSIM simulation model. The simulation results are tested through the student t-test statistical method.

3.2 Delay model validation

Figure 1 shows the difference between the proposed delay model and CORSIM QDELAY output in the four approaches at a signalized intersection. The horizontal axis of the diagram represents the simulation time while the numbers in the vertical axis represent the cumulative link delay in vehicle-seconds. The delay results obtained in SOURCAO is slightly higher than those obtained by CORSIM QDELAY model. The proposed delay more reasonably approximates the control delay defined in Highway Capacity Manual (HCM) than the current CORSIM QDELAY does.

The success of the proposed optimization using the above proposed delay model proves that the delay model is valid; otherwise, the optimization results would have been wrong.
3.3 Neural network model validation

In the test case, the data set comes from the first five runs of CORSIM in 16 surveillance links. Different random number seeds are assigned to each of CORSIM run. The MLP training is based on an Object Oriented Programming (OOP) implementation. After about fourteen days (about 340 hours) of training, the errors measured are shown in Table 1. The error is the summation of the square of the difference of MLP calibrated delay (seconds/vehicle) and the delay (seconds/vehicle) proposed in this research. The MLP is verified by a Cross-Validation procedure. The estimation subset (the first five simulation cases) is applied to select the weights and the next two cases (case 6 and case 7) are the validation subsets, which were used to test and validate the model.

There are 920 points in the first data subset. From the table, it is demonstrated that the neural network training converges exceptionally well. The errors in 841 out of 920 data points (or 91.4%) are below 1% and the errors only in 3 out of 920 data points (or 0.3%) are larger than 5%. While in the validation set, there are only 5 out of 336 data points (or 1.5%) with error larger than 5%. Usually, in engineering studies, it’s acceptable that the estimation error is 5% or less.
An intelligent agent senses situations in the traffic network and chooses the appropriate next phase. A test case is introduced first, to show how the intelligent agent is validated. Before the arrival of the train, if the queue backs on the tracks, the inference engine chooses a phase to de-queue the vehicles on the railroad tracks. In Figure 2, both the right and the left snapshots are taken at the same time (07 hour, 56 minutes and 32 second of the simulation time).

Figure 2 shows that in both scenarios, the grade crossing signal is in amber, which means the grade crossing is about to close. The signal on the right hand side at node 12 indicates that traffic is open to east west bound while south and north approaches are closed. Checking the grade crossing, highway vehicles are queued on the tracks. The situation seriously endangers grade crossing safety. On the contrary, the intelligent agent in SOURCAO on the left side chooses a phase (signal is open to traffic leaving the grade crossing) to de-queue the vehicles on the tracks before the grade crossing is closed. The queue on the tracks is cleared and the clearing phase is still going on.
4 System testing on a real network

4.1 The geometry of the test case

The case study area map and the traffic volumes in the simulation come from the Long Island Traffic Study by Parsons Transportation Groups [3] and are shown in Figure 3. Detailed description of the study area can be obtained from a paper from reference [4].

4.2 Grade crossing modeling

CORSIM simulation package doesn’t support any grade crossing simulation function. Before SOURCAO can be tested and evaluated, a grade crossing function is added to CORSIM.

4.3 Traffic surveillance and control

The surveillance detectors around node 12 are shown in Figure 3. The surveillance detector is referred to in one or two letters followed by a number. The letters represent the types of surveillance, as explained at the bottom of the figure.
Figure 3- The layout of surveillance detectors for node 12

(q: The queue detector; d: the left turn detector; dc: the grade crossing detector; f: the full detector)

4.4 Evaluation results

There were 3600 seconds of simulation time for each of 20 simulation runs with different random number seeds. The results indicate that the average control delay in the entire network is reduced from 3.919 minutes per vehicle to 3.445 minutes per vehicle, or a 13.8% saving. The rest of the section proves the average delay by SOURCAO is 0.3 minute per vehicle lower than the average control delay without SOURCAO by the student test.

Hypotheses

\[ H_0: \mu_{diff} = 0 \]
\[ H_1: \mu_{diff} > 0 \]

Level of Significance \( \alpha = 0.05 \)

Where:

\( \mu_{diff} \) is the mean difference of control delays without SOURCAO in which case the phase length is calibrated by HCM (Error! Reference source not found.) and control delays with SOURCAO.
To test the difference between means before- and after-type of studies, Microsoft Excel Data Analysis tool provides paired data analysis function to do so. The output of Data Analysis in Microsoft Excel is generated in Table 2.

From Table, since $t=1.772$ exceeds $t(\text{criteria one-tail})=1.722$, the null hypothesis must reject $H_0$ and accept $H_1$ at the level of significance 0.05. The error of rejecting $H_0$ and accepting $H_1$ is called Type I error. In this case, the probability to commit such error is less than 0.05 or is equal to 0.04616 (Table 2).

Table 2 Data analysis of paired control delay

<table>
<thead>
<tr>
<th></th>
<th>Current</th>
<th>SOURCAO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3.919</td>
<td>3.445</td>
</tr>
<tr>
<td>Variance</td>
<td>0.368472632</td>
<td>0.29522631</td>
</tr>
<tr>
<td>Observations</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

From the above statistical analysis, it is concluded that the effort of 0.3 (or 8.7%) minutes per vehicle in control delay reduction has been achieved at the level of significance of 0.046 by SOURCAO.

4.4.1 Safety improvement
It is hypothesized that the summation of unsafe time, during which the grade crossing is occupied by a highway vehicle when it should be closed to highway traffic, is an indicator of grade crossing safety. The criterion to choose the average case is based on how close the mean and variance for an individual case are to the mean and variance in Table 2. The visual exam of average case in Table 3 shows such queue time under SOURCAO and current (phase length calibrated by HCM) scenarios. The table demonstrates that the safety of grade crossing can indeed be improved.
Summary

By integrating artificial intelligence and optimization technologies, the SOURCAO model optimizes the traffic signal near railroad grade crossings with the consideration of promoting grade crossing safety. The independent simulation evaluation by TSISKORSIM in a case study demonstrates that the objectives are reached. While the safety of grade crossing was promoted, the average network delay is reduced by over eight percent by a t-test at a level of significance 0.046.

The logic of an inference engine works as intended through the simulation validation and evaluation process. When the queue backs onto a grade crossing, it triggers the inference engine safety feature embedded in the system. The system responds to the preemption call, chooses the appropriate phase to clear vehicles on the railroad tracks and to prevent the queue from spilling back on nearby highway intersections. The inference engine dynamically responds to the grade crossing status and traffic surveillance data. It skips the unnecessary phases during HRGC closure time. The visual exam of an average case demonstrated that summation of unsafe time, during which the queue backs onto the grade crossing while the gate is closed to highway traffic, is reduced significantly.

SOURCAO has developed a delay model, which takes the surveillance detector data and grade crossing closure information as the input. The delay model in this research approximates better control delay of HCM than the current CORSIM QDELAY. A multilayer perceptron neural network is applied to forecast traffic delay based on the proposed delay model. The training of neural network converged to a satisfactory accuracy in both training data set and verification data set. The optimization algorithm (Successive Quadratic Programming) is implemented through mixed language function calls (C++/FORTRAN). SQP is proven successful in reducing the network traffic delay with the variables (phases length) constrained by safety consideration.

SOURCAO has potential for practical uses, one of which is to assist grade crossing preemption design after some modifications of the proposed system. One of the motivations behind this research is to try to bridge the gap between highway traffic signal optimization and railroad operations, or equivalently, try

<table>
<thead>
<tr>
<th>Observation</th>
<th>Current</th>
<th>SOURCAO</th>
<th>Current</th>
<th>SOURCAO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Start</td>
<td>End</td>
<td>Start</td>
<td>End</td>
</tr>
<tr>
<td></td>
<td>Min</td>
<td>Sec</td>
<td>Min</td>
<td>Sec</td>
</tr>
<tr>
<td>51</td>
<td>46</td>
<td>51</td>
<td>48</td>
<td></td>
</tr>
<tr>
<td>56</td>
<td>34</td>
<td>56</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>58</td>
<td>30</td>
<td>58</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Total Unsafe Time</td>
<td>29 seconds</td>
<td>8 seconds</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5 Summary

By integrating artificial intelligence and optimization technologies, the SOURCAO model optimizes the traffic signal near railroad grade crossings with the consideration of promoting grade crossing safety. The independent simulation evaluation by TSISKORSIM in a case study demonstrates that the objectives are reached. While the safety of grade crossing was promoted, the average network delay is reduced by over eight percent by a t-test at a level of significance 0.046.

The logic of an inference engine works as intended through the simulation validation and evaluation process. When the queue backs onto a grade crossing, it triggers the inference engine safety feature embedded in the system. The system responds to the preemption call, chooses the appropriate phase to clear vehicles on the railroad tracks and to prevent the queue from spilling back on nearby highway intersections. The inference engine dynamically responds to the grade crossing status and traffic surveillance data. It skips the unnecessary phases during HRGC closure time. The visual exam of an average case demonstrated that summation of unsafe time, during which the queue backs onto the grade crossing while the gate is closed to highway traffic, is reduced significantly.

SOURCAO has developed a delay model, which takes the surveillance detector data and grade crossing closure information as the input. The delay model in this research approximates better control delay of HCM than the current CORSIM QDELAY. A multilayer perceptron neural network is applied to forecast traffic delay based on the proposed delay model. The training of neural network converged to a satisfactory accuracy in both training data set and verification data set. The optimization algorithm (Successive Quadratic Programming) is implemented through mixed language function calls (C++/FORTRAN). SQP is proven successful in reducing the network traffic delay with the variables (phases length) constrained by safety consideration.

SOURCAO has potential for practical uses, one of which is to assist grade crossing preemption design after some modifications of the proposed system. One of the motivations behind this research is to try to bridge the gap between highway traffic signal optimization and railroad operations, or equivalently, try
to bring the railroad preemption and safety to highway traffic signal optimization. We expect integration of the safety into optimization could present better grade crossing preemption design elements.

6 Acknowledgement

This research is partially supported by the Federal Railroad Administration, the US Department of Transportation through Eisenhower Grants for Research Fellowship. In addition, this research is partially sponsored by the Federal Highway Administration, the US Department of Transportation and ITT Industries, Systems Division.

References