Hybrid Neural Network Modeling for Multiple Intersections along Signalized Arterials - Current Situation and Some New Results

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Keynote Presentation
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Hong Wang’s Brief Background Information

https://www.ornl.gov/staff-profile/hong-wang-0

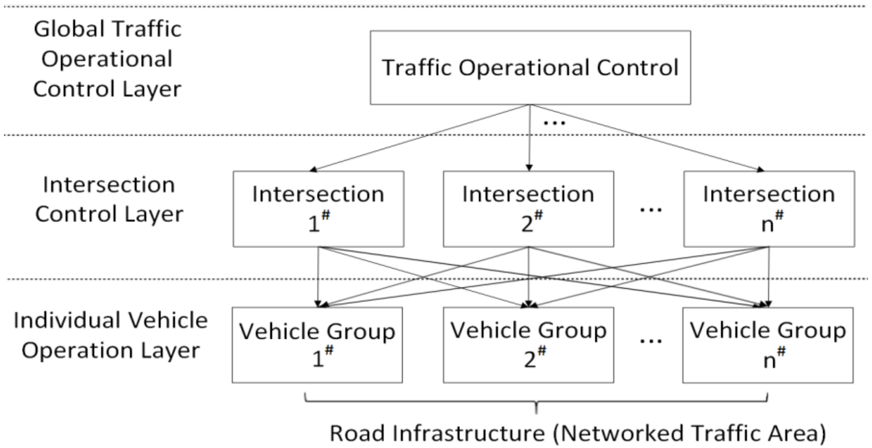
- Hong Wang (Fellow of IEE (now IET), Fellow of InstMC, Senior Member, IEEE) received the master’s and Ph.D. degrees from the Huazhong University of Science and Technology, Wuhan, China, in 1984 and 1987, respectively. He was a Research Fellow with Salford University, Salford, U.K., Brunel University, Uxbridge, U.K., and Southampton University, Southampton, U.K., before joining the University of Manchester Institute of Science and Technology (UMIST), Manchester, U.K., in 1992. He was a Chair Professor in process control of complex industrial systems with the University of Manchester, U.K., from 2002 to 2016, where he was the Deputy Head of the Paper Science Department, the Director of the UMIST Control Systems Centre from 2004 to 2007, which is the birthplace of Modern Control Theory established in 1966. He was a University Senate member and a member of general assembly during his time in Manchester.
- From 2016 to 2018, he was with the Pacific Northwest National Laboratory (PNNL), Richland, WA, USA, as a Laboratory Fellow and Chief Scientist, and was the Co-Leader and the Chief Scientist for the Control of Complex Systems Initiative. He joined the Oak Ridge National Laboratory in January 2019 as a senior distinguished scientist at corporate fellow grade, US Department of Energy. His research focuses on stochastic distribution control, fault diagnosis and tolerant control, and intelligent controls with applications to transportation system area, and has published more than 200 journal papers and 6 books.
- He was an Associate Editor of the IEEE TRANSACTIONS ON AUTOMATIC CONTROL, the IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, and the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING. He is also a member for three Technical Committees of International Federation of Automatic Control (IFAC).

Outline

- Operational structure for transportation systems and signal control systems overview
- Neural network based approaches – current situation and challenges
- Hybrid neural network modeling - some new results
- The future

1. Operational structure for transportation systems and signal control systems overview

3 –Layered Structure for Transportation Systems



Information flow

- ❑ Mass flow
- ❑ Energy flow

Available data:

- ❑ Data from fixed sensors such as probe detector, intersection camera images
- ❑ Moving data such as the data provided by individual vehicles

1.2 Intersection Control Basics

- Road Networks
- Junctions/Cameras
- Traffic Lights

Traffic flow distribution = smooth and energy savings as widely required objectives

1.2 Intersection Control Basics

- Traffic Signal Design
  - Ring and barrier diagram
- Conventional mode of traffic signal
  - Pre-time
  - Actuated

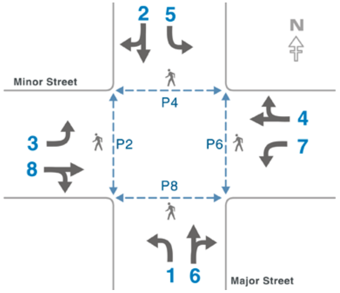
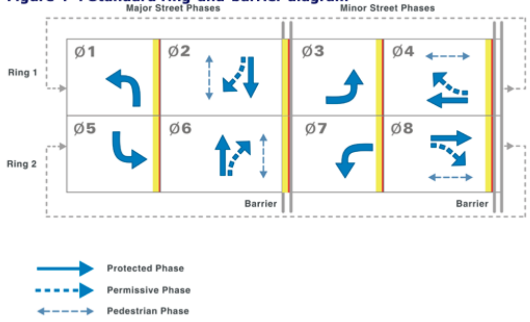


Figure 4-4 Standard ring-and-barrier diagram



Source(USDOT: Traffic Signal Design)

Table 5-1. Relationship between intersection operation and control type.

	Pre-timed		Actuated		
Type of Operation	**Isolated**	**Coordinated**	**Semi-Actuated**	**Fully-Actuated**	**Coordinated**
Fixed Cycle Length	Yes	Yes	No	No	Yes
Conditions Where Applicable	Where detection is not available	Where traffic is consistent, closely spaced intersections, and where cross street is consistent	Where defaulting to one movement is desirable, major road is posted <40 mph and cross road carries light traffic demand	Where detection is provided on all approaches, isolated locations where posted speed is >40 mph	Arterial where traffic is heavy and adjacent intersections are nearby
Example Application	Work Zones	Central business districts, interchanges	Highway operations	Locations without nearby signals; rural, high speed locations; intersection of two arterials	Suburban arterial
Key Benefit	Temporary application keeps signals operational	Predictable operations, lowest cost of equipment and maintenance	Lower cost for highway maintenance	Responsive to changing traffic patterns, efficient allocation of green time, reduced delay and improved safety	Lower arterial delay, potential reduction in delay for the system, depending on the settings

Source(USDOT: Traffic Signal Timing Manual)

1.2 Intersection Control Basics – Pretimed Control

Pretimed (Fixed) timing control

- The duration and sequence of the phases "green" vs "red" and "yellow" are fixed regardless of the actual traffic conditions,
- The actual timing and cycle are designed based upon historic traffic data in line with the traffic demand at different times of the day (TOD).

Disadvantage: An open loop control infrastructure that cannot cope with real-time variable traffic flow.

1.2 Intersection Control Basics – Adaptive Control

Adaptive timing control

"green" vs "red" and "yellow" signs cycle at road intersections are tuned adaptively using the measurements of the real-time approaching traffic flow near intersections

Advantage: Can cope with variable traffic conditions

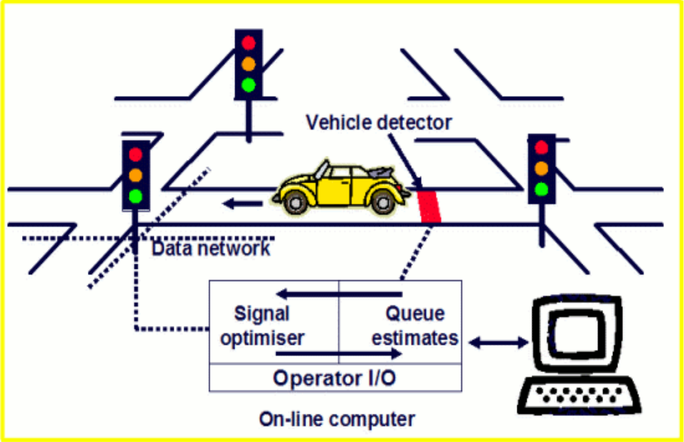


Fig. 1 General framework on adaptive signal control systems (SCOOT)*

*Hunt, P.B., Robertson, D.I., Bretherton, R.D. and Royle, M.C., 1982. The SCOOT on-line traffic signal optimisation technique. *Traffic Engineering & Control*, *23*(4)

Example 1. Adaptive LQR Control in Smart Mobility 1.0

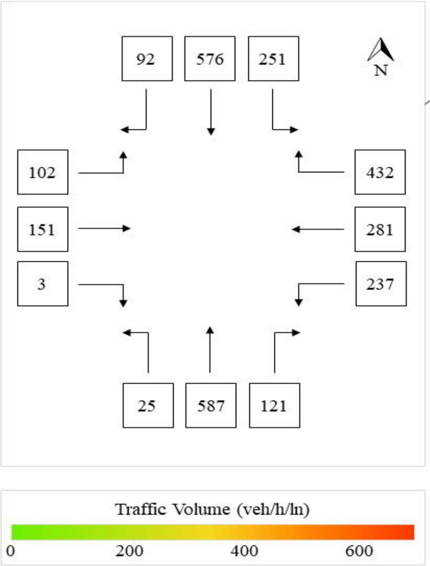
Objective: Using green timing with fixed cycle to smooth traffic flows over the network

Downtown Bellevue street network

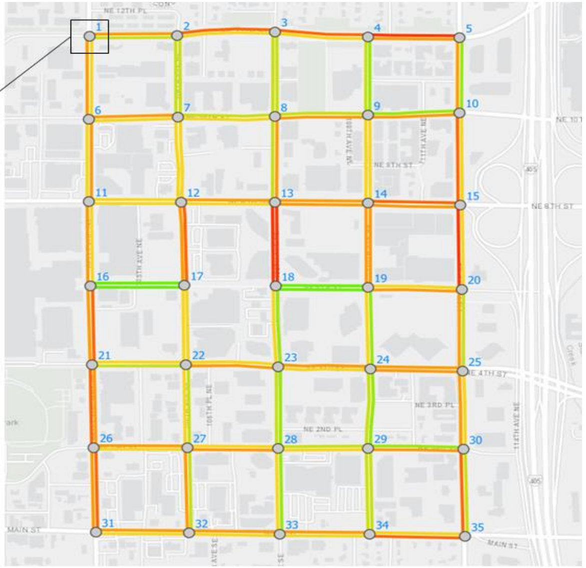
- Grid road system
- 7×5, 35 intersections
- 57 bi-directional road links

Traffic Data

- Provided by the City of Bellevue
- Road geometrics (e.g., length, number of lanes)
- Traffic count by movement at each intersection during midday off-peak period (1 – 2 PM) in 2017



(a) Traffic count data

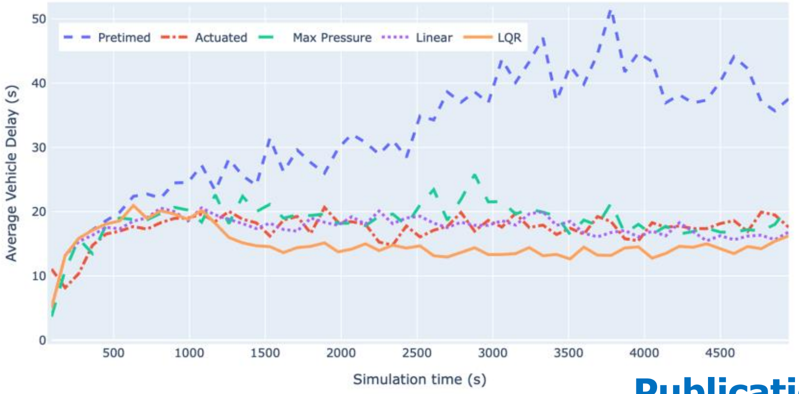


(b) Road network and traffic volume

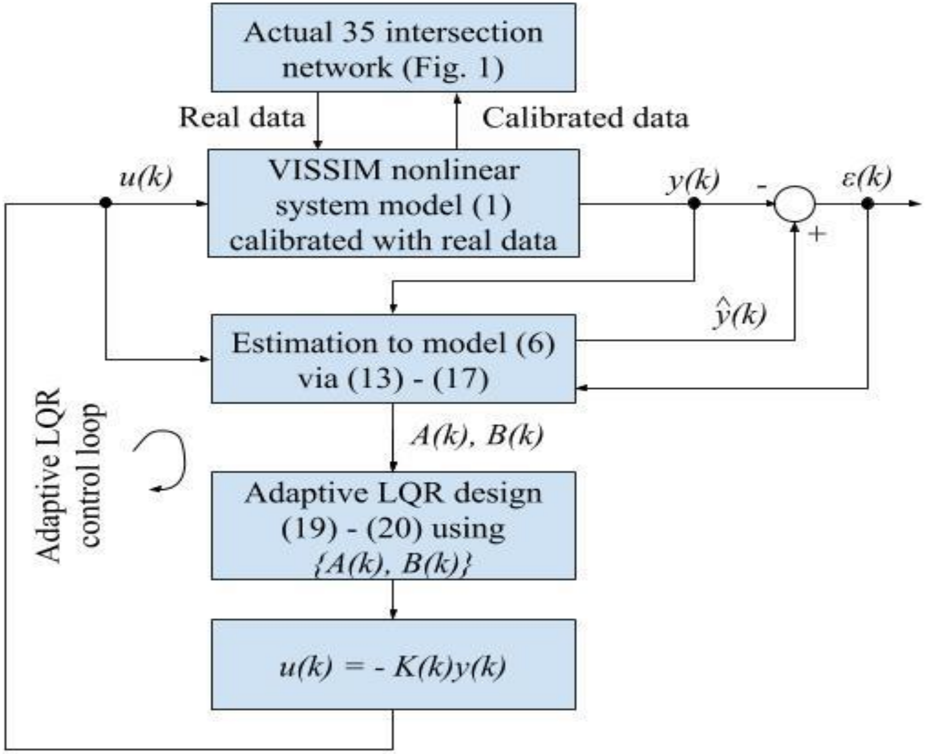
Example 1. Adaptive LQR Control in Smart Mobility 1.0

- **Objective:**

Using green timing with fixed cycle to smooth traffic flows over the network



(c) Initial N-S green time = 60s



Publications: Two long papers in *IEEE Transactions on Intelligent Transportation Systems*, 2020

One Keynote talk at an International Conference, one IEEE Conf

1.3 Advanced Traffic Signal Control – Connectivity via Communications

- Advanced traffic control with **Connected and Autonomous Vehicles (CAVs)**
  - (1) Actuated traffic signal enhanced using CAVs data
    - Estimate <u>aggregated</u> traffic measures (traffic volume, queue)
    - Loop detector (inaccurate and limited spatially) + CAV data
    - Light computation burden
    - (Day and Bullock, 2016; Goodall et al., 2013)
  - (2) Platoon-based signal control
    - Group individual vehicles to platoons
    - Allow the platoons to pass the intersections without severe interruptions
    - Traffic <u>prediction</u> on <u>mid-level</u> traffic flow states (e.g., volume, arrival time of platoon)
    - Light computation burden – group vehicle into platoons
    - May generate sub-optimal signal plans due to the simplicity
    - (He et al., 2012; Pandit et al., 2013)

1.3 Advanced Traffic Signal Control – Connectivity via Communications

- Advanced traffic control with CAVs
  - 3) Planning-based signal control
    - Detailed trajectories of individual vehicle – better describe the real traffic conditions
    - Predict trajectories and arrival time of each vehicle & predict traffic states in a forward time horizon
    - More accurate and complex
    - (Li and Ban, 2018; Li and Ban 2020; Feng et al., 2015)
  - 4) Transit priority control based on CAVs
    - Multimodal traffic control → Special case of planning-based signal control
    - Aims to reduce delay of public transit by phase extension/insertion
    - May disrupt normal traffic progressions
    - First-come-first-serve strategy to resolve conflicting requests
    - (Zlatkovic et al., 2012; He, et al., 2014).

1.4 Traffic Flow Modelling at Intersections

Plan to be controlled

<u>Input:</u> Traffic signals ("green" vs "red" and "yellow" signs);

<u>Output:</u> Traffic flow represented by travel delays, queue length, etc;

<u>Modelling:</u> Establish relationship between inputs and outputs

1.4 Traffic Flow Modelling at Intersections

- **First principle modelling** ⟹ **basic flow dynamics and balance**

- **Data driven modelling** ⟹ **detector/camera data and machine learning to obtain the traffic flow models**

- **Semi-physical modelling** ⟹ **Combination of the first principle modelling with data driven modelling (Wang, 1997)***

*H. Wang and A. Afouxenidis, "A new approach for semi-physical modelling for unknown dynamic systems", Proc. of the IEEE Singapore, International Symposium, 1997.

1.4 Traffic Flow Model – Nonlinear and Stochastic Nature

Traffic flow can be modeled as stochastic distribution process using kinematic wave theory*,

*Lighthill, M. J., G. B. Whitham. 1955. A theory of traffic flow on long crowded roads. Proc. Roy. Soc. A229 317–345.

$$q(x,t)=\frac{\partial N(x,t)}{\partial t}$$

$$k(x,t)=\frac{-\partial N(x,t)}{\partial x}$$

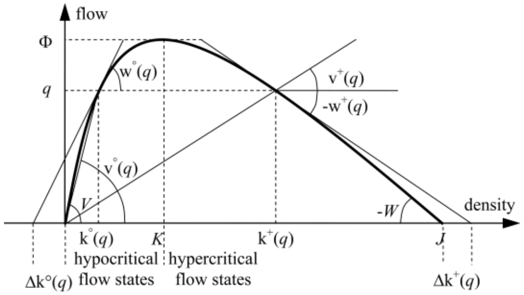
Flow *q* and density *k* at a point in space *x* and time *t, N:* Vehicle count

$$\frac{\partial k(x,t)}{\partial t}+\frac{\partial q(x,t)}{\partial x}=0$$

Flow conservation equation

$$w\,(q,x) = \partial k(q,x)/\partial q$$

w(q, x): The average speed of a traffic stream/flow, *w*



Example of traffic flow, density, and speed relationship. (Image source: **Gentile, Guido. "The General Link Transmission Model for dynamic network loading and a comparison with the DUE algorithm." *New developments in transport planning: advances in Dynamic Traffic Assignment* 178 (2010): 153

Picture from www.google.com

1.4 Traffic Flow Model – Nonlinear and Stochastic Nature

- With control inputs as the distribution of the traffic lights (**red** – **yellow** – **green**), the above model can be expressed as

$$\frac{\partial k(x,t)}{\partial t} + \frac{\partial k(x,t)w(x,t)}{\partial x} = Bu(t) + noise(x,t)$$

$$u(t) = \begin{bmatrix} Time \quad in \quad Green \\ Time \quad in \quad Yellow \\ Time \quad in \quad Red \end{bmatrix}$$

- Systems are nonlinear and unknown
- Systems are subjected to random input noises, where control should be performed using neural networks and AI-approaches

2. Neural Network Based Approaches – Current Situation and Challenges

This belongs to adaptive timing control – intelligent traffic signal control

In forming intelligent traffic signal control strategies, the following has been used:

- Fuzzy systems,
- Artificial neural networks,
- Evolutionary computing,
- Swarm intelligence,
- Reinforcement learning, and
- Adaptive dynamic programming

2.1 Fuzzy Logic - Fuzzy-Neuro for Traffic Signal Control

- Wei and Zhang (2002)
- <u>Input :</u> Queue length & # of vehicles on each approach
- <u>Output:</u> Proportion of vehicle passing through the stop line.
- Fuzzy NN:
  - Layer 1: crisp input and output
  - Layer 2: Trapezoidal membership
  - Layer 3: Rule layer
  - Layer 4: Output-linguistic layer
- Gradient descent method to minimize error of y.

$$f_i^{(1)} = x_i$$

$$f_i^{(3)} = \prod_i^n f_i^{(2)}$$

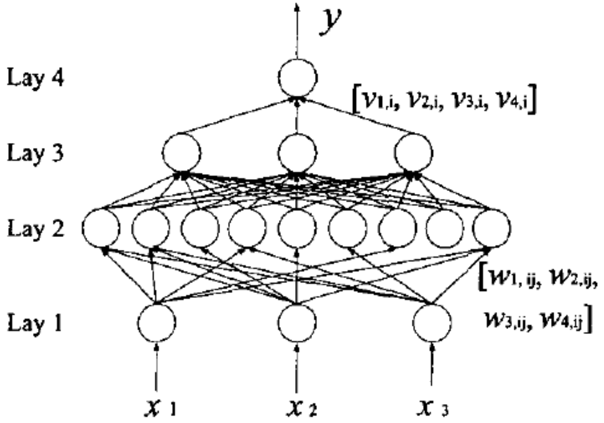


Fig. 2: Fuzzy neural network structure

2.1 Fuzzy Logic - Fuzzy-Neuro for Traffic Signal Control

- <u>Urgent Degree of signal phases</u>: Fuzzy set in Fig. 4 provide analogy to human characterization .
- <u>Parameter a, b, c, d</u> describe Trapezoidal shape: Fuzzy NN was used to updated and optimize these parameters.

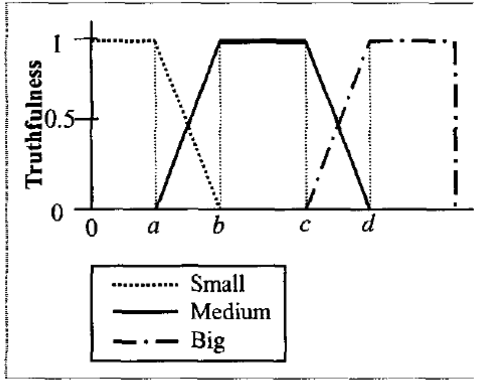


Fig. 4: Trapezoidal fuzzy memberships sets for traffic variables

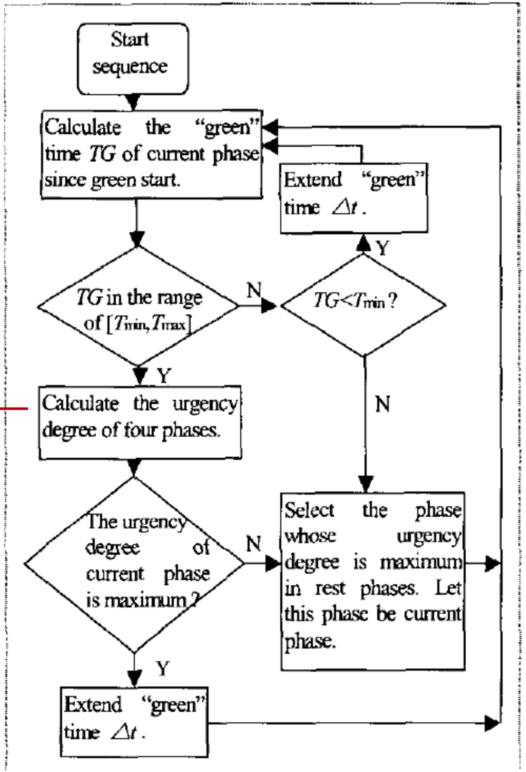


Figure 5: The flow chart of decision-making

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2.2 Reinforcement Learning for Traffic Signal Control

- Wei et al (2018)
- Reinforcement Learning:
  - <u>State</u>: queue, # of vehicles, and waiting time of each lane, vehicle position, current signal phase.
  - <u>Action</u>: change the light to next phase or not.
  - <u>Reward</u>: weighted sum of queue, delay, waiting time, indicator of light switches, # of vehicle, and travel time.

$$Reward = w_1 * \sum_{i \in I} L_i + w_2 * \sum_{i \in I} D_i + w_3 * \sum_{i \in I} W_i + w_4 * C + w_5 * N + w_6 * T.$$

  - <u>Goal</u>: Find an action that maximizes the long-term reward:

$$q(s_t, a, t) = r_{a,t+1} + \gamma \max q(s_{a,t+1}, a', t+1)$$

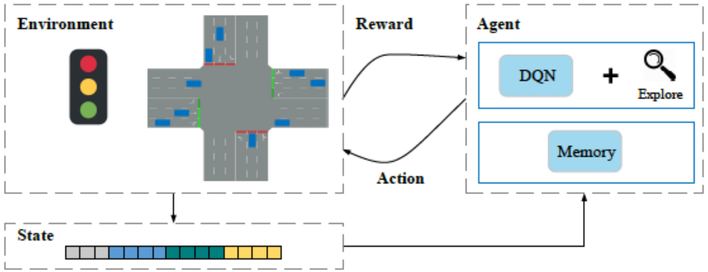

Figure 1: Deep reinforcement learning framework for traffic light control.

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2.2 Reinforcement Learning for Traffic Signal Control

Q-network:

- Image features: learnt by two Convolutional NN (CNN) layer
- Outputs of CNN concatenate with other features
    - Queue
    - Waiting time
    - Signal phase
    - # of vehicles
- All features are fed into a fully-connected NN
- Gate control learning process (by phase = 0 or 1) map reward to action.

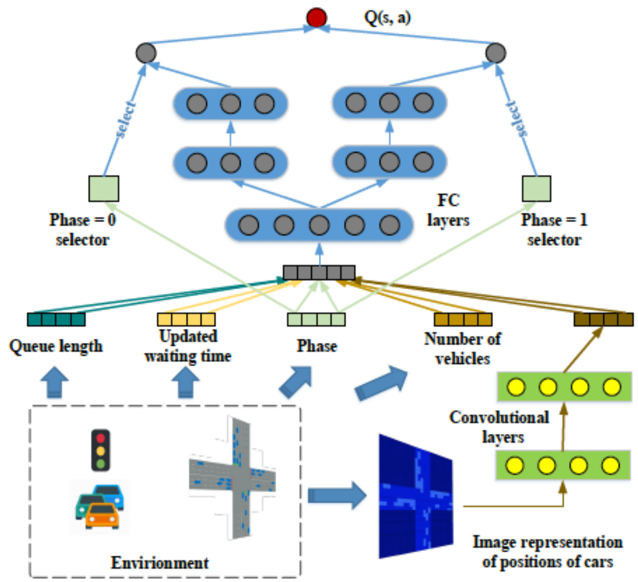

Figure 5: Q-network

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2.2 Reinforcement Learning for Traffic Signal Control

Model Framework:

- Offline:
  - Set a fixed timetable for the lights
  - Let traffic go through the system to collect data samples
- Online:
  - Observe state *s* and take action *a* according to ϵ-greedy strategy combinir exploration and exploitation.
  - Get reward *r* from the environment
  - The tuple (s, a, r) will be stored into memory

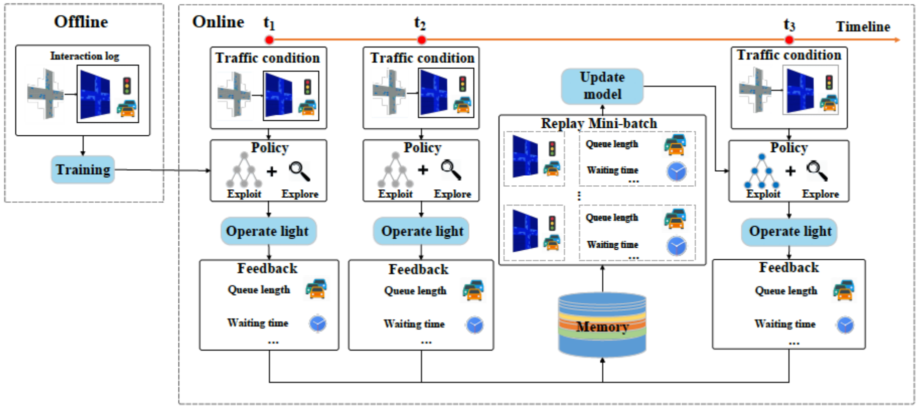

Figure 4: Model framework

2.3 Probabilistic Graph NNs for Traffic Signal Control - Coordination

- Zhong et al (2021)
- Objective: minimize travel time of all approaches of all intersections
- Probabilistic graph NNs:
  1) Graph attention NN module: learn dependence and importance of intersections

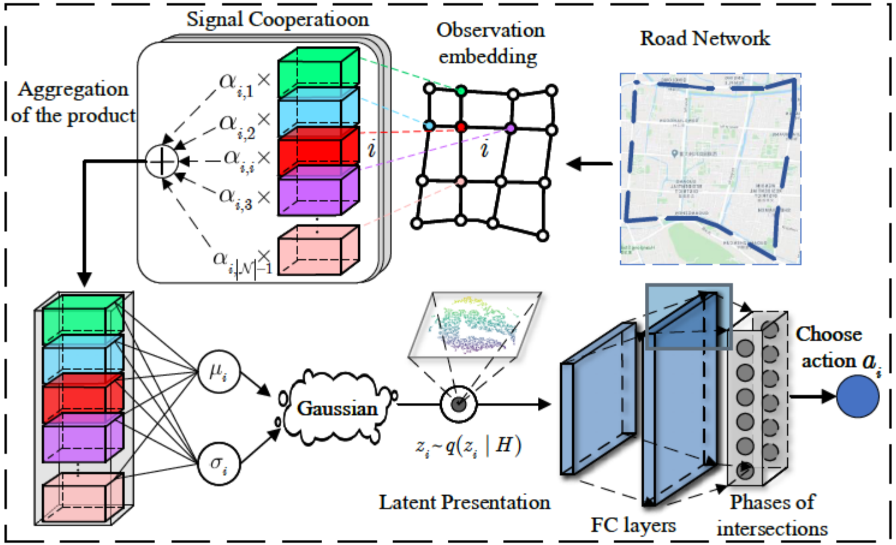

Fig. 1. Overview of the proposed TSC-GNN model.

NN for embedding features: $h_i^t = \sigma(o_i^t W_e + b_e)$

Similarity coefficient between neighboring intersection *i* and *j*: $e_{ij}^t = a\left(W_s h_i^t, W_s h_j^t\right)$

Influence of all neighboring intersections on intersection *i*: $H_i^t = \sigma(W_q \cdot (\sum_{j \in \mathcal{N}_i} \alpha_{ij}^t (h_j^t W_c) + b_q)).$

2.3 Probabilistic Graph NNs for Traffic Signal Control - Coordination

- Probabilistic graph NNs:
  1) Graph attention NN
  2) Graph inference module: learn latent representation of intersections considering the uncertainty of traffic conditions.
  3) Q-value prediction module
     - State: queue, signal phase, # of vehicles
     - Action: select a phase
     - Reward: Queue of approaching lane minus pressure of intersection

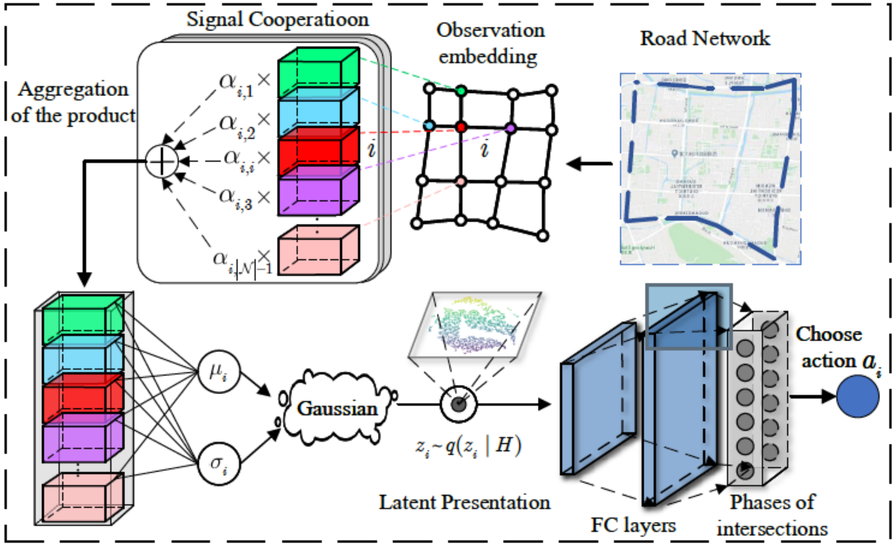

Fig. 1. Overview of the proposed TSC-GNN model.

2.4 Representative NN-based Traffic Signal Control Studies

TABLE I. REPRESENTATIVE NN-BASED TRAFFIC SIGNAL CONTROL STUDIES

Reference	Method	Traffic features	Coordination	Road Network	# of Intersections
Wei and Zhang [21]	Fuzzy neural network	# of vehicles; queue length	No communication	Synthetic	1
Bingham [22]	Neurofuzzy traffic controller	# of vehicles; queue length	No communication	Synthetic	1
Srinivasan et al [23]	Fuzzy neural network with stochastic approximation theorem	Traffic flow; occupancy	Distributed control with communication	Real (CBD Singapore)	25
Choy et al [24]	Hybrid neural network with reinforcement learning and evolutionary algorithm	Traffic flow; occupancy	Distributed control with communication	Real (CBD Singapore)	25
Li et al [25]	Value-based reinforcement learning	Queue length	No communication	Synthetic	1
Wei et al [26]	Value-based reinforcement learning	Queue length; # of vehicles; waiting time; Image	No communication	Synthetic	1
Wei et al [27]	Value-based reinforcement learning with max pressure control	# of vehicles	No communication	Real (New York City)	16
Chen et al [28]	Value-based reinforcement learning	# of vehicles	No communication	Real (New York City)	2510
Wei et al [29]	Graph attention network for cooperation	Queue length	With communication	Real (New York City)	196
Zhong et al [30]	Probabilistic graph neural network	Queue length, # of vehicles	With communication	Real (Hangzhou)	16

3. Some New Results - Hybrid Neural Network Modeling

- **Data from Econolite Platform**

  High resolution data available from the platform as shown in Fig 2.

- **Neural Network Modeling**

  Use neural networks to model the dynamics of the intersections for travel delays and signal timing. The following modeling exercises have been conducted since Feb 2021:

  - Linear (intersection # 4)
  - Neural Network (intersection # 4)
  - Hybrid Neural Network 1 (intersection # 4)
  - Hybrid Neural Network 2 (7 intersections)

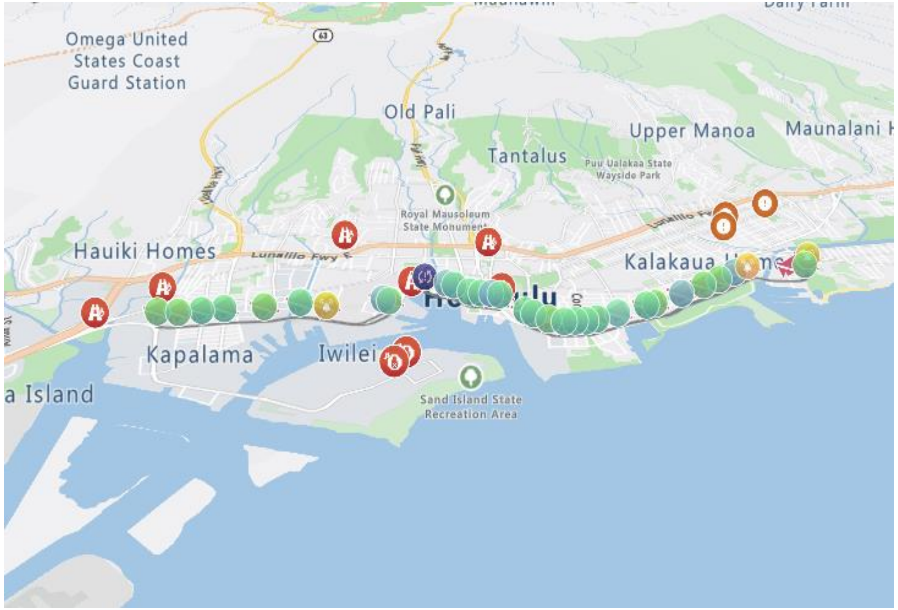

Figure 2. Econolite data and intersectional controls

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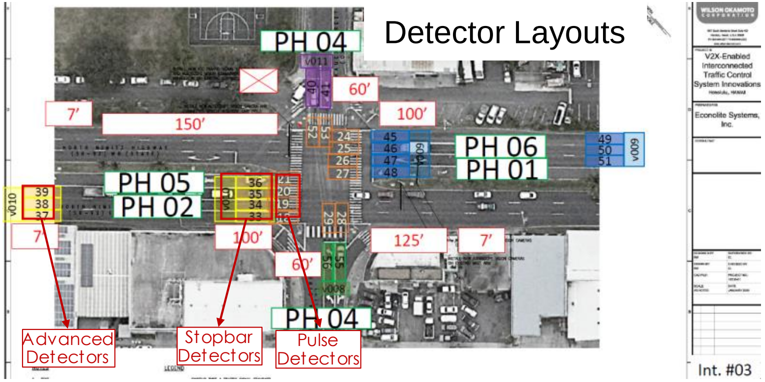
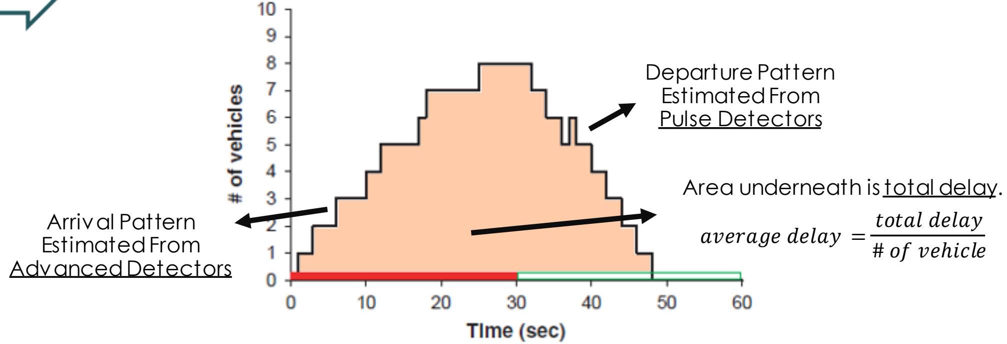
3. Some New Results - Hybrid Neural Network Modeling
3.1 Obtain High-Resolution Delay Data from Econolite System

timestamp	Event code	Event Param	
2/1/2021 11:27:30	44	1	
2/1/2021 11:27:31	7	1	
2/1/2021 11:27:31	8	1	
2/1/2021 11:27:31	63	13	
2/1/2021 11:27:33	81	36	
2/1/2021 11:27:33	44	5	
2/1/2021 11:27:33	82	37	Detector on, Detector id 37
2/1/2021 11:27:33	7	5	Green off, phase 5
2/1/2021 11:27:33	8	5	Yellow on, phase 5
2/1/2021 11:27:33	63	15	
2/1/2021 11:27:33	81	37	Detector off, Detector id 37
2/1/2021 11:27:35	10	1	Red clearance on, phase 1
2/1/2021 11:27:35	9	1	
2/1/2021 11:27:35	64	13	
2/1/2021 11:27:35	65	13	
2/1/2021 11:27:36	0	2	
2/1/2021 11:27:36	11	1	Red clearance off, phase 1
2/1/2021 11:27:36	1	2	Green on, phase 2
2/1/2021 11:27:36	2	6	
2/1/2021 11:27:36	12	1	
2/1/2021 11:27:36	21	2	
2/1/2021 11:27:37	10	5	
2/1/2021 11:27:37	9	5	
2/1/2021 11:27:37	64	15	
2/1/2021 11:27:37	65	15	
2/1/2021 11:27:38	0	6	
2/1/2021 11:27:38	11	5	
2/1/2021 11:27:38	1	6	
2/1/2021 11:27:38	12	5	
2/1/2021 11:27:38	21	6	





- All events from advanced, stopbar and pulse detectors are extracted as well as signal timing of all phases.
- Queue length of each phase is estimated to calculate delay.

3.2 Linear System Modeling: Is the System Nonlinear?

Objective: To explore whether the system is linear or nonlinear

The intersection 4" is considered with the input as the green time and output as average per vehicle delays, denoted respectively as $u(k)$ and $y(k)$.

k = sample index once every 5 cycles.

The model is assumed to be the 1st order of the following structure

$$y(k+1) = ay(k) + bu(k) + \omega(k)$$

where $\{a, b\}$ are unknown parameters to be estimated, $\omega(k)$ is a noise.

Denote

$$\theta = \begin{bmatrix} a \\ b \end{bmatrix}, \qquad \varphi(k) = \begin{bmatrix} y(k) \\ u(k) \end{bmatrix}$$

Then the following recursive least squares (RLS) algorithm is used to estimate $\{a, b\}$ using the data collected from Econolite/UH platform

$$\theta(k+1) = \theta(k) + \frac{P(k)\varphi(k)\varepsilon(k)}{1 + \varphi^T(k)P(k)\varphi(k)}$$

$$\varphi^T(k) = [y(k)\ u(k)]$$

$$\epsilon(k) = y(k+1) - \theta^T(k)\varphi(k)$$

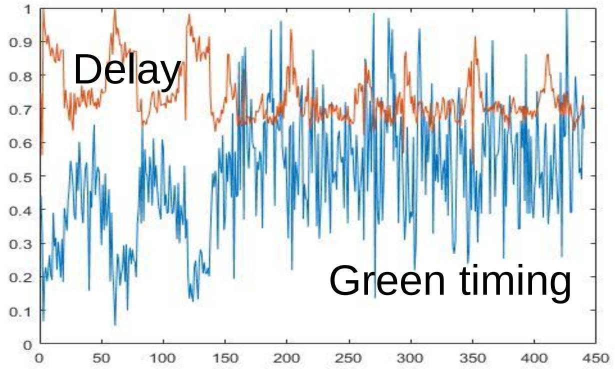
$$P^{-1}(k+1) = P^{-1}(k) + \varphi(k)\varphi(k)^T$$

where

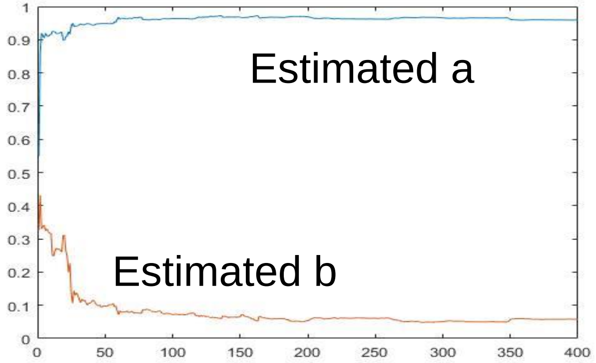
- $\theta(k)$ is the estimate of θ at sample time k (of every 5 cycles),
- $P(k)$ is the variance matrix,
- $\varepsilon(k)$ is the estimation residual.

3.2 Linear Model Results – First Order Dynamics

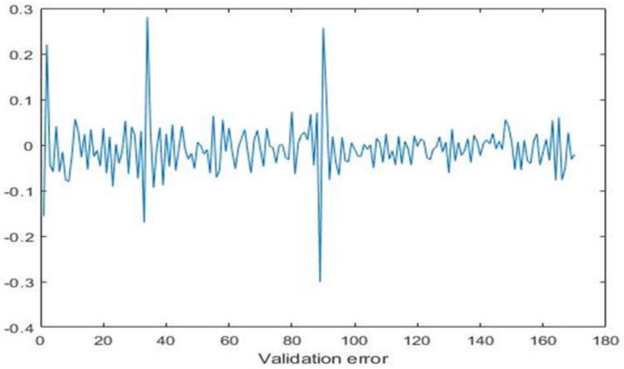
The following figures shows the modeling results, $\theta(0) = 0, P(0) = 100I_{2\times2}$

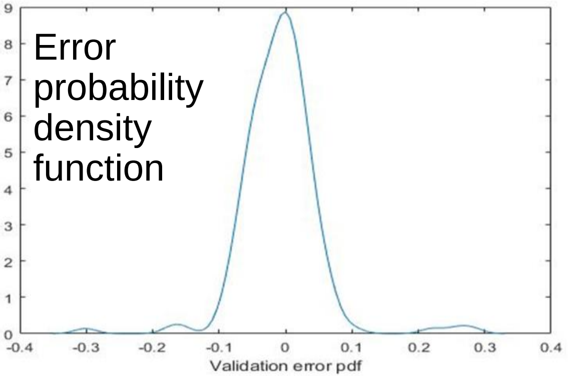


Original data – normalized to [0, 1]



Estimated a and b





3.3 Hybrid Neural Network (HNN) Model – Multiple Intersections

- **Study area**: Intersection 1-7
- **Date**: March 3-5, 8-12, 15-19, 22-26, 29-31, April 1-2 (23 weekdays)
- **Time**: 4pm – 7 pm
- **Signal phase**: all phases of major and minor streets
- **Traffic volume**: all movements
- **Delay**: all movements
- **Sample Index**: 5 signal cycles (Each cycle ≈170s)

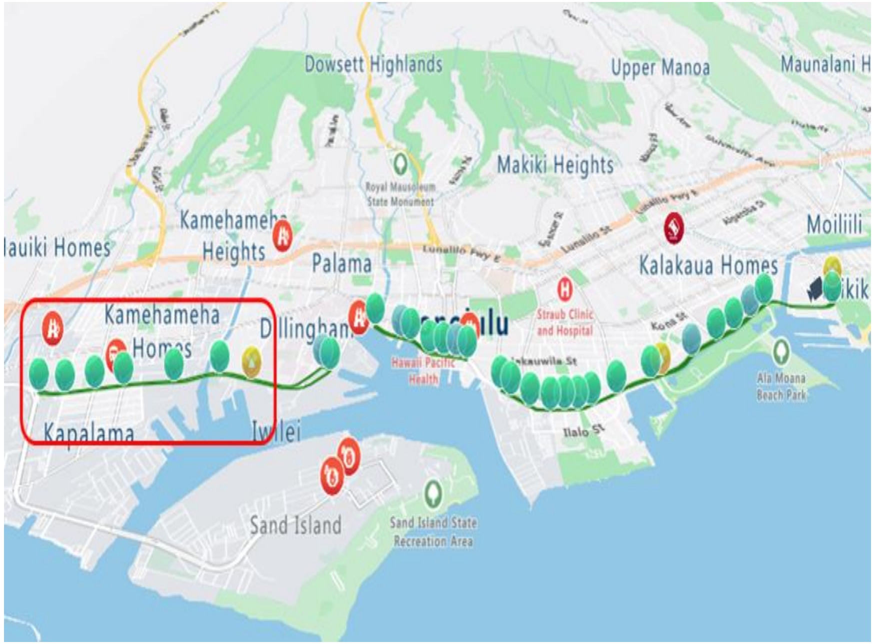
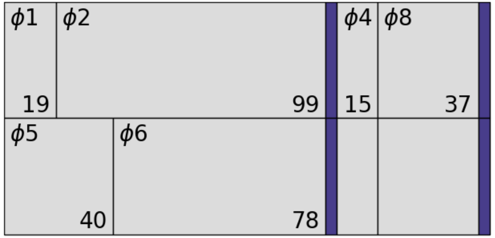
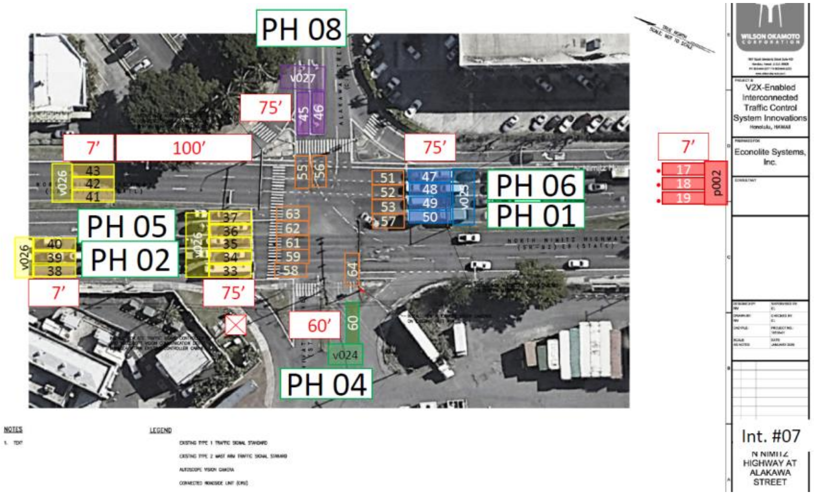


Figure 3. The First 7 intersections along Nimitz Highway

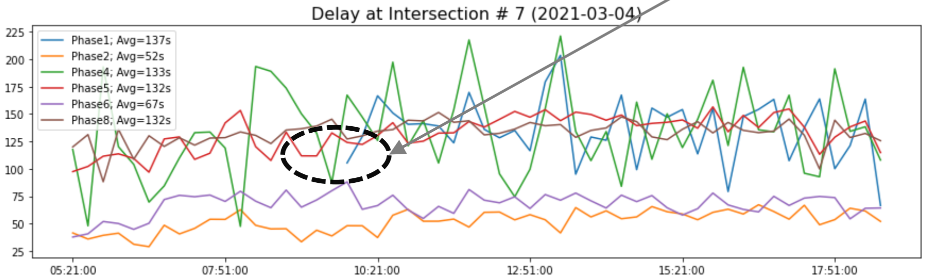
3.3 Hybrid NN Model – Data Visualization

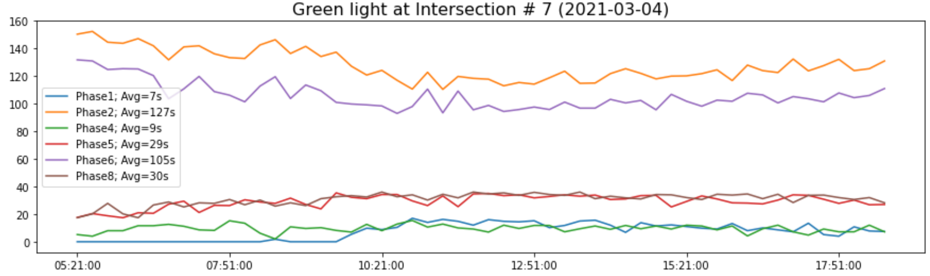
6 phases:

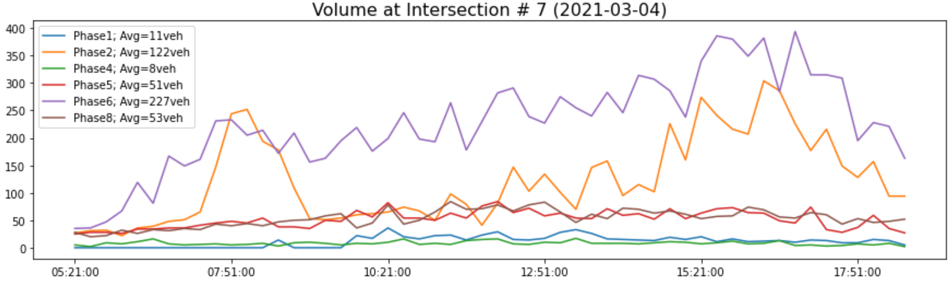




Missing data







3.3 Hybrid Neural Network (HNN) Modeling – Model Structure

- **HNN Model**

Linear　　Nonlinear Term　　Traffic volume

$$y(k+1) = \boxed{Ay(k) + Bu(k)} + \boxed{f(y(k), u(k-1), v(k))} \quad (1)$$

HNN

where $y(k)$ and $u(k)$ denote average delay per vehicle and green time for multiple intersections at time index k. $\omega(k)$ is noise. {A, B} are the weight matrix. Let $f\big(y(k), u(k-1), v(k)\big)$ be approximated and learned by $\hat{f}(y(k), u(k-1), v(k), \pi)$ using the real-time data, and $v(k)$ denote traffic volume.

This is Achieved by minimizing Eq.(3) using gradient approach.

$$\text{Min } J = \frac{1}{2}(\hat{y}(k+1) - y(k+1))^2 \quad (2)$$

Objective

$$\hat{y}(k+1) = Ay(k) + Bu(k) + \hat{f}(y(k), u(k-1), v(k), \pi) \quad (3)$$

{*A*, *B*, π} are parameters to be trained. π groups all NN weights and bias.

3.3 Hybrid NN - Model Training Algorithm

- Model parameters {A, B, π} are trained simultaneously by (6)-(11):

$$\hat{A}(k+1) = \hat{A}(k) - \lambda_1 \frac{\partial J}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (6)$$

$$\hat{B}(k+1) = \hat{B}(k) - \lambda_2 \frac{\partial J}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (7)$$

$$\hat{\pi}(k+1) = \hat{\pi}(k) - \lambda_3 \frac{\partial J}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (8)$$

Parameter update rules

where λ_1, λ_2, λ_3 are learning rates.

$$\frac{\partial J}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{y}}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\, y(k) \quad (9)$$

$$\frac{\partial J}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{y}}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\, u(k) \quad (10)$$

$$\frac{\partial J}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{f}}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (11)$$

where y(k+1) is the measured data.

3.4 Hybrid NN – Experiment Results

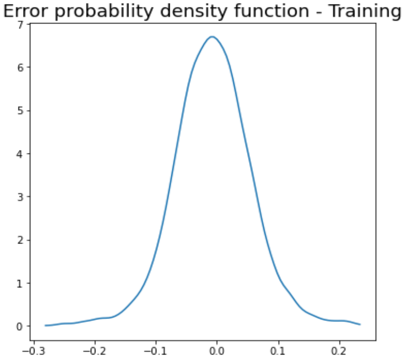


TABLE 1: Training and Testing Results

	Training (all)	Testing (all)	Testing (Main streets)	Testing (Side streets)
Mean Absolute Percentage Error (MAPE)	6.31%	6.51%	5.67%	6.98%
Rooted Mean Square Error (RMSE)	9.62 s	10.18 s	4.14 s	12.33 s
Mean Absolute Error (MAE)	6.72 s	6.99s	3.03s	9.21 s

TABLE 2: Testing results at each intersection

Intersection	1	2	3	4	5	6	7
Mean Absolute Percentage Error (MAPE)	4.03%	5.09%	5.7%	7.74%	7.75%	6.74%	6.12 %
Rooted Mean Square Error (RMSE)	3.79s	5.74s	10.76s	11.03s	12.61s	8.86s	10.30s
Mean Absolute Error (MAE)	2.29s	4.36s	6.65s	8.72s	9.18 s	6.23s	7.60s

$$MAPE = \frac{1}{NK}\sum_{k=1}^{K}\sum_{n=1}^{N}\left|\frac{y_n(k) - \hat{y}_n(k)}{y_n(k)}\right|$$

$$RMSE = \frac{1}{NK}\sum_{k=1}^{K}\sum_{n=1}^{N}\sqrt{(y_n(k) - \hat{y}_n(k))^2}$$

$$MAE = \frac{1}{NK}\sum_{k=1}^{K}\sum_{n=1N}|y_n(k) - \hat{y}_n(k)|$$

$y_n(k)$: True delay at time *k* of phase *n*.
$\hat{y}_n(k)$: Predicted delay at time *k* of phase *n*.

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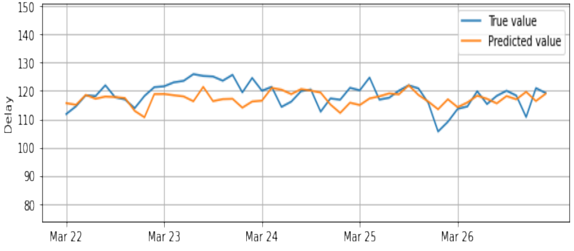
3.4 Hybrid Neural Network Modeling – Experiment Results

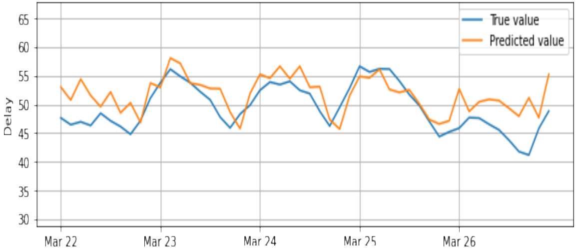
- **Testing**: Intersection 1 (March 22 - 26), Total cycle length = 180 (sec)

Comparisons – Testing data – Intersection #1 Phase # 1

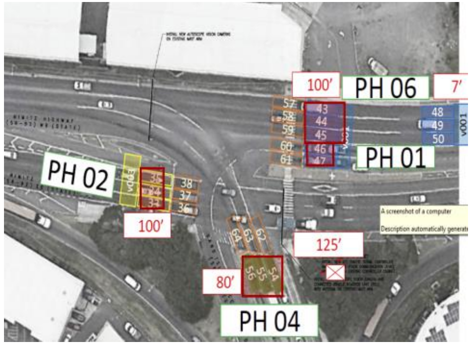


Testing Samples

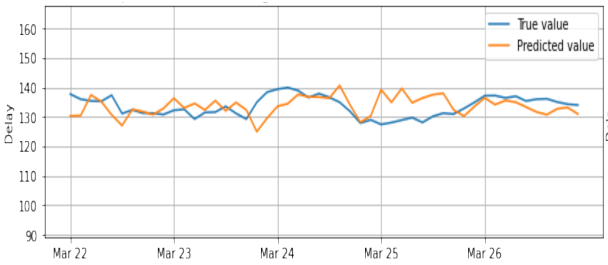
Comparisons – Testing data – Intersection #1 Phase # 2



Testing Samples

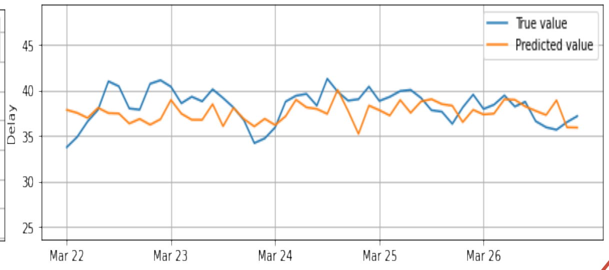


Comparisons – Testing data – Intersection #1 Phase # 4

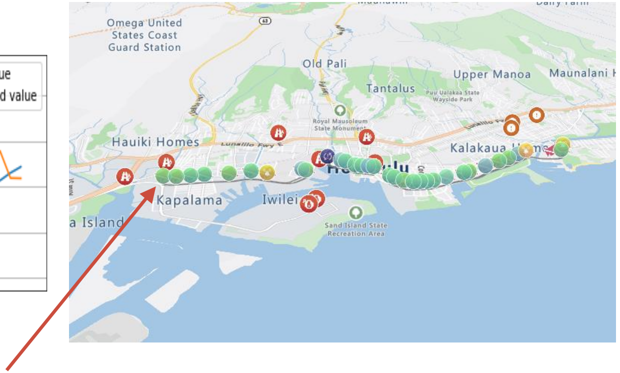


Testing Samples

Comparisons – Testing data – Intersection #1 Phase # 6



Testing Samples



Intersection 1

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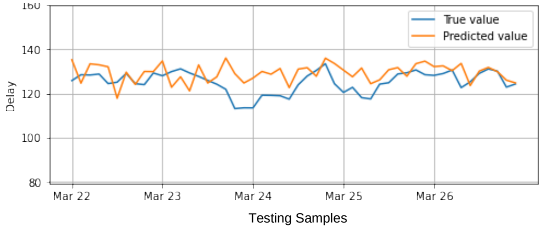
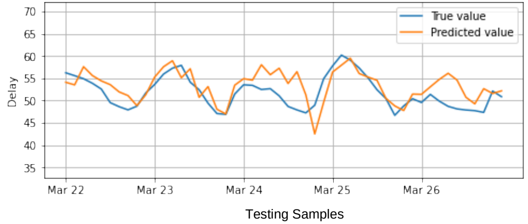
3.4 Hybrid Neural Network Modeling – Experiment Results

- **Testing:** Intersection 4 (March 22 - 26)

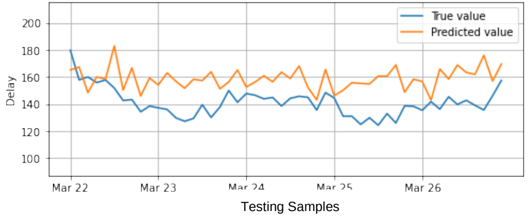
Comparisons – Testing data – Intersection #4 Phase #1



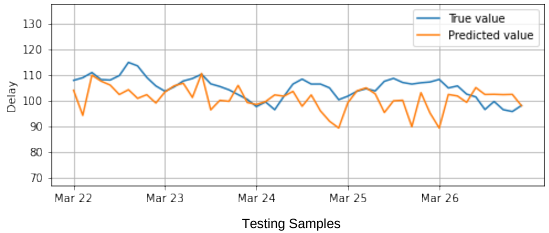
Comparisons – Testing data – Intersection #4 Phase #2



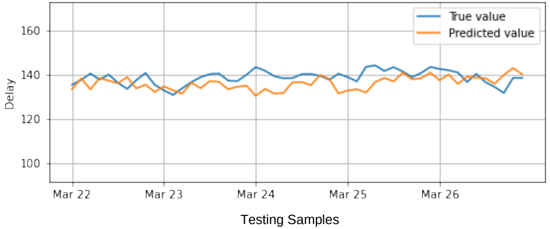
Comparisons – Testing data – Intersection #4 Phase #3



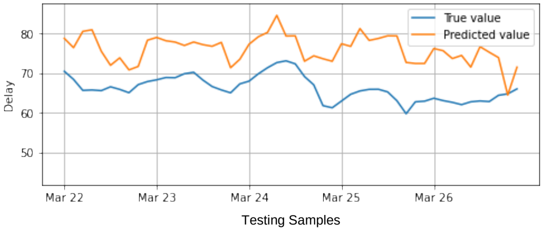
Comparisons – Testing data – Intersection #4 Phase #4



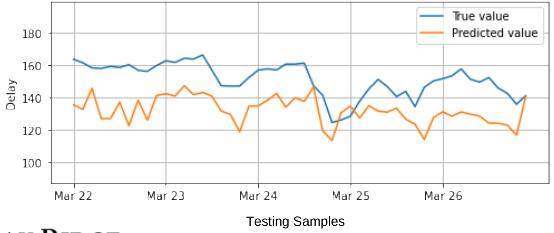
Comparisons – Testing data – Intersection #4 Phase #5



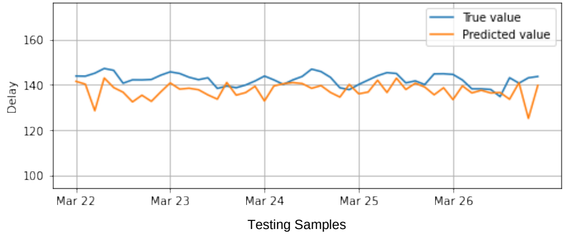
Comparisons – Testing data – Intersection #4 Phase #6

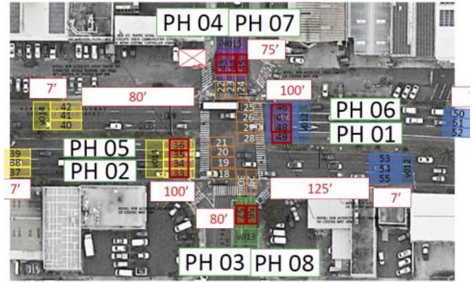


Comparisons – Testing data – Intersection #4 Phase #7



Comparisons – Testing data – Intersection #4 Phase #8





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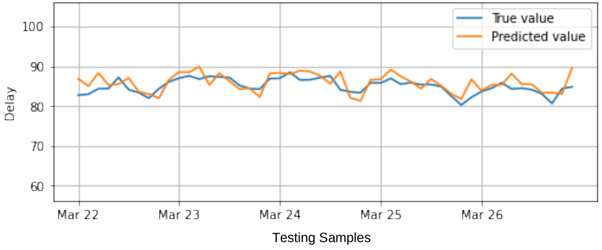
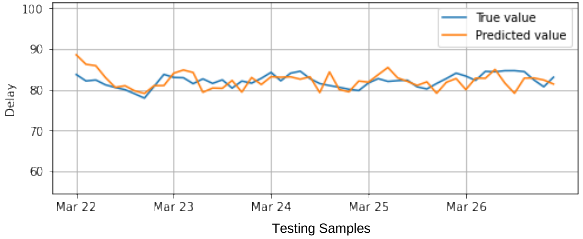
3.4 Hybrid NN – Experiment Results

- **Testing**: Average travel delays at all 7 intersections

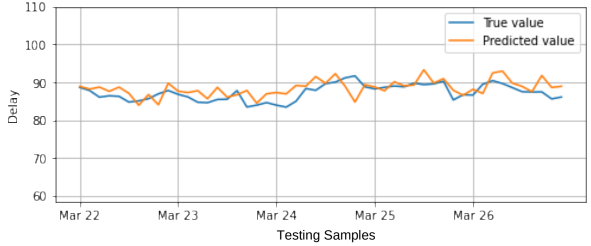
Comparisons – Testing data – Intersection #1



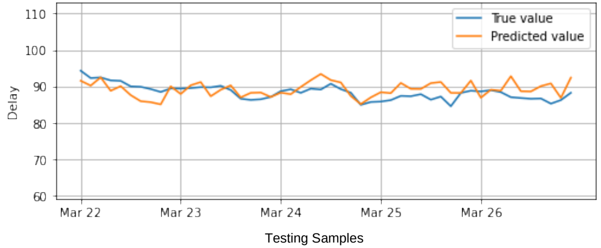
Comparisons – Testing data – Intersection #2



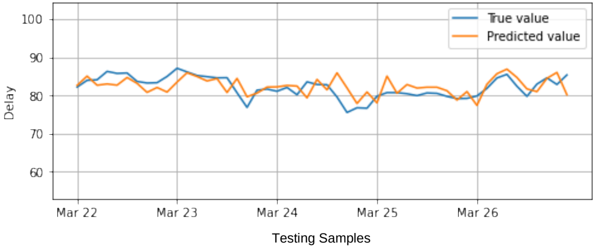
Comparisons – Testing data – Intersection #3



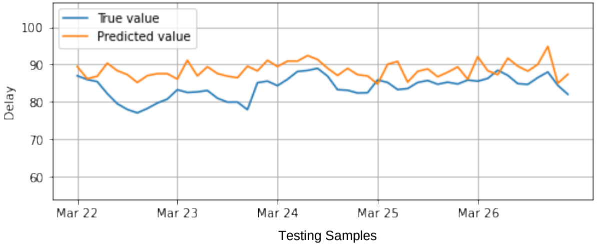
Comparisons – Testing data – Intersection #4



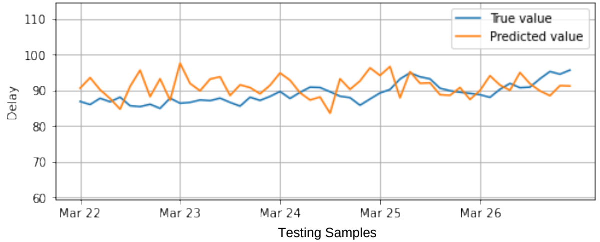
Comparisons – Testing data – Intersection #5



Comparisons – Testing data – Intersection #6



Comparisons – Testing data – Intersection #7



4. Remaining Challenges and Barriers

Most studies on AI for intersectional signal control only consider a few intersections, and no real-time learning system has been deployed for large-scale field testing because of the lack of comprehensive real-time data and user-friendly interfaces to the implementation. These shortcomings have limited the current research on AI for mobility at the simulation level.

Moreover, energy efficiency has not been well addressed for these AI-based modeling and controls. This constitutes the following challenges and technical barriers:

- Although the theory of AI-based modeling and control for signal control is maturing, the field testing and closed-loop control implementation for large number of intersections is still limited because of the insufficient real-time data for fast feedback control realization;
- The existing AI-based modeling for transportation systems cannot yet capture the nonlinear and dynamic stochastic nature with high reliability and robustness; and
- Guaranteed control performance for the energy minimization is still lacking.

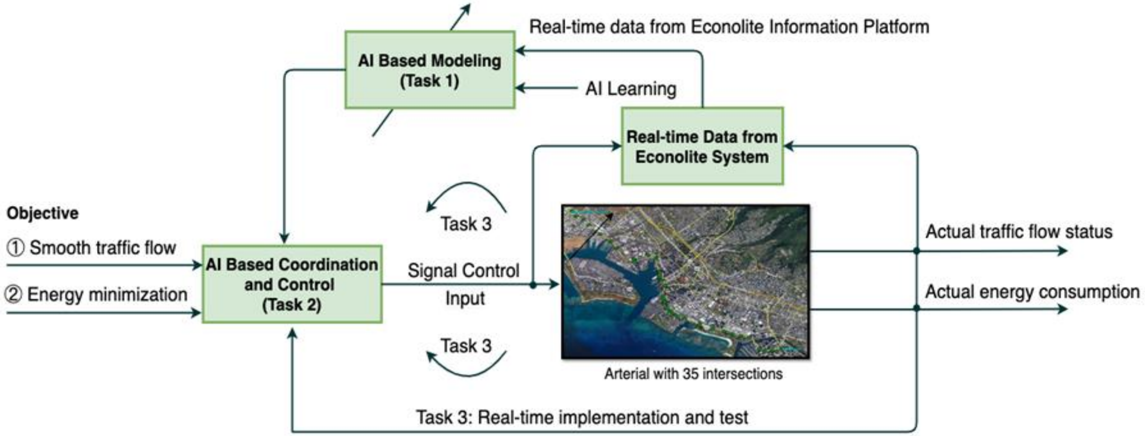
The current project therefore focuses on the development and implementation of real-time learning and adaptation for the signal control along the arterial, where both NN modeling and control will be adaptively learned during the real-time system operations.

5. Traffic Signal Control – the Future

- Future Research
  - Network-level control
    - Network partition/decomposition, e.g.,~1000 intersections
    - Distributed control, hierarchical control
    - AI-based traffic signal control with real-world big data
  - Impact of CAV penetration and level of automation
    - The signal control performance would undergo a significant change when the penetration rate > 25–30% (Ban et al., 2011)
    - Relationships between CAV penetration and traffic performance
    - Quantify the benefits of different levels of vehicle automation levels for traffic signal control by simulation and real-world tests.

6. Summary

- **A review of the existing AI based signal control has been described**
- **New results have been presented**
  - Complete AI-based modeling for the 7 intersections along Nimitz Highway and Ala Moana Boulevard arterial with a <10% modeling error as expected.
- **Future perspectives**
  - CAV with V2X communication presents a new solution to signal timing control,
  - Big data processing presents further challenges for the real-time implementation of AI-based control strategies for multiple intersections, especially for a large urban area.



Thank you for your attention