

Number of Vehicles and Travel Time Estimation on Urban Traffic Network using Bayesian Network Model and Particle Filtering Method

Gilang S. Kuswana, Satria A. Ramadhan, Endra Joelianto, and Herman Y. Sutarto

Abstract—Travel time is one of the key variables that reflect the performance of traffic systems. The travel time is affected by the interaction between traffic demand (the number of incoming vehicles) and the characteristics of traffic supply (such as road capacity, traffic signaling, and driving speed). Therefore, any traffic conditions will result in different travel times. The traffic conditions are determined by the complex interactions of drivers, vehicles, and road or site characteristics. In this paper, the dynamics of traffic are modeled by taking a hydrodynamic theory approach, using standard assumptions commonly used in traffic engineering. Stochastic models of traffic evolution are derived and parameterized by turning ratio and the number of outgoing vehicles of each link. In addition, the travel time variability is modeled by statistical approach. The delay time experienced by a vehicle and its free flow speed are the two main sources of uncertainty that can be captured from the statistical model. The relationship between traffic dynamics and travel time is represented by the Dynamic Bayesian Network model. Using floating data (the position of the vehicle at each time interval) obtained from the Vissim simulator and probabilistic modeling framework, the paper focuses on a method for estimating travel time and traffic state. The particle filter method is used to estimate the traffic state of each link on the network, which is the hidden variable of the Bayesian model. The traffic process built in the Vissim simulator has been validated with the observed data collected directly on the real location of this study. Implementation of the estimation algorithm with Bayesian Network model has proved that this methodology is successful enough to give estimation results which are close to the actual data.

Index Terms—Urban Traffic Network, Bayesian Network, Travel Time, Delay Time, Particle Filter, Vissim

I. INTRODUCTION

THE transportation system is one of the critical infrastructures and it is hoped that transportation systems can provide travel services with a short travel time. Of the various types of existing transportation systems, land transportation using 4-wheeled vehicles and 2-wheel is the

type of transportation mostly used by the community. Unfortunately, this type of transportation is often faced with congestion problems that occur in urban traffic network. In many big cities in Indonesia such as Bandung, Jakarta, Surabaya, and Medan, congestion has been a commonplace.

The first important step to prevent or to break down traffic is to build a real-time traffic monitoring system which monitors and evaluates the performance of the traffic system. To build the system, sensors that can produce data that represent the traffic conditions are required. This raw data is then processed to get the traffic feature such as travel time, vehicle number, and vehicle flow.

Travel time is an important aspect of transportation. Travel time reflects the performance of a road network. Providing travel time information to road users is useful for road users in order to make better decisions when traveling (such as: the type of vehicle used, the selected route, and the best departure time) [4]. These behavioral changes have a positive impact on the overall road network (potentially reducing congestion and improving efficiency) [2].

Furthermore, reliable and accurate travel time predictions can also give benefit to road users by reducing uncertainty and reducing stress [1]. In addition, travel time information on each network segment can be utilized as an input when developing a route guidance system as one of the control systems that can be applied to reduce congestion in an urban traffic network. As a result, building a new travel time prediction model for use in real-time operations is an exciting new research area that needs to be developed.

Predictions of travel time for highways have been observed. On the other hand, research on urban traffic networks is still rare [18]. Most traffic information systems on highways depends on data coming from loop detectors, radar, and video cameras. All three types of sensors are classified into the fixed-location sensor category whose location has been set. Disadvantages of this type of sensor are the data generated only capable of recording information in a range of short distances. Therefore, to enclose an urban traffic network requires a large number of sensors. This is considered ineffective because the cost required to do so is enormous. This lack of data is one reason for the lack of research on urban network traffic compared to highways networks.

In addition to data limitations, systems on highways have different characteristics than urban traffic. Traffic flow on the highway is usually uninterrupted flow, i.e. the frequency of interruptions in vehicle flow is small or rarely occurs. However, traffic flow on urban traffic is an interrupted flow,

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which means that the flow of vehicles goes through many disturbances such as delay due to traffic lights, parking or stopped vehicles, and turning vehicles. Since traffic on highways is different from urban traffic, the prediction model of travel time for highways cannot be applied directly to the context of urban traffic.

In practice, the availability of traffic data will affect the methodology used to predict the travel time. The urban traffic network is not usually covered entirely with the measurement instruments, unlike on highways networks [19]. Lack of data slows the development of models for urban networks because the data available for calibration and model validation are few.

GPS system is one system that has the potential to provide tracking information with good accuracy and especially has a very wide coverage capability. This makes the use of GPS as a tracking tool on vehicles that are intended to collect traffic information. GPS devices mounted on vehicles are capable of delivering large amounts of traffic data covering the entire urban network. This data is usually referred to as floating car data (FCD).

This research will develop algorithm prediction of travel time for urban network by utilizing GPS data from vehicles. Utilization of GPS data is carried out to overcome the problem due to lack of available data for urban network, making it difficult to develop a model to predict traffic conditions on urban networks. With the development of travel time prediction algorithm based on GPS data, it is expected that the developed model can make estimation and prediction of traffic conditions in nearly real-time. In addition, it is expected that the model developed is robust enough when there is lack of data and still has a good accuracy.

A. Introduction to Vissim

Vissim as a traffic simulation software already provides various features that make it a very complete simulation software. Through Vissim, users can conduct in-depth analysis of the junction geometry, planning infrastructure development, capacity management, development of traffic control systems, to simulate the development of public transport.

As a simulation software, Vissim also equips itself with various additional modules (APIs), which can help users integrate Vissim with various applications. One of the most useful APIs is the COM Interface. Some things that can be used through COM Interface are [1]:

- Preparation and postprocessing of data
- Efficiently controlling the sequence for the examination of scenarios
- Including control algorithms which you have defined
- Access to all network object attributes

Figure 1. shows a network model built on Vissim Simulator. In this paper, a fixed time traffic light strategy is implemented based on the real data located in Simpang Lima, Bandung. This network consists of 18 links, and 6 traffic lights with 3600s simulation period. The traffic processes in the simulator has been validated with volume and travel time data from the real observation.

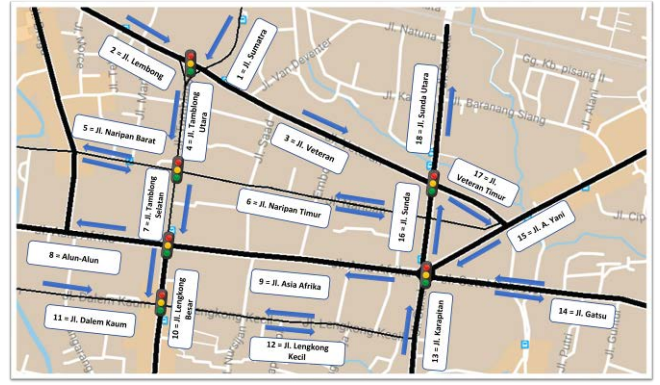


Figure 1. Vissim Network Model

II. MODEL FORMULATION

The travel time experienced by vehicles within the network of urban traffic is caused by two factors. First, the traffic state, which this situation will be perceived by all vehicles entering the link. Second, arrival time, which means the time of arrival of each vehicle to a link determines how much delay that will be experienced due to traffic light (traffic signal) and the presence of other vehicles.

The explanation in the above paragraph means that under the same traffic conditions, drivers will have different travel times depending on arrival time. Using the assumption that the arrival density is constant, the arrival time is uniformly distributed for each cycle. This assumption will facilitate the derivation of the probability distribution of delay time, which depends on the characteristics of traffic lights and traffic conditions.

A. Delay Probability Distribution

The total delay experienced in a location between x_1 and x_2 is a random variable with a mixture distribution consisting of two components. The first component represents vehicles that do not stop as they pass x_1 and x_2 (mass distribution at 0). The second component represents vehicles that reach the queue between x_1 and x_2 (uniform distribution on $[\delta^u(x_1), \delta^u(x_2)]$). The cumulative distribution of the total delay is [13]:

$$H^t(\delta_{x_1, x_2}) = \begin{cases} 0 & \text{if } \delta_{x_1, x_2} < 0 \\ (1 - \eta_{x_1, x_2}^u) & \text{if } \delta_{x_1, x_2} \in [0, \delta^u(x_1)] \\ (1 - \eta_{x_1, x_2}^u) + \eta_{x_1, x_2}^u \frac{\delta_{x_1, x_2} - \delta^u(x_1)}{\delta^u(x_2) - \delta^u(x_1)} & \text{if } \delta_{x_1, x_2} \in [\delta^u(x_1), \delta^u(x_2)] \\ 1 & \text{if } \delta_{x_1, x_2} > \delta^u(x_2) \end{cases} \quad (1)$$

B. Travel Time Probability Distribution

Travel time is the duration of the vehicle moving from x_1 to x_2 . Travel time is the sum of two independent random variable that is: delay time and free flow travel time.

$$y_{x_1, x_2} = \delta_{x_1, x_2} + y_{f; x_1, x_2} \quad (2)$$

$$y_{f; x_1, x_2} = p_f(x_1 - x_2)$$

If it is known that the free flow pace p_f has a distribution then the free flow time distribution $y_{f; x_1, x_2}$ is denoted by ϕ^p , the probability density of the travel time is [12]

$$g^u(y_{x_1, x_2}) = \begin{cases} 0 & \text{if } y_{x_1, x_2} \leq 0, \\ (1 - \eta_{x_1, x_2}^u) \phi_{x_1, x_2}^u(y_{x_1, x_2}) & \text{if } y_{x_1, x_2} \in [0, \delta^u(x_1)], \\ (1 - \eta_{x_1, x_2}^u) \phi_{x_1, x_2}^u(y_{x_1, x_2}) + \frac{\eta_{x_1, x_2}^u}{\delta^u(x_2) - \delta^u(x_1)} \int_0^{y_{x_1, x_2} - \delta^u(x_1)} \phi_{x_1, x_2}^u(z) dz & \text{if } y_{x_1, x_2} \in [\delta^u(x_1), \delta^u(x_2)], \\ (1 - \eta_{x_1, x_2}^u) \phi_{x_1, x_2}^u(y_{x_1, x_2}) + \frac{\eta_{x_1, x_2}^u}{\delta^u(x_2) - \delta^u(x_1)} \int_{y_{x_1, x_2} - \delta^u(x_2)}^{y_{x_1, x_2}} \phi_{x_1, x_2}^u(z) dz & \text{if } y_{x_1, x_2} \geq \delta^u(x_2). \end{cases}$$

C. Traffic State Evolution

The time evolution of the traffic state depends on the probability of vehicles coming out from a link inside the network. For example, L_{out}^k is a collection of links from which the vehicle originated at the junction k . At the time interval t , $n_{in}^{i,t}$ is the number of vehicles entering the link i for one cycle. Similarly, $N_{in}^{i,t}$ represents the number of vehicles entering a link for the duration of Δt at the time interval t . For two adjacent links i and j (with i as upstream of j), $n_{in}^{i,j,t}$ is the number of vehicles entering the link j of link i for one cycle and $N_{in}^{i,j,t}$ is the number of vehicles entering the link j from link i for one-time interval t . The above notations are illustrated more clearly in figure 2.

The dynamics of traffic state are characterized by turning behavior on the network. The probability of movement from link i to link j is called turn ratio and denoted by $v^{i,j}$. This variable is positive (non-negative) and satisfies

$$\sum_{j \in L_{out}^k} v^{i,j} = 1$$

Any vehicles coming out of link i at an intersection k will enter link j with probability $v^{i,j}$. Based on the model, the random vector of vehicles entering link j satisfies one multinomial distribution with parameters $(v^{i,j})_{j \in L_{out}^k}$ and $N_{out}^{i,t}$, hence

$$P(N_{in}^{i,j,t} : j \in L_{out}^k) = \begin{cases} \frac{N_{out}^{i,t}}{\prod_{j \in L_{out}^k} N_{in}^{i,j,t}!} \prod_{j \in L_{out}^k} (v^{i,j})^{N_{in}^{i,j,t}}, & \text{if } \sum_{j \in L_{out}^k} N_{in}^{i,j,t} = N_{out}^{i,t} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

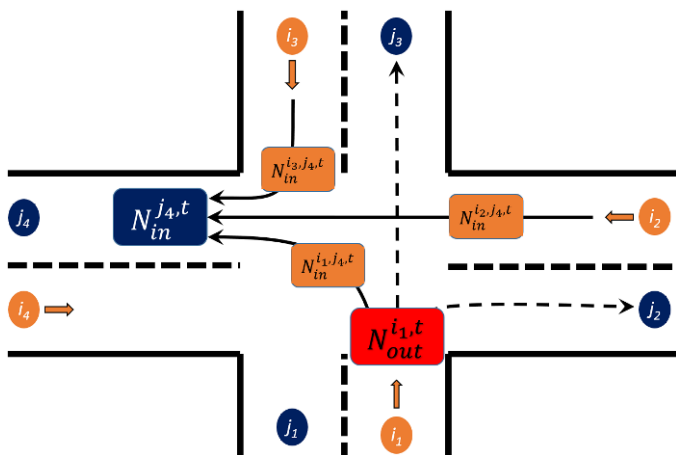


Figure 2. Schematic Representation of a junction k , illustrates the definition of incoming link $L_{in}^k = \{i_1, i_2, i_3\}$ and outgoing link $L_{out}^k = \{j_1, j_2, j_3\}$.

The number of vehicles traveling to the link j at the junction k and the state (number of vehicles) of link j at time

t ($\xi^{j,t}$) is the factor that determines the state at time $t+1$ ($\xi^{j,t+1}$) [13].

- State $t+1$ on undersaturated condition

At time t , the link j is in undersaturated condition ($\xi^{j,t} \leq \xi_s^j$) and the number of incoming vehicles per cycle is less than the outgoing vehicles per cycle ($n_{in}^{j,t} \leq k^j \xi_s^j$). These two conditions imply undersaturated condition on the link j at the time of t and $t+1$. State at time $t+1$ is

$$\xi^{j,t+1} = \frac{N_{in}^{j,t} R^j \xi_s^j}{k^j \Delta t \xi_s^j - (C^j - R^j) N_{in}^{j,t}} \quad (4)$$

- State $t+1$ on congested condition

If the incoming vehicles are greater than the outgoing vehicles that can exit in one cycle, then there will be an increase or reduction in the number of vehicles on the link during the period t time. The number of vehicles at time interval $t+1$ is

$$\xi^{j,t+1} = \xi^{j,t} + \frac{\Delta N^{j,t}}{k^j} \quad (5)$$

III. RESULTS

In this section the results that have been achieved from the experiment estimation of travel time using Bayesian Network model is presented. As a comparison of estimation quality, the measurement of the average travel time and the measurement of vehicle number from Vissim simulation result are also presented.

A. Estimation Result of Number of Vehicles per Cycle

The dynamics occurring in the research area due to the interaction between incoming flow from the input links and the driving behavior of drivers modeled by gamma distribution will be seen in the other links in the network, especially in the links belonging to the estimation zone. In addition, the dynamics occurring in the estimation zone are also strongly influenced by the characteristics of each link that are parameterized by the duration of the traffic signal, the width of the road, the turning ratio, and the length of the link.

The impact of dynamic or static variables in this research area is represented by a change or evolution of the state, the state at time t is estimated with Bayesian network model that has been built. The state estimation results are compared with the direct measurement data taken from the Vissim simulation. Figure 3 is one of the estimation results compared to the direct measurement data.

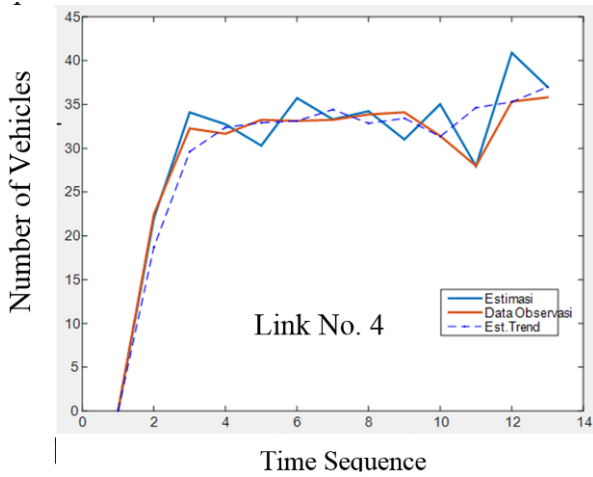


Figure 3. Comparison of Estimation and Observed Data of Link No. 4

From the results obtained for all 18 links, it can be drawn some information, namely:

1. The trend of the state estimation may follow or adequately match the trend of the actual state from direct measurement. The smoothed trend of the estimation is indicated by the dashed line in the figure.
2. Errors between estimation results with observation data on each link are quite varied.

To see further how big the error in each link and how correlated the estimation results then 2 types of the following metrics are calculated:

- Mean Absolute Error (MAE), Fig. 4
- Correlation Coefficient (R Value), Fig. 5

Based on MAE values, the biggest error occurs in link no. 17 with values ranging from 3-4 vehicles. This is most likely due to the fact the link no. 17 does not have a traffic light (see figure 1), so model assumptions are not met here. However, it has been made some manipulation of the model for link no. 17, to include parameter of cycle duration and red duration at dynamics model of link no. 17 so it seems to have a traffic light and the dynamics of the queue length are periodic following the traffic light cycle.

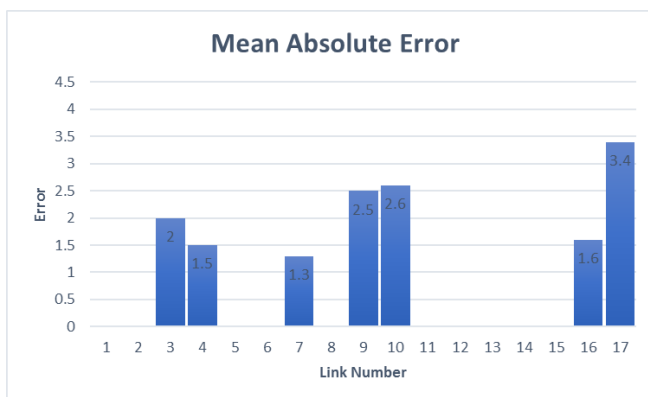


Figure 4. MAE of Link States

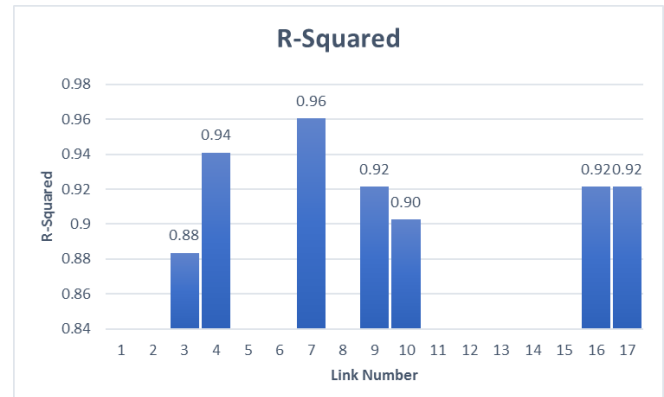


Figure 5. Correlation Coefficient of Link States

The result of this estimation was quite able to follow the actual dynamics that occur in the link no. 17 this is due to several reasons, namely:

1. Link no. 17 has a short road length, so the generation of the queue is quite frequent although there are no traffic lights. This matter making the manipulation done by the author to be quite compatible with the dynamics that occur
2. Link no. 17 is connected to link no. 15 which is an input link with a large input volume, so the queue of vehicles on the link no. 15 can reach the outlet point of link no. 17. This causes the vehicle exit period from link no. 17 follows the cycle period of link no. 15, so indirectly this phenomenon describes as if there is a traffic light on the link no. 17.

The last conclusion is from the analysis of the value of correlation coefficient of each link. It appears that a high correlation occurs for all links with values > 0.95 . This high correlation value confirms the temporary conclusion made above, that the estimation trend is sufficiently able to follow the trend of the actual observational data.

B. Estimation Result of Link Travel Time

The final goal is to estimate travel time of each link in the network area of Bandung city. To be able to compare estimation results with observed travel time data, then the value of expectations which is a representation of the average value of the travel time distribution obtained given the estimated number of vehicles at time t is calculated.

The average value of observational data and the expected value derived from the distribution in each link was compared. The MAE and the correlation coefficient are also calculated. Figures 7 and 8 show the comparison between the estimated travel time and the mean value by the conventional averaging technique (uniform weighting).

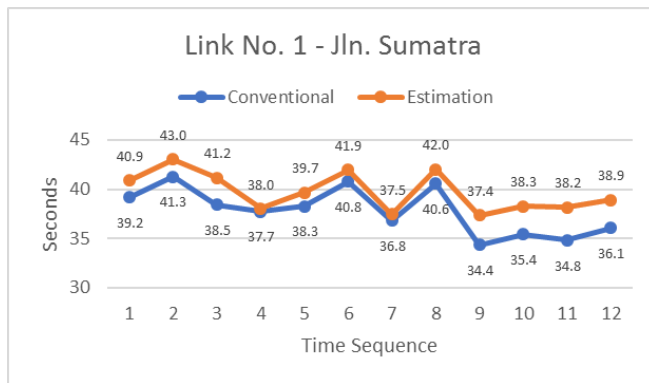


Figure 6. Comparison of Estimation and Observed Data of Link No. 1

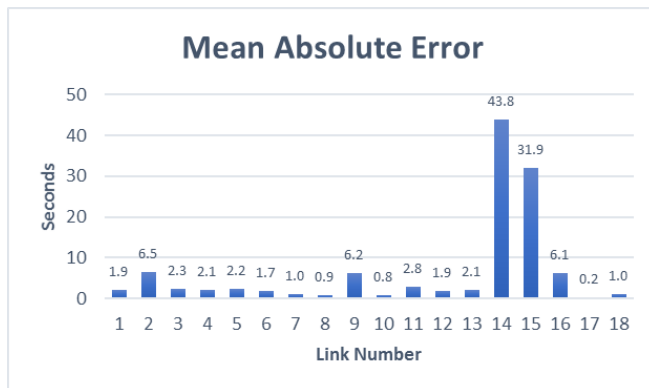


Figure 7. MAE of Link Travel Times

Based on the results of MAE calculation, significant errors occur in the link no. 14 and 15. When it is looked at the study area map, these links represent input links and there are some special things on these links:

- **Link no. 14**, in this link there is a *sink* that causes disruption to the flow of vehicles going towards the intersection. This Disturbance is due to the flow of vehicles moving towards the sink are crossing the lane and cut the flow of vehicles going towards intersection. This incident occurs quite often so it gives a significant impact on the travel time measurement and the calculation of the average value which were obtained by conventional averaging technique.
- **Link no. 15**, in this link there is a *source* which is an output of link no. 17 and there is also a direct path to turn left to the link no. 14. This leads to a high variation of travel time, so the average value of the travel time is not accurate.



Figure 8. Corr. Coefficient of Link Travel Times

While from the correlation data obtained, it can be seen that it is on the link no. 14 and no. 15 that the average of the

travel time is quite disturbed due to the sink and source. The conclusion that can be obtained from the estimation of travel time is the value of travel time experienced by each vehicle in a link is very sensitive to disruptions that occur in the link, whether it is a sink, a source, or other disturbances.

IV. CONCLUSION

Based on the research that has been done, the following conclusions are withdrawn: Implementation of the vehicle number estimation algorithm and the travel time with Bayesian Network model has proved that this methodology is successful enough to give estimation results which are close to the actual data. Based on the results of error evaluation on the estimated number of vehicles, large errors occur due to traffic processes that occur do not meet the assumptions-built models, such as the link no. 17. Based on the results of error evaluation on the estimated travel time, large errors occur due to the existence of sink and source on the links, as in the link no. 2, 9, 14, 15, and 16. The travel time experienced by drivers in a link, is very sensitive to the existence of disturbances that occur within the link

From the results, it was found some development opportunities to get better estimation algorithm, such as: The addition of parameter estimation algorithms to enable identifying system parameters in real time, because changes in traffic parameters such as turning ratio and the duration of traffic lights are very common. Model development includes the dynamic of a link that has no traffic light. The addition of parameters in the model includes the effects of the left-turn lanes. The model can be further developed to include phase differences in signaling and queue dynamics differences between lanes in one link, integration of estimation and prediction algorithm of travel time and number of vehicles with route guidance algorithm.

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