A Visual Analysis of Congestion Pricing Policy Effect on Congestion Alleviation

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ABSTRACT

The congestion pricing policy is effective in solving the problem of traffic congestion in urban areas. Therefore, studies were conducted on the target area, collection scheme, and collection amount to designate a congestion pricing policy in urban areas. The techniques of existing studies verify the congestion mitigation effect by relying on simulation data. Since there is little traffic data with congestion tax applied, analyzing traffic congestion through learning models is problematic. Therefore, it is difficult to determine the congestion pricing policy that has the congestion mitigation effect. This paper proposes a visual analysis framework for establishing an appropriate congestion pricing policy. We use SUMO, an urban traffic simulation model, to generate data with congestion tax applied for learning. We also trained the DCRNN model on the data we created. DCRNN predicts congestion in real road networks. We analyze the congestion mitigation effect using the model prediction as a traffic congestion indicator.

Index Terms: Congestion Pricing—Visual analytics—Visualization analysis—;

1 INTRODUCTION

The primary cause of traffic congestion is insufficient road capacity due to the concentration of traffic demand. The metropolitan experiences periodic traffic congestion as the traffic demand is concentrated more than the designed road capacity. However, the area required for road expansion is insufficient because the metropolitan buildings are densely populated. The congestion pricing policy is a way to relieve traffic congestion in urban areas by distributing traffic volume and reducing travel demand by imposing a congestion tax. Since passengers regard the cost and travel time required to travel to their destination, they bypass areas or change the transportation from their vehicles to public transportation to lower the monetary cost required for traveling.

The congestion mitigation effect of congestion pricing policies varies according to the target area, pricing scheme, and price. The congestion pricing policy is mainly applied to downtowns in urban areas with dense traffic and congested roads where periodic congestion occurs. As for the pricing scheme of the congestion pricing policy, there is a cordon, which charges a fee every time drivers pass lines set in Stockholm, and zonal based, which charges a fee for movement inside lines in London [2]. The price for the congestion pricing policy is set by considering the cost of infrastructure construction, travel demand, and alternative transportation methods [6]. Therefore, setting a policy for a suitable congestion mitigation effect is difficult.

Congestion pricing policy studies to alleviate traffic congestion in urban areas have been proposed [1, 3]. However, existing studies rely on simulated data to evaluate the effect of mitigating congestion because there is little traffic data with actual congestion tax applied. Therefore, it is difficult to determine a suitable congestion pricing policy for a real road network. This paper analyzes the congestion alleviation effect of congestion pricing policies on real roads. Therefore, we propose a visual analysis framework for establishing an appropriate congestion pricing policy for real road networks. Our framework generates data for model training through Simulation of Urban Mobility (SUMO) [5]. DCRNN learns from the generated data to predict the speed of a real road network with congestion tax applied [4]. We use the Traffic Congestion Indicator (TCI) to analyze the congestion mitigation effect at the rate predicted by DCRNN [7]. We visualize it as a color-scaled heatmap on the map to intuitively grasp the degree and distribution of congestion on the road. The congestion alleviation effect over time is visualized on a line chart. The distribution of TCI is visualized as a grid heatmap, showing roads where traffic congestion is not resolved despite the application of the congestion pricing policy. In addition, we make the final decision by modifying the details of the congestion pricing policy using the grid heatmap.

2 BACKGROUND

This section describes SUMO, DCRNN, and TCI used in our framework. SUMO is an open-source traffic simulation tool that models complex transport systems, including vehicles, public transport, and pedestrians. Traffic data is a graph structure with spatiotemporal patterns. Also, the traffic data scale becomes large depending on the size of the road network to be modeled, the period of data, and the collection period. The DCRNN model shows high prediction accuracy in learning large-scale data. We use sampled vehicle GPS data from real road networks in this paper. Therefore, TCI is calculated as $TCI(t,i) = \frac{V(t,i)}{FFS(i)}$, where t is time, i is the road, V is the vehicle speed, and FFS is the free flow speed. FFS is the 90th percentile value observed on the road. We classify roads with a TCI value of 0.7 or less as congested roads.

3 VISUAL ANALYSIS FRAMEWORK

Figure 1 shows the visual analysis framework we propose. The calendar heatmap and histogram in Figure 1 (a) show the congestion of the road network by date and time, respectively. We select the target date and time zone in (a) to analyze the congestion mitigation effect. (b) visualizes the TCI according to the time and date set in (a) on a map. Note that map visualization uses color-scaled encoding, and the darker the red, the higher the congestion. The user sets the target area to which the congestion tax is applied using (b-1). The grid heatmap in (c) shows the average TCI of the road network at the cell level. The pricing scheme and price are set in (c-1). However, even with the congestion tax applied, there are areas with severe traffic congestion. Therefore, we make detailed congestion tax settings for road networks with still high congestion in (c-2). The line chart in (d) shows the average TCI value of the road network before and after applying the congestion tax. Also, we update the grid heatmap in (c) and the line chart in (d) according to the modified congestion pricing policy. We determine the policy with the optimal congestion mitigation effect by comparing the TCI values of (c) and (d).

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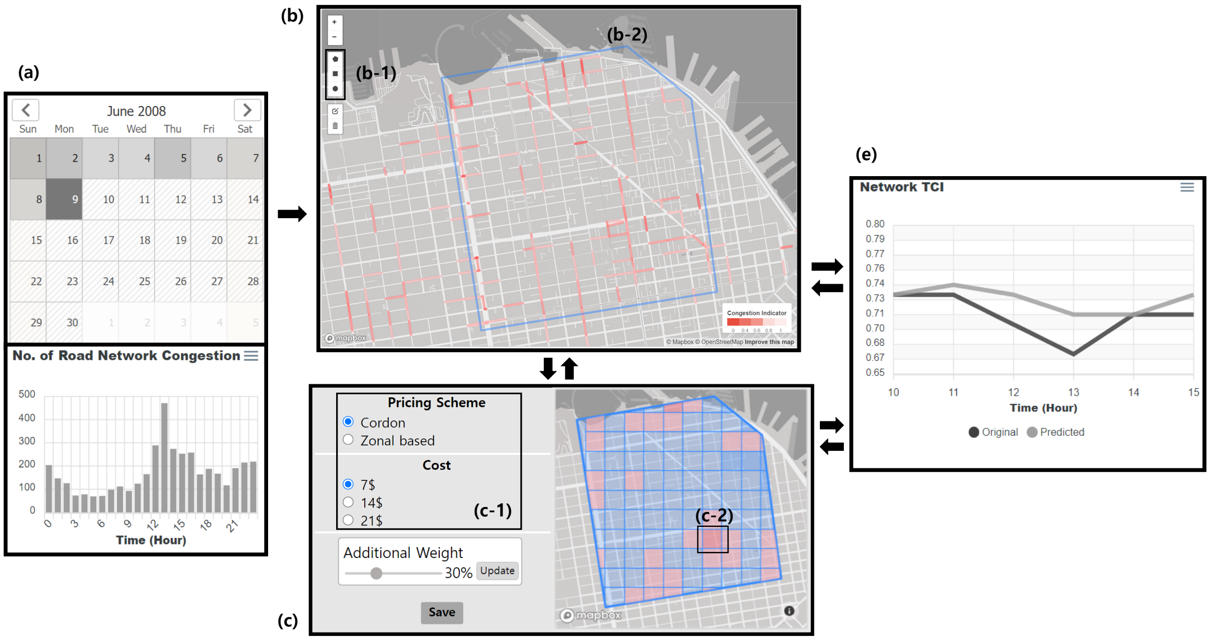

Figure 1: The figure shows the visual analysis framework for determining the optimal congestion pricing policy. (a) is a calendar heatmap and histogram showing the number of congested roads in the transportation network by date and time. (b) is a color-scaled encoding map of the average TCI of the selected date and time. (c) is a grid heatmap showing congestion tax target areas in cell units. (e) is a line chart visualizing the TCI indicators before and after applying the congestion tax.

4 Use Scenario

In this work, we describe the process of determining the appropriate congestion pricing policy using our framework in San Francisco. In this scenario, we target a manager with experience in traffic congestion management and policy design. We use GPS data from 537 taxis sampled at 5-minute intervals. In the calendar heatmap and histogram of Figure 1 (a), we set the busiest date, June 9 and hour 12∼14, as the analysis target. (b) shows the average number of congested roads for each road on the date and time set in (a). (b-2) is an area where roads with low TCI are concentrated. Therefore, we set (b-2) as a congestion tax target. Daily traffic in the San Francisco area is about 400,000, and many vehicles come from outside. Therefore, we select cordon as a pricing scheme that collects congestion tax at entry and exit. The price of the congestion pricing policy proposed by SFTMA in 2015 is 6$, which is calculated as 6 minutes when the average income for the year is converted into hours. The price of the congestion pricing policy proposed in New York in 2022 is 23 $, which is calculated as 22 minutes when the average income for the year is converted into hours. Therefore, we set the price to $7 according to the average income in San Francisco to set the congestion pricing policy. (d) shows the average TCI value of the road network before and after applying the congestion tax. We analyze that the policy effectively alleviates congestion as the TCI rises after applying the congestion tax. However, even after applying the congestion tax, there are still areas with severe congestion, such as cell (c-2). We increase the price by 30% to alleviate congestion in cell (c-2).

5 Conclusion

In this paper, we introduced a visual analysis framework to determine an optimal congestion pricing policy for a road network. Our framework applies congestion-taxed effects to real data using SUMO and DCRNN. The congestion pricing policy in our framework effectively alleviated traffic congestion, but the amount was small. We believe this is because we do not fully consider various factors such as time of day, day of the week, seasonality, irregular events, economy, and environment to determine the congestion pricing policy [2]. Therefore, we plan to discover the elements necessary for setting the congestion pricing policy applicable to real data, add them to the framework, develop a new visualization that can intuitively analyze various parameters, and improve it as a future work.

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