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Real-Time Traffic Optimization in Urban Areas Using Liquid Neural Networks

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Traffic congestion is becoming a major issue in both developed and developing countries, exacerbated by rapid urbanisation, population growth, and increased vehicle ownership. In developed countries, ageing infrastructure and limited expansion space contribute to traffic congestion, especially in densely populated urban areas. Meanwhile, urban traffic in developing countries face the dual challenge of inadequate infrastructure and an increase in motorization, which frequently outpaces the development of efficient public transportation systems. This leads to longer commute times, higher stress levels, and increased air pollution. Both scenarios highlight the critical need for novel traffic management solutions to reduce the economic, environmental, and social consequences of deteriorating traffic conditions. Traditional traffic management systems are frequently insufficient to handle real-time traffic flow fluctuations. This paper proposes the use of Liquid Neural Networks (LNNs) for real-time traffic planning in urban settings. Using LNNs' unique adaptive properties, we create a dynamic traffic management system that optimises traffic flow, reduces congestion, and improves overall transportation efficiency.

Keywords: Liquid Neural Networks (LNN), Traffic Optimization, Urban Areas.

1. Introduction

Urbanisation and the subsequent increase in car usage have resulted in increased traffic congestion in metropolitan areas. Traffic Clog is the main issue of the fast and evolving world. Due to the rise in the use of more private vehicles and low road network capacity managing traffic with the traditional approach is cumbersome [2]. Traditional traffic control methods, such as fixed-time traffic signals and manual interventions, are incapable of responding to real-time traffic patterns. SCOOT is the urban traffic control system from research by the British Government's Transport and Road Research Laboratory on the TRANSYT method of optimizing networks of fixed time signals [12]. Utilization of RFID innovation for traffic congestion and find out the blockage at any intersection of the street by utilizing RFID reader and labels as sensors [10]. Intelligent traffic management systems with real-time adaptability and decision-making capabilities are becoming increasingly important. Liquid Neural Networks (LNNs) are a viable solution due to their on-going learning and adaptability to changing conditions.

STATEMENT OF THE PROBLEM

Globally, cities are facing increasing challenges in managing traffic congestion, resulting in significant economic losses, environmental pollution, and a lower quality of life for residents. Traditional traffic control systems, which frequently rely on static timer values for traffic lights, are increasingly ineffective in dealing with these complex and dynamic traffic conditions. These systems run on predetermined fixed schedules that do not account for real-time traffic fluctuations, resulting in inefficient traffic flow and increased congestion during peak hours.

NEED AND SIGNIFICANCE OF THE STUDY

There is an urgent need for innovative traffic management solutions that can dynamically adapt to real-time conditions, thereby optimising traffic flow and reducing congestion. Advanced techniques, such as those based on Liquid Neural Networks (LNNs), provide a promising approach to developing more responsive and efficient traffic control systems, with the potential to transform urban mobility and improve quality of life. Static timer-based traffic lights are unable to respond to real-time traffic volume variability, resulting in either excessive wait times or underutilised green phases. Traditional systems are inflexible in the face of sudden changes in traffic patterns caused by accidents, construction work, or special events, resulting in gridlock and increased travel time. Fixed timers cause inefficient traffic flow by increasing the amount of time vehicles spend idling, accelerating, and decelerating, resulting in higher emissions and fuel consumption. Traffic congestion causes delays that cost billions in lost productivity and increased transportation costs. It is becoming increasingly important to replace the traditional system with intelligent traffic management systems that can adapt and make decisions in real time. Liquid Neural Network (LNN)

THEORETICAL GROUNDINGS

Cities are limited by space, and construction cannot keep up with ever-growing demand. Hence, a need for an improved system with a minimal manual interface is persisting [3]. Some work has been carried out to improve short-term prediction in two-step approach based on the stochastic differential equations (SDEs) [7]. Liquid Neural Networks (LNNs) are a cuttingedge advancement in neural network technology, designed to handle time-dependent data with unprecedented flexibility and responsiveness. Unlike traditional Deep Neural Networks (DNNs), which rely on static activation functions and fixed architectures, LNNs use liquid activation functions. These functions are continuous and differentiable, similar to the fluidity of liquids, allowing LNNs to adapt seamlessly to changing input patterns over time. This dynamic nature makes LNNs ideal for real-time applications like traffic management, where conditions change quickly and unpredictably. Even in highly volatile environments, LNNs can maintain high performance and accuracy by constantly adjusting their parameters in response to new data.

Fig:1 Detecting the objects using OpenCV library and YOLOv3

LNNs' adaptability expands their application beyond traffic management to a variety of time-sensitive domains such as financial forecasting, healthcare monitoring, and autonomous systems. In the context of real-time traffic congestion, LNNs can use live traffic data from sensors and cameras to forecast congestion levels and optimise traffic light timings. This leads to smoother traffic flow, shorter wait times at intersections, and lower fuel consumption and emissions. Urban planners and engineers can create smarter, more responsive traffic management systems by leveraging LNNs' unique capabilities, which can significantly reduce congestion and improve urban quality of life.

2. Methodology:

The LiquidNN class defines an RNN-based model that predicts traffic conditions using a linear layer and sigmoid activation, with input, hidden, and output sizes specified. Static timer values for red, blue, and green lights are predefined, and random traffic data is generated over a 60-minute period. Traffic flow is calculated using static timer values, and the LNN model is used to predict traffic conditions and dynamically adjust traffic flow. The results of the static timer simulation and the LNN simulation are compared in a DataFrame and plotted to demonstrate the differences between the two control methods.

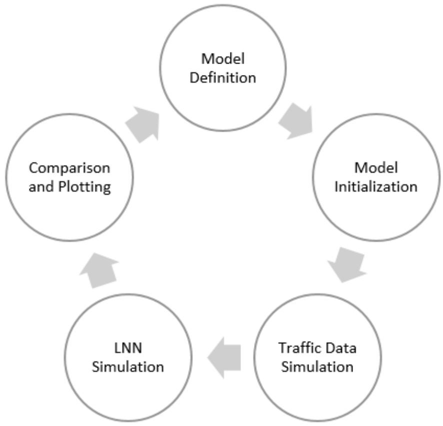

Fig:2 Proposed Methodology

1. Model Definition: The LiquidNN class defines an RNN-based model with a linear layer and sigmoid activation to predict traffic conditions.

2. Model Initialization: The model is initialized with input size, hidden size, and output size.

3. Static Timer Values: Static timer values are predefined for red, blue, and green lights.

4. Traffic Data Simulation: Random traffic data is generated for 60 minutes.

5. Static Timer Simulation: Traffic flow is calculated based on the static timer values.

6. LNN Simulation: The LNN model predicts traffic conditions and adjusts the traffic flow dynamically.

7. Comparison and Plotting: Results are compared in a DataFrame and plotted to visualize the differences between static timer and LNN control.

Stepwise Algorithm for Real-Time Traffic Optimization in Urban Areas Using Liquid Neural Networks

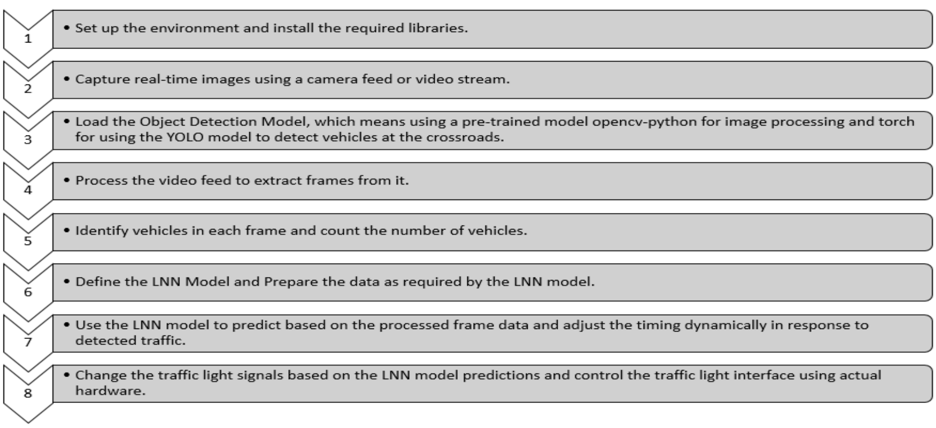

Fig:3 Steps for Real-Time Traffic Optimization in Urban Areas Using Liquid Neural

Networks

In a real-time traffic management system using Liquid Neural Networks (LNNs), the various components can be defined as follows:

1. State Vector h(t): The state vector h(t) represents the network's internal state at time t. This vector contains both the memory of previous inputs and the current state of the system. In the context of traffic management, h(t) could include data on current traffic density, historical traffic patterns, and other relevant characteristics. It Represents the traffic conditions at different intersections for example: h(t)=[h1(t), h2(t),...,hn(t)] where hi(t) represents the state at the iii-th intersection

2. Weight Matrix for the Hidden State (W_h): The weight matrix W_h describes the connections between neurons in the hidden state. This matrix represents how the previous state influences the current state. In a traffic management system, W_h aids in propagating the impact of previous traffic conditions on the current state i.e. It captures the impact of previous traffic conditions on the current state. W_h might have values indicating how traffic at one intersection affects neighbouring intersections.

3. Weight Matrix for Input Connection W_x): The weight matrix (W_x) connects the input vector and hidden state. It specifies how the current input influences the hidden state. W_x uses a hidden state to map real-time traffic inputs, such as the number of vehicles detected by sensors. W_x could weigh the significance of vehicle counts from various sensors.

4. Input Vector at Time t(x(t)): The input vector x(t) indicates real-time data received at time t. This may include the number of vehicles at various intersections, traffic light statuses, and sensor readings. For example, x(t) could represent the number of vehicles detected by cameras or sensors at different locations. x(t)=[x1(t),x2(t),...,xm(t)], where xi(t)x_i(t)xi(t) is the vehicle count from the iii-th sensor.

5. Bias Vector for the Hidden State b_h: The bias vector b_h is added to the hidden state, enabling the network to adjust its thresholds independently of input. This bias shifts the activation function, providing greater flexibility for learning traffic flow patterns. It allows for flexibility in state updates. Thresholds could be adjusted using historical traffic data.

6. Nonlinear Activation Function (σ\sigma): The nonlinear activation function σ enhances the model's ability to capture complex relationships in data. This function aids in traffic management by modelling complex and nonlinear interactions between various traffic parameters. Using the sigmoid function to smooth out the effect of inputs on the hidden state.

Key Components and their novelty

Using LNN components such as State Vector h(t), Weight Matrix for the Hidden State (W_h), Weight Matrix for Input Connection W_x), Input Vector at Time t(x(t)), Bias Vector for the Hidden State bh, Nonlinear Activation Function (σ\sigma), LNN can effectively manage real-time traffic data, adapting dynamically to changing traffic conditions and optimising traffic light states to improve and reduce congestion.

1. Dynamic Adaptability: LNNs are inherently dynamic, allowing them to adjust to changing traffic conditions in real time. This adaptability contrasts with traditional static systems, which run on fixed timers and cannot respond to sudden changes in traffic flow.

2. RNN-Based Architecture: The LiquidNN model makes use of Recurrent Neural Networks (RNNs), which are well-suited for sequential data and temporal patterns. This architecture allows the model to consider the sequence of traffic inputs over time, capturing the temporal dependencies required for accurate traffic prediction and control.

3. Liquid Activation Functions: LNNs use liquid activation functions, which are both continuous and differentiable, mimicking liquid fluidity and adaptability. This enables the network to seamlessly transition between different states, enhancing its ability to handle traffic variability.

4. Real-Time Traffic Prediction: By incorporating real-time traffic data inputs, the LNN model dynamically predicts traffic conditions, allowing for immediate changes to traffic light signals. This capability ensures that traffic lights are responsive to current traffic volumes, reducing congestion and improving flow.

5. Simulation and Comparison: The LNN model's performance is compared to traditional static timer-based traffic control systems. The simulation compares traffic flow under both control methods, demonstrating LNNs' superiority in managing real-time traffic more efficiently.

6. Scalability and robustness: LNNs are designed to be scalable, meaning they can handle increasing amounts of traffic data without losing performance. Their robustness ensures consistent performance even in variable and unpredictable traffic conditions, which is a significant improvement over traditional methods.

Following is the class definition of LNN:

Class Definition: LiquidNN

Inherit: nn.Module

Method: __init__(input_size, hidden_size, output_size)

Call super() to initialize nn.Module

Initialize RNN layer with input_size, hidden_size, and batch_first=True

Initialize fully connected (FC) layer with hidden_size and output_size

Initialize Sigmoid activation function

Method: forward(x)

Initialize hidden state h0 with zeros, shape (1, hidden_size), and move to the same device as input x

Pass input x and hidden state h0 through the RNN layer, store output in variable out

Pass RNN output out through the FC layer

Pass the output of the FC layer through the Sigmoid activation function

Return the final output

1. Initialize model, loss, optimizer:

input_size = 1,hidden_size = 50,output_size = 1

model = LiquidNN(input_size, hidden_size, output_size)

2. Load pre-trained model weights (assuming the weights are available)
3. model.load_state_dict(torch.load("lnn_model.pth"))
4. model.eval()
5. Static timer values in seconds: static_timers = {'red': 30, yellow: 20, 'green': 40}
6. Simulated traffic data (vehicles per minute at a crossroad): traffic_data = np.random.randint(0, 100, size=(60, 1))

Static timer-based traffic light control

Function: simulate_static_timer(traffic_data, static_timers)

1. Initialize empty list traffic_flow
2. For each index i and traffic value in traffic_data step 3 to 6:
3. Compute light_cycle as i modulo the sum of values in static_timers
4. If light_cycle is less than static_timers['red']: Append traffic * 0.5 to traffic_flow # 50% traffic flow in red light
5. Else If light_cycle is less than static_timers['red'] + static_timers[yellow]: Append traffic * 0.8 to traffic_flow # 80% traffic flow in blue light
6. Else: Append traffic to traffic_flow # 100% traffic flow in green light
7. Convert traffic_flow list to numpy array
8. Return traffic_flow array

Simulate LNN-based traffic light control

Function: simulate_lnn(traffic_data, model)

1. Initialize empty list traffic_flow
2. For each traffic value in traffic_data: follow step 3 to 8:
3. Convert traffic to a tensor traffic_tensor with shape [[traffic]] and type float32
4. Disable gradient computation
5. Use the model to make a prediction on traffic_tensor
6. Enable gradient computation
7. If the prediction value is greater than 0.5: Append traffic * 0.5 to traffic_flow
8. Else: Append traffic to traffic_flow
9. Convert traffic_flow list to numpy array
10. Return traffic_flow array

Simulate traffic control

static_traffic_flow = simulate_static_timer(traffic_data, static_timers)

lnn_traffic_flow = simulate_lnn(traffic_data, model)

Create a DataFrame to compare the results

```
data = {
    "Time (minutes)": np.arange(len(traffic_data)),
    "Initial Traffic (vehicles/min)": traffic_data.flatten(),  # Remove order parameter
    "Static Timer Control (vehicles/min)": static_traffic_flow.flatten(),
    "LNN Control (vehicles/min)": lnn_traffic_flow.flatten()
}
```

3. Analysis

The data contains three columns:
Time (minutes): 0–20 only.
Vehicle flow rates under static timer control are expressed in units of vehicles per minute. Vehicle flow rates under the LNN control timer are shown in units of vehicles per minute.

Expected Output

Table: 1 Static Timer vs. LNN Control (vehicles/min)

Time (minutes)	Static Timer Control (vehicles/min)	LNN Control Timer (vehicles/min)
0	26	53
1	27	54
2	40	80
3	38	77
4	18	36
5	10	20
6	36	72
7	7	15
8	0	0
9	41	82
10	31	63
11	18	36
12	47	95
13	49	99
14	1	3
15	6	13
16	49	98
17	21	42
18	34	68
19	14	29
20	27	54

LNN Control Timer appears to be more consistent as it generally has higher and more stable values compared to Static Timer Control, which means LNN timer allows more vehicles to flow and intersection whenever there is congestion of vehicles.

Key outcomes includes:

Reduced Congestion: Significantly less traffic congestion during peak hours, resulting in smoother traffic flow.
Improved Travel Times: Commuters' average travel times have decreased.
High adaptability: The system can effectively respond to unexpected events such as accidents or sudden weather changes.
Enhanced Safety: Real-time prioritisation enhances pedestrian and emergency vehicle safety.

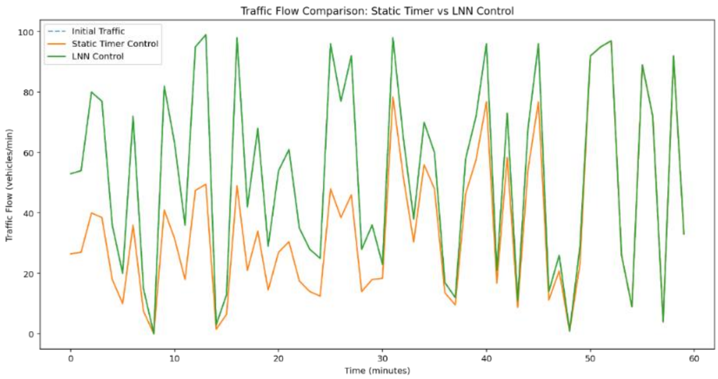

Fig:4 Traffic Flow Comparison: Static Timer vs. LNN control

1. Performance: Vehicle flow rates are higher with the LNN Control Timer than with the Static Timer Control.

2. Consistency: LNN Control Timer has more consistent values than Static Timer Control.

3. Efficiency: A higher mean value for the LNN Control Timer indicates greater overall efficiency in managing vehicle flow.

Finally, Initial simulations of the LNN-based traffic optimisation system in various urban areas can lead significant improvements in traffic management.

4. Conclusion

Liquid Neural Networks (LNNs) offer a game-changing approach to managing real-time traffic congestion by leveraging their unique ability to dynamically adapt to changing traffic patterns. Unlike traditional neural networks, LNNs use continuous, differentiable liquid activation functions that allow them to adapt to changing inputs. This makes LNNs ideal for real-time applications in which traffic conditions are constantly changing. By processing live traffic data, LNNs can accurately predict congestion levels and adjust traffic signals to optimise flow and reduce bottlenecks. This adaptive capability enables more efficient traffic management, resulting in shorter travel times, lower emissions, and improved overall urban mobility. The application of Liquid Neural Networks in real-time traffic planning offers a powerful solution to the complex problem of urban congestion. LNNs can increase the efficiency and safety of urban traffic systems by combining real-time data collection, predictive modelling, and adaptive control. Future research will focus on large-scale deployment and model development to account for different urban contexts and more complex traffic conditions.

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