

DEVELOPMENT OF DISTRIBUTED REAL-TIME DECISION SUPPORT SYSTEM FOR TRAFFIC MANAGEMENT CENTERS USING MICROSCOPIC CA MODEL*

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Abstract– Post incident traffic management on a freeway network depends mainly on the decisions of traffic managers that surface from their individual exposure to similar conditions. This manual approach to tackle a dynamic scenario induces uncertainty, inconsistency and inefficient use of rescue resources. This paper suggests a decision support scheme known as Freeway Incident Analysis System, (FIAS). The novel idea presented here is the use of real time data from the Toll Collection System (TCS) and Vehicle Detection System (VDS). This data is conjugated with the historical data on a microscopic simulation platform to predict traffic flows in a post-incident scenario. The system employs Cellular Automata for the microscopic simulation of vehicle movement, and we also suggest two additional rules in the modified version of the conventional model. This has enabled us to model the dynamic flow parameters in a post incident scenario more realistically. The evaluation of FIAS indicates that it yields significantly accurate post incident information about traffic flows for the use of traffic managers.

Keywords– Intelligent transport systems, incident management, microscopic simulation, decision support system

1. INTRODUCTION

In the world of Intelligent Transport Systems, the Traffic Management Center (TMC) plays a pivotal role that is akin to the central nervous system in the human body. This role becomes even more crucial in the post-incident scenario when managers tackle non-recurrent congestion and have to make important decisions to coordinate the rescue operation [1]. In most of such scenarios, traffic managers employ their *guesswork* about the impacts of an incident on the traffic flow and make crucial decisions based on certain suppositions. However, these individual assumptions may vary from person to person and incident to incident. This induces inconsistency in the whole incident management operation and may result in the inefficient use of resources [2], [3]. Further, they fail to incorporate the flow pattern based on Origin and Destination (O/D) and driver's behavior.

This paper is a part of the project taken up by the Korea Highway Corporation to address the problems of the management staff of the TMC to tackle non-recurrent congestion on the freeway network in Korea. In this project, 'FIAS', a Freeway Incident Analysis System, is developed that exploits a micro-simulation model to predict post-incident traffic flows. It is suggested to be a complementary part of the sitting Freeway Traffic Management System (FTMS)[4]. The aim of this paper is to present the functional architecture of FIAS and to evaluate the model by comparing its output with the real data in a post-

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incident scenario. The idea presented here is the incorporation of the historical data with the real-time data from the Toll Collection System (TCS) and the Vehicle Detection System (VDS) to forecast post-incident traffic flows. The most important feature of FIAS is the use of the microscopic simulation model ‘Cellular Automata’ (CA) with certain adaptations in the CA model presented in [5] to accommodate the drivers’ behavior in the incident scenario.

2. REVIEW

Initial attempts towards the design of a decision support system for the incident related congestion were mainly based on analytical models, a knowledge based expert system and Geographic Information System (GIS) based tools [6-8]. According to Ritchie’s investigation [2] the Santa Monica Freeway Smart Corridor project was one of the very first attempts in which a full-fledged real-time knowledge based expert system was employed for traffic surveillance and control purposes. Zhang and Ritchie [9] proposed a knowledge based expert system with the name of FRED- Freeway Real-time Expert system Demonstration. In the later stages with the advent of faster computers and the search for an ITS solution to growing traffic problems, a number of simulation models have been employed. For example, Xaichen and Dailey [10] used a CA model for the prediction of flows using real time inductance loop data for freeway traffic. Another attempt was made by Hegyi *et al.* [11], who suggested a Fuzzy Decision Support System-FDSS, using fuzzy logic and METANET, a macroscopic flow model. The software uses historic data for the prediction of traffic flows in a simulated environment that gives an idea of the performance of the control measure.

3. FRAMEWORK

There are four fundamental units of FIAS (Fig. 1) that include data accessing, manipulation, and simulation and output module.

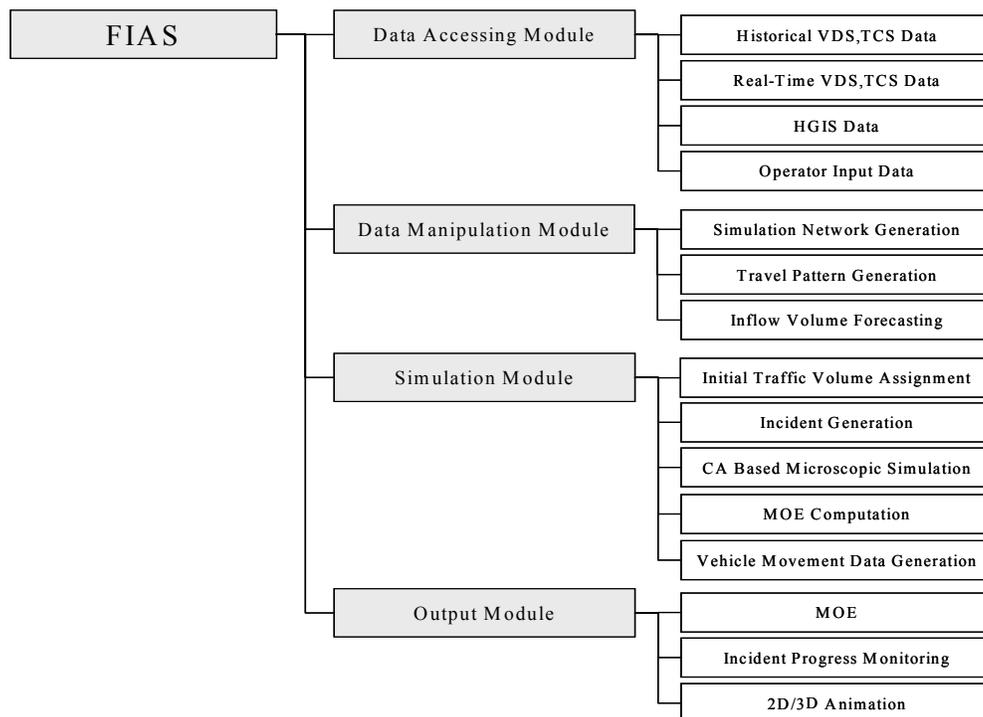


Fig. 1. Conceptual framework of FIAS

a) Data accessing module

FIAS uses both the real-time as well as historical data in the analytical framework. For this purpose the VDS and TCS data is extracted periodically from the existing FTMS database server by using the Open Database Connectivity (ODBC) method. For the purpose of geographic data collection and incorporation, the whole stretch of the freeway is divided into smaller sections based on the geometry of the road, the VDS location or both, and designates them as 'links'. These links data are stored in the HGIS database as the 'road network data' along with the location of neighboring VDS stations and their unique identity number.

The real time input data used in this research are the aforementioned TCS and VDS data. The TCS data are freeway inflow and out-flow traffic volume counted on tollgates and the VDS data are link traffic volume, average speed and occupancy of the section. Similarly the corresponding historical data is also collected from the TCS and VDS servers. These real time and historical data are amalgamated and 'fine tuned' for any correction or missing data at the data filtering stage.

b) Data manipulation module

This level is imperative for the simulation environment and therefore we regard it as the 'interfacing' or 'enabling' phase. Here the simulation network generation module tackles the geographical data regarding the road network at the GIS platform, along with the locations of various VDS stations. It then marks a corridor all along the link with the size of the corridor depending upon the roadway width. This corridor is represented on MS Access file format, which is the required format for the simulation platform. Next, in the travel pattern generation module we employ TCS data to ascertain the O/D pattern and the route pattern. Concurrently, filtered TCS data is used to forecast the inflow volumes. The forecasted volumes along with the O/D pattern and the route pattern data initiate the simulation process, which is described below.

c) Simulation module

In the simulation module, the analyzed and filtered data is assigned to various links using the initial volume assignment module. Simultaneously, the operator injects incident parameters in the incident generation module and simulation parameters in the CA microscopic simulation module. Thus the final route and O/D pattern data, inflow volume data and initial traffic volume assigned link data, along with the incident parameters are modeled in the microscopic simulation platform. This simulation model yields the required MOEs and individual vehicle tracing data through a vehicle movement data generation module.

The CA model has several advantages such as speed of simulation run time, range and applicability in various geometric designs and traffic conditions. In this research, the adaptive CA model that improves the existing NaSch CA model is developed. The distinguishing feature of the adaptive CA is that it can simulate congested flows more elastically. It can also simulate breakdown on the bottleneck sections along with the simulation of 'Stop' and 'Go' phenomena more realistically.

d) Output module

This is the terminator level of the architecture where traffic managers can view simulated traffic flows in the pre and post-incident scenario. They can assess and monitor the computed MOEs in an animated environment. If they desire they can also see the individual vehicle movement in 2D vehicle animation and 3D CCTV animation with play and speed control options. It is anticipated that the incident analysis

result in this format will help traffic managers to make appropriate rescue decisions based on tangible information rather than the speculative approach.

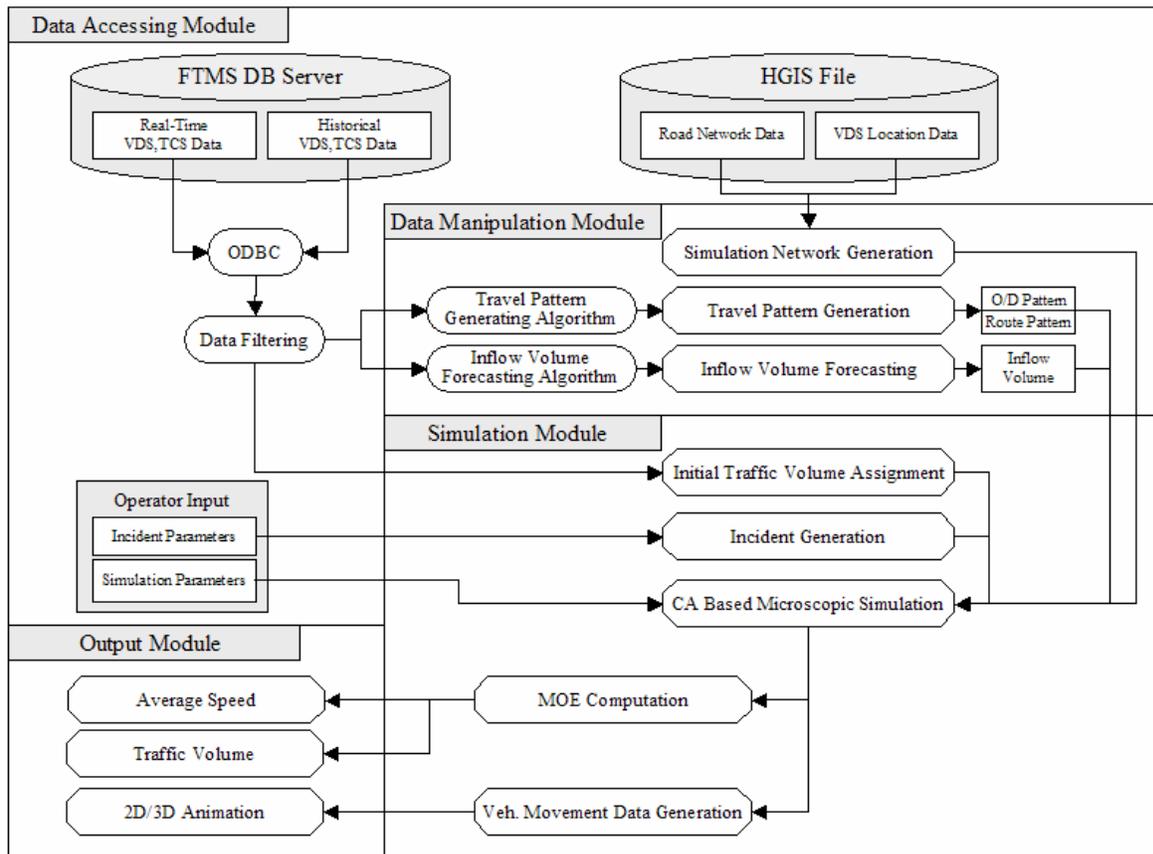


Fig.2. Functional architecture of FIAS

4. MODELING TRAFFIC FLOWS WITH CELLULAR AUTOMATA

Road traffic is influenced by a number of factors such as the driver's behavior, road geometry, and the land use pattern of the abutting property. The depiction of such phenomena through general mathematical expression or models is both difficult, as well as time consuming because of the complexity, randomness and interdependency of the parameters [12].

Traffic flow simulators rather than analytical models are often employed to simulate traffic on various spatio-temporal scales. Traffic flow models can conventionally be classified as microscopic and macroscopic in nature. In microscopic modeling the movement of an individual vehicle is focused so that it yields a more detailed description of the vehicle, whereas macroscopic modeling depicts the accumulative behavior of traffic flows through traffic density, mean speed and volume. The latter approach considers traffic flow a compressible fluid and employs fluid-dynamical partial differential equations to propagate flow and density between large discrete time and space sections. The use of these parameters in the model reduces the computation time considerably. However researchers like Xaichen and Dailey [10] argue that although the macroscopic traffic model reduces the computation time, it cannot estimate travel time, turning movement and other control parameters on a short time scale. Thus the macroscopic model in the incident scenario cannot be regarded as the best option, wherein short time scale

information becomes significantly more important in taking immediate relief measures in order to limit the spreading of congestion effects.

a) Cellular automata

Cellular Automata (CA) is an artificial approach in which physical quantities are transformed into a finite set of discrete units. Von Neumann and Ulam originally pioneered this simulation modeling approach in the 1960s for the representation of the biological self-reproduction phenomenon. Since then, CA has been regarded as a promising tool for high-speed micro simulation and is used to model a variety of physical scenarios [10].

Nagel and Schreckenberg [5] employed CA to depict traffic flow on a single lane of a highway. The model, which is here referred to as “NaSch model”, (a term used in [13]), proposed a simple rule-based approach to simulate driver behavior in free flow conditions. The car following model is a key element in modeling driver behavior and is also employed in the NaSch model. For an elaborate review, the model is briefly described for single lane traffic. The full stretch of the road is subdivided into ‘ n ’ boxes (‘cells’) of 7.5 meters in length, which can be either occupied or be empty by one vehicle at any discrete instant of time ‘ t ’. The velocity v of the vehicles is an internal parameter that characterizes its state. It can take on only integer values, i.e., $v = 0, 1, 2, \dots, v_{max}$. The dynamics of the model is described by speed update and movement rules for the velocities which are given below:

Speed update step

Acceleration: IF ($v_i < g_i$) THEN $v_{i+1} = \min[v_{max}, v_i + 1]$

Deceleration: IF ($v_i \geq g_i$) THEN $v_{i+1} = \min[v_i, g_i]$

Randomization: IF ($p_{noise} > \text{random value}$) THEN $v_{i+1} = \max[v_{i+1} - 1, 0]$

Movement step $x_{i+1} = x_i + v_{i+1}$

where, ‘ v_i ’ ($0 \leq v_i \leq v_{max}$, cell/timestep) is a velocity of car at time step ‘ t ’, and ‘ g_i ’ the Number of Unoccupied Cells (NUC) behind the leading car. ‘ p_{noise} ’ is the random noise parameter (0~1) and illustrates the deviation from the optimal way approach encompassed in acceleration and deceleration rules. Thus the stochastic nature of traffic flows is incorporated in the model which explains the phantom jam dynamics. Without this parameter the dynamics would be purely deterministic as the system shows strong dependence on the initial condition. The randomization or the movement step takes into account natural fluctuations in the driver’s behavior.

b) Velocity dependent randomization

Real traffic delivers strong hysteresis effects near the maximum flow due to the existence of meta-stable states in certain density regimes [13, 14]. Traffic stays laminar when approaching from the low densities till a threshold point ‘ ρ_2 ’ and then breaks down into start-stop traffic. However, it does not become laminar in the reverse direction until ‘ ρ_1 ’, which is about 30% smaller than ρ_2 [15]. Barlovic *et al.* [13] incorporate this behavior into the NaSch model and term it the *Slow-to-Start* [STS] rule to more realistically capture the breakdown flow behavior. Also, the acceleration rate of stopped vehicles can be modeled by the STS rule using a different random noise parameter ‘ p_s ’ that has higher value than NaSch’s employed p_{noise} . ($p_s \gg p_{noise}$). In such scenario, drivers escaping out of a jam will hesitate so that a jam grows and moves backward. The STS rule is directly added to the NaSch model, and dubbed the *modified*

NaSch model. However both versions of the NaSch model have the following common shortcomings in view of microscopic behaviors:

- (a) Unrealistic braking capability to avoid back collision in one time step (i.e., 1 second) from v_{max} to 0.
- (b) No distinguished drivers' behavior between staying in a jam and escaping from it.

c) Additional movement rules

Two additional movement rules, the Stopping Maneuver Rule (SMR) and the Low Acceleration Rule (LAR), are introduced here to tackle the aforementioned two defects and to capture velocity quantities more realistically under heterogeneous traffic flow conditions. SMR is to describe a decelerating vehicle to arrive and stop in the tail of a jam, and LAR is to capture an accelerating vehicle which follows a stopped leading vehicle in a jam. Further, the two rules are easily and directly added into the modified NaSch model.

1. Stopping Maneuver Rule (SMR): An approaching vehicle with the velocity $v_i > 0$ (cell/sec) to the back of a stopped leading vehicle needs an appropriate Stopping Distance (SD) to accomplish a smooth, safe stop. The distance is expressed below.

$$SD = \sum_{i=1}^{v_i} i + v_i \text{ for all vehicles with } v_i > 0$$

SMR incorporates SD and NUC along with random noise, ' p_{sm} ' ($p_{noise} \leq p_{sm} \leq 1$) as follows.

IF ($(SD \geq NUC$ or $(v_i - 1 \geq v_{lead}$ and $v_i \geq g_i)$) and $(p_{sm} > \text{random value})$)

THEN $v_{i+1} = \min[v_i - 1, g_i]$

ELSE the speed update step of the modified NaSch model

2. Low Acceleration Rule (LAR): LAR is introduced to describe a low acceleration rate in a jam. In the modified NaSch model, noise parameter values, namely p_{noise} and p_s , are used for both the acceleration of stopped vehicles in a wide moving jam $(1 - 1/(v_{max} + 1)) \ll \rho \leq 1$ and the acceleration of an escaping vehicle from a jam. But an aggressive accelerating maneuver with a high acceleration rate to escape a jam is different from an accelerating maneuver in a jam because in a jam, an accelerating maneuver is physically accomplished with a low acceleration rate and drivers psychologically hesitate about accelerating. Let us make assumptions about the following:

1. A stopped vehicle with $g_i = 1$, following a stopped vehicle, stays in a jam.
2. A stopped vehicle with $g_i = 1$, following a running vehicle, escapes from a jam.

And then LAR are modeled with random noise ($p_{la}, p_{noise} \leq p_{la} \leq 1$ or $p_s \leq p_{la} \leq 1$) as follow:

IF ($v_i = 0, g_i = 1, v_{lead} = 0, p_{la} > \text{random value}$) THEN $v_{i+1} = 0$

ELSE $v_{i+1} = 1$

SMR and LAR are directly integrated into the modified NaSch model as follows:

1. Velocity update step

IF ($(v_i > 0, SD \geq NUC)$ or $(v_i - 1 \geq v_{lead}, v_i \geq g_i)$) THEN SMR

ELSE the speed update step of the modified NaSch model

IF ($v_i = 0, g_i = 1, v_{lead} = 0$) THEN LAR

ELSE the speed update step of the modified NaSch model

2. Movement step $x_{i+1} = x_i + v_{i+1}$

If $p_{noise} = p_s = p_{sm} = p_{la}$, then SMR and LAR have the same function as the NaSch model, and if $p_{noise} \ll p_s$, $p_{noise} = p_{sm}$, $p_s = p_{la}$, then the modified results can be achieved that are shown in Fig. 3. This shows vehicle trajectories on a 1-lane periodic system with a parallel update. Dots in the figure represent vehicles that move to the right. The horizontal direction is discrete space to the right and the vertical direction downward is discrete time. The left box of the figures portrays a NaSch model with $p_{noise}=0.135$ and $v_{max}=5$, whereas the right box represents the flow pattern with the incorporation of the SMR and LAR rules ($p_{noise}=0.135$, $v_{max}=5$, $p_{sm}=0.8$, $p_{la}=0.8$) into the NaSch model. The full experimental results calculated by the integrated model are presented in [16].

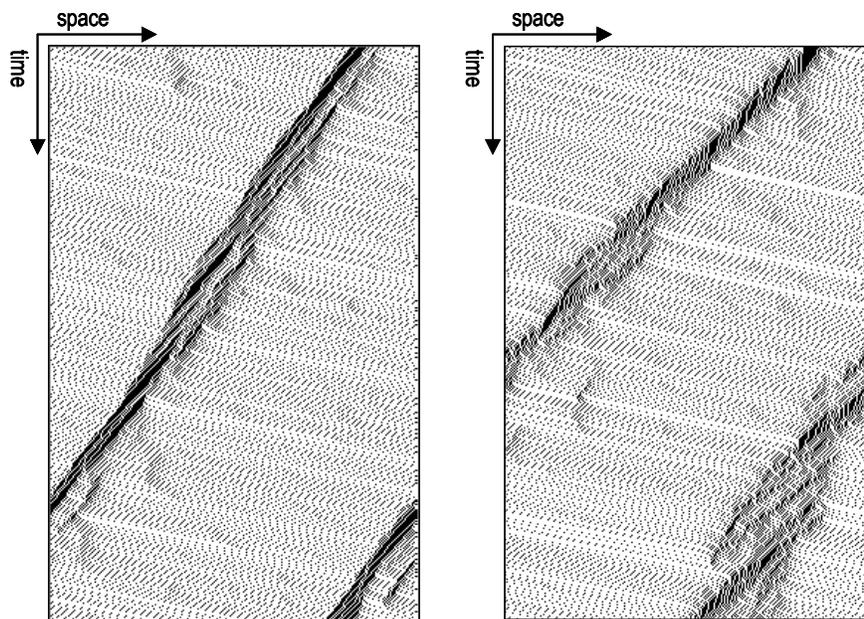


Fig. 3. Comparison of vehicle trajectories on a 1-lane periodic system with parallel update using NaSch model (left) and the modified model(right)

5. CASE STUDY

Two functions of FIAS, namely, inflow volume forecasting and MOE computation are investigated here to test its performance. For this purpose, 78.4 km of the Seohean line that extends southward from the West Seoul tollgate at a Reduced Distance (RD) of 327 km to Seosan tollgate at RD 248.6 km, is labeled as the “case study section” (Fig.4). There are eight tollgates and 79 VDS stations on this section of the freeway. However in this experiment, inflow volume data from all eight tollgates and MOE data from only four VDS stations are focused for the comparative study. The location of all tollgates is shown in Table 1.

Table 1. The location of tollgates on the study section

Name	West Seoul	Maesong	Bibong	Balan	West Pyeongtaek	Songak	Dangjin	Seosan
Location RD (km)	327	316.9	312.8	299.2	284.9	272.6	264.6	248.6

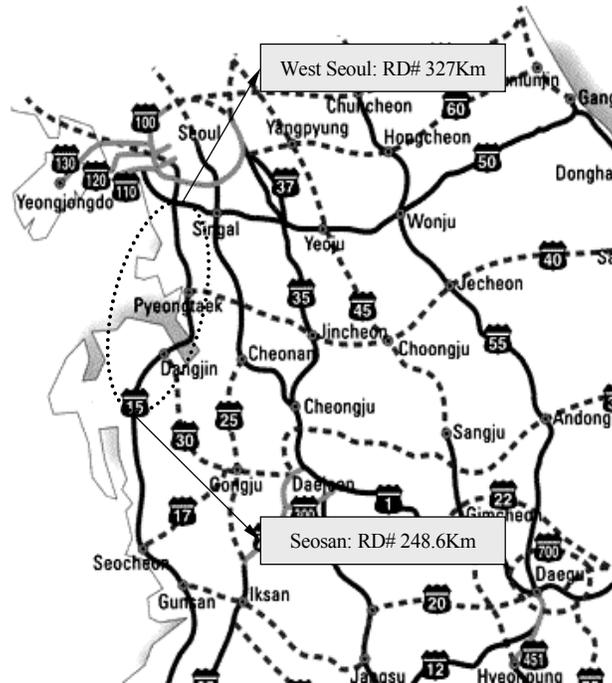


Fig. 4. Study section of Seohean line near Seoul (Source: Extracted from [17])

a) Real data collection

TCS real data is recorded from all tollgates of the study section after every fifteen minutes for four hours. Thus at every tollgate, 4 datasets per hour or 16 observations per stipulated time were registered. The MOE data that include link volume and average speed are captured after every five minutes, making 12 data sets per hour from each VDS station or 24 observations per station in the stipulated time. For the post incident real data, an incident that occurred on 18th November, 2003 was selected. The detail incident parameters are shown in Table II below. Fig. 5 shows these parameters along with the location of four VDS stations which were selected for the VDS data collection.

Table 2. Description of the selected incidents for comparative study

Description	Incident
Incident point	317.0 km
Incident day	2003.11.18 Tuesday
Incident hour	4:15 pm
Incident lasting duration	30 min
Incident effect sweeping point	16km to upstream (RD #: 303km)
Net capacity of the incident section	460 veh/hr/lane

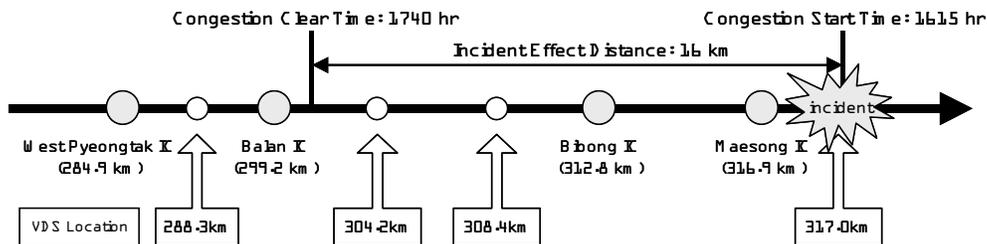


Fig. 5. Location of VDS stations for data collection and actual incident point

b) Experimental results

Experimental results are divided into two sections with the first section comparing inflow volume data from eight tollgates (Fig. 6) against the predicted data by FIAS, whereas the second section compares the incident induced traffic flow data of the link volume (Fig. 7) and the average flow speed from the VDS (Fig. 8). Mean Absolute Relative Error (MARE) is employed here to translate the comparative results in tangible format using the following expression:

$$MARE = \frac{1}{n} \sum_{i=1}^n \frac{|x_i - y_i|}{x_i} \times 100$$

Where,

- x_i real data at i th time interval;
- y_i predicted data at the i th time interval
- n number of data sets or observation ranging from 1 to n

c) Comparison of inflow volume data at tollgates

The value of the mean absolute error changes in the range of 5% to 9% with an average of 7%. Although on very few sections (Fig 6-d) the local error does look slightly higher, nonetheless, by and large, the model predicts the inflow volume to the network quite accurately.

d) Comparison of MOE data

VDS data for volume: The analysis indicates that an average error of 9%, though it varies from 4% to 16%. The accident happening time is indicated as section '1' (1615 hrs) of Fig. 7a and VDS at RD 317.0 km indicates a drop in the volume at the time section '2' (1620 hrs). From Fig. 7 it is evident that the simulation data curve follows the drop and rise in the volume of the real data with significant precision, though it does also look at departing from some VDS stations (Fig. 7c). This indicates the limitation of the model and the scope for further improvement. Nonetheless, for all practical purposes and from the manager's perspective, it is more important to know the behavior of the flows and forecast the time when the effected section will be experiencing most retarded flows. Our model depicts that phenomenon quite correctly (Fig. 7a-d).

VDS data for average speed: Fig. 8 depicts slightly higher values of the MARE between the predicted and the real link speed data, though it drops to 16% while taking the average of all four stations. It is important here to note that in the vicinity of the incident point (Fig. 8b) the real data depicts a quick fluctuation in the speed, whereas our proposed model is slightly lagging behind, resulting in as high as 24% error. A bit away from the incident point (Fig. 8d), the simulation data appears to be in harmony with the real data with only a 6% average error. However even when the local error is 24%, our model is capturing, quite accurately, the disturbed flow time from time section 8 to time section 14 (i.e., 1640 hours to 1710 hours). The simulation data corresponding to the three VDS stations show the impacts, while at the next immediate station the impact is not apparent. This helps the traffic manager to identify the stretch of the road that may be experiencing the impacts of the incident.

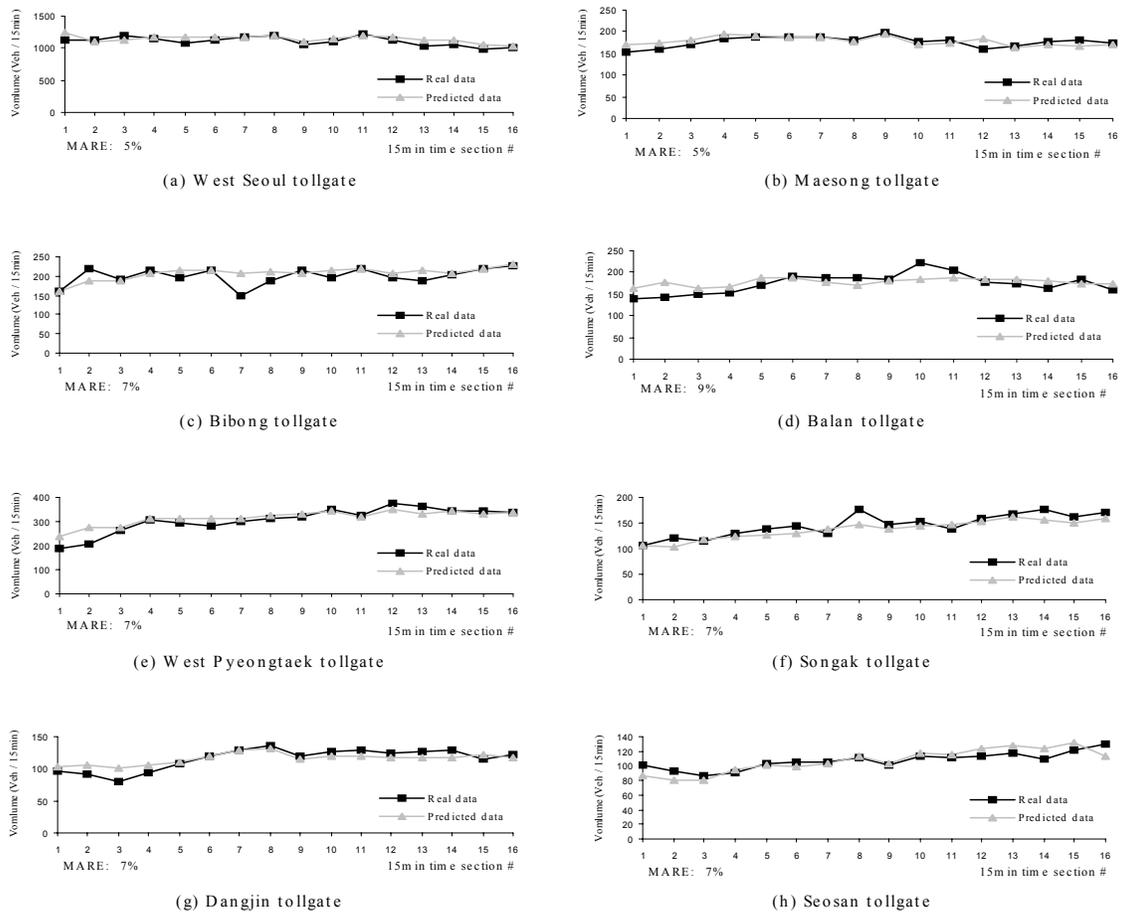


Fig. 6. A comparative study of inflow volume in all tollgates on the study section

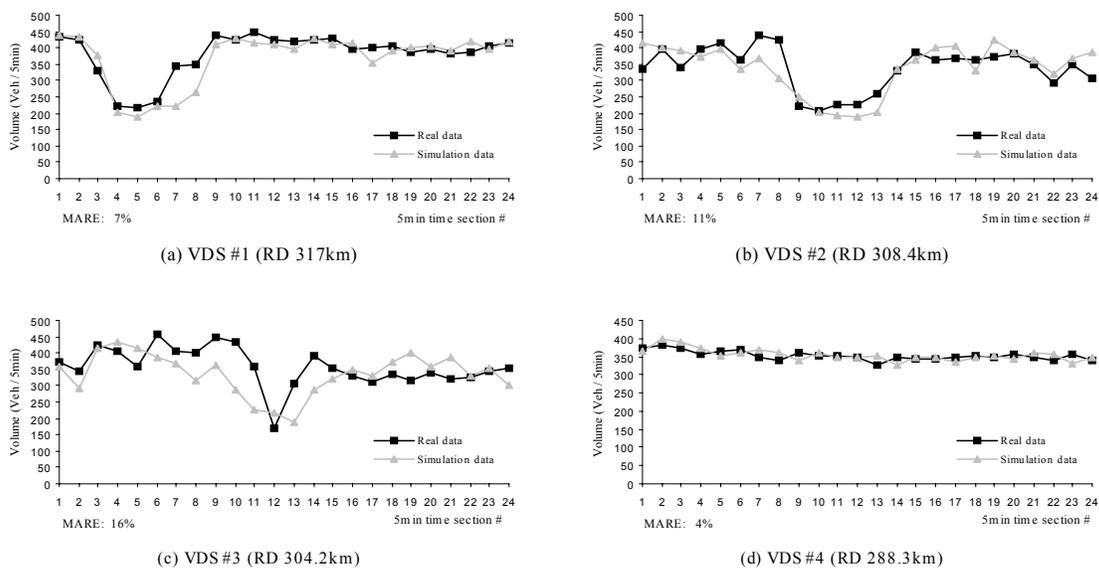


Fig. 7. Comparison of the real VDS volume data with the FIAS forecasted data

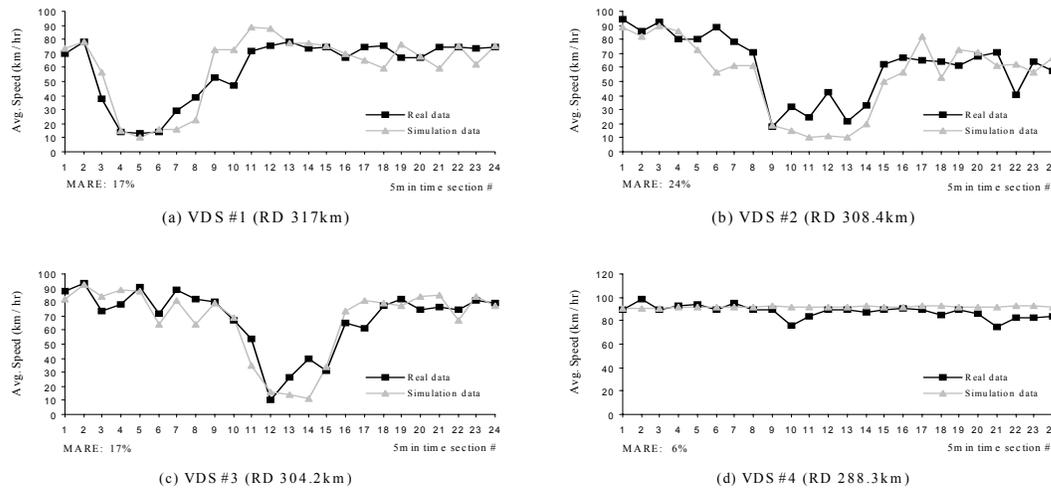


Fig. 8. Comparison of the VDS average speed data with the FIAS forecasted data

6. CONCLUSION

This study is based on the problem faced by the traffic managers at the TMC in the post incident scenario. It suggests a decision support system that will enable them to look into the post incidents impacts on a simulated platform and manage the rescue operation more efficiently. The salient features and characteristics of FIAS are summarized below. It can:

- predict the inflow volume to the freeway based on the O/D pattern
- predict the link traffic volume and speed correctly based on the conjugated historical and real-time data.
- predict the time when the road section experiences the most retarded flows.
- display the simulation results in both 2D animated and 3D CCTV environment as per requirements and convenience of the traffic management personnel.

This paper also discussed the limitations of the conventional approach to tackle the post incident traffic flows and suggest a model which is more versatile than the existing versions of CA. The distinguishing feature of our proposed model is the incorporation of two additional rules to the conventional model so that it can simulate congested flows more elastically. It can also simulate breakdown on the bottleneck sections along with the simulation of Stop/Go phenomena more realistically. The future work may consider functions like the dynamic traffic model for providing an optimal path to the driver.

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