Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

Bratislav Predic, Dejan Rancic and Aleksandar Milosavljevic
Department of Computer Science, Faculty of Electronic Engineering
University of Nis
A. Medvedeva 14
18000 Nis, Serbia
Phone: +381 18 529 331
Fax: +381 18 588 399
bratislav.predic@elfak.ni.ac.rs
dean.rancic@elfak.ni.ac.rs
aleksandar.milosavljevic@elfak.ni.ac.rs

The proliferation of cheap and compact Global Positioning System (GPS) receivers has led to most Automatic Vehicle Location (AVL) systems today relying almost exclusively on satellite-based locating systems, as GPS is the most stable implementation of these. This paper presents the characteristics of a proposed system for tracking and analysing public bus transport in a typical medium-sized city and contrasts the characteristics of such a system to those of general purpose AVL systems. Specific properties of the routes analysed by the AVL system used for the analysis of public transport in our study include cyclic vehicle routes, the need for specific performance reports, etc. This paper specifically deals with vehicle motion predictions and the estimation of station arrival time, coupled with automatically generated reports on timetable conformance and other performance measures. Another side of the observed problem is efficient transfer of data from the vehicles to the control centre. The ubiquity of GSM packet data transfer technologies coupled with reduced data transfer costs have caused today’s AVL systems to rely mainly on packet data transfer services from mobile operators as the communications channel between vehicles and the control centre. This approach raises many security issues in this potentially sensitive application field.

Keywords: Automatic Vehicle Location (AVL), prediction of arrival times, AVL security, information services, intelligent transport systems (ITS), map matching

ACM Classifications: D.2.11 [Software Engineering]: Software Architectures – domain-specific architectures; H.3.3 [Information Storage and Retrieval]: Information Search and Retrieval — information filtering; H.4.2 [Information Systems Applications]: Types of Systems – logistics; J.7 [Computers in Other Systems]: real time, command and control

1. INTRODUCTION
Recent advances in automatic vehicle location (AVL) systems based on the global positioning system (GPS) have provided the transit industry and public transport enterprises with tools to monitor and control the operation of their vehicles and manage their fleets in an efficient and cost effective way as shown in Papadoglou and Stipidis (2001). They also provide customers with

Copyright© 2010, Australian Computer Society Inc. General permission to republish, but not for profit, all or part of this material is granted, provided that the JRPIT copyright notice is given and that reference is made to the publication, to its date of issue, and to the fact that reprinting privileges were granted by permission of the Australian Computer Society Inc.

Manuscript received: 31 May 2009
Communicating Editor: Clement Leung
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

reliable, up-to-date information on transit status through traveller information services (TIS). One major component of such a service is travel time/location information, i.e., the time when a vehicle will reach a desired location, or the location where a vehicle will be at a specific time. The provision of timely and accurate travel time/location information for travel services is important because it attracts additional users and increases commuter satisfaction and convenience. Such reliable real-time information assists customers in planning their transit and multimodal trip itineraries and enables them to make better decisions, both before the trip and while en route. Apart from maritime and aeronautical applications, in which GPS has a long history of use, recent applications of GPS and GIS in land based transport systems have provided numerous improvements in terms of system control capabilities, as presented in Mintsis, Basbas, Papaioannou, Taxitaris and Tziavos (2003).

The city of Nis, Serbia, began to deploy an AVL system in 2006 for public bus transport, with the goal of monitoring and tracking buses in real-time for the purpose of analysis and management of the public bus system, as well as to provide traveller information services and travel time/location status for all commuters. At the heart of such services are methodologies, models and techniques to predict transit travel time/location and bus arrival times. These issues are the focus of this paper.

Research on the topic of vehicle arrival time prediction in public transport systems can significantly improve the reliability and effectiveness of traveller information services and commuters’ satisfaction with the service offered. In our work, we have developed and applied a model to predict bus locations and arrival times using real-time AVL data and historical data from previous bus runs on the same route for which the prediction is being made. Our travel time prediction model includes static bus schedule data and schedule adherence, bus motion and traffic flow histories divided into classes depending on time of the day/day of the week (rush hour, morning, evening, etc.), as well as real-time traffic events such as traffic congestion events and bus breakdowns that affect bus transfer and arrival times.

The test bed consisted of bus routes running in the city of Nis, Serbia, with AVL data obtained every 15 seconds from each bus and collected by our server. The model and algorithms for predicting bus location are also based on vector data for bus lines/routes, bus stops and road network with segments and junctions. The results of extensive experiments performed on real AVL data show that our model and algorithms offer acceptable performance and accuracy in predicting bus locations and arrival times.

Aside from bus arrival time estimation, raw positional data acquired from the AVL subsystem is also used to visualise bus locations and movement in real-time and to perform daily and monthly analyses of timetable conformance and plan fulfilment. The full history of vehicle trajectories is recorded and can be replayed on demand. Different geospatial analyses are also usually performed on positional data acquired from AVL histories; therefore, integration with GIS is a natural extension of traditional AVL.

We are currently working to enable the distribution of traveller information services in many forms. At bus stops and other key locations throughout the city, the estimated arrival time of the next vehicle will be shown on electronic display signs, as well as via other public information devices, such as interactive kiosks. Customers with access to the Internet will be able to obtain real-time transit information and receive notifications, as well as static and general transit information (e.g., schedule and fare data), from a city portal or from the transit agency’s web site. Customers with a mobile phone or a wireless personal digital assistant (PDA) will be able to acquire real-time transit information and retrieve notifications for any part of the city via SMS or some other wireless push mechanism (Maclean and Dailey, 2001).
This paper is structured as follows. The second section presents an overview of the most relevant research and development projects in the literature or that have been completed and implemented. The third section offers an analysis of the characteristics of city public transport traffic that further influence any analysis and prediction work. The fourth section describes in detail an implemented system used for public bus transport monitoring and analysis. This section also includes a detailed overview of the relevant vehicle arrival prediction algorithms. The fifth section presents experimental results acquired after extensive field tests of the presented system in the city of Nis, Serbia. Since the presented system uses a general purpose GPRS packet data transfer service offered by mobile operators, sections six and seven discuss certain security issues that can arise when transmitting possibly sensitive information. The eighth and final section concludes the paper and suggests directions for future research.

2. RELEVANT PROJECTS AND RESEARCH

Systems dealing with prediction problems in public transport contexts exist either as scientific projects or as commercial software solutions that have been implemented in various cities.

MYBUS (2001) is the result of a scientific project developed in the laboratory for intelligent transport systems at the University of Washington, Seattle, United States. The location and velocity data for each bus are first streamed through a Kalman filter (Ramjattan and Cross, 1995) and then mapped to the geometry of the line on which the bus is operating. For the purpose of estimating the time it will take the vehicle to arrive at the station, the algorithm divides the complete route geometry into several smaller line segments. The segments are sufficiently small that it is reasonable to assume that the vehicle will be travelling at a constant speed on each segment. The final estimated time is calculated as a sum of the calculated times per segment (Dailey, Wall, Maclean and Cathey, 2000) The main problem with such an approach is that it is based solely on current speed data reported by the vehicle. Since city traffic conditions vary unpredictably, vehicle speed can also change rapidly. Consequently, predictions based exclusively on speed, even on small road segments, can be very unstable.

Traveller information systems offering bus arrival time prediction are not new and have been implemented in major cities around the world. These prediction systems are not necessarily based on data acquired from a general purpose AVL subsystem. However, since AVL is frequently presented as a source of vehicles’ position information, the question is whether AVL data is appropriate for use in arrival time predictions as discussed in Strathman, Dueker and Kimpel (2000). In the past, these systems were based on signal posts, various proximity detectors, travelled distance measurements and other numerous hardware sensors implemented either in the buses or along bus routes. The recent increase in availability and decreases in the price and size of integrated GPS sensors have made them the preferred choice today when implementing traffic data acquisition systems. They are easily installed and maintained, and they are now also cheaper than many conventional traffic data acquisition sensors. Most contemporary AVL research in the literature is focused on experiments to determine whether a simple stream of positional updates acquired from GPS will be sufficient to perform complex traffic analysis. A representative overview of a modern, centralised, general purpose AVL system is given in Al-Bayari and Sadoun (2005). Analysis of this overview can identify specific requirements for a public transport AVL system that differentiate it from a general-purpose AVL.

Shalaby and Farhan (2004) introduce a bus dwell time metric for each bus stop into the prediction algorithm in their paper. This approach is innovative, since travel time between consecutive bus stops can be significantly influenced by the time it takes for all the passengers to
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

board/disembark from the bus. Separating the bus dwell time prediction from the bus running time prediction in this modelling framework enhances the algorithms’ ability to capture the effects of late or early bus arrivals at stops and of bus dwell times at those stops. This allows for better predictions of bus departure times from such stops. In addition, since the model treats dwell time separately, it is sensitive to stop-based control strategies such as bus holding and expressing. This characteristic of the model is important since these two are most commonly used techniques for fine tuning buses’ performances during operation. Prediction of the traversal time between two consecutive bus stops is based on two Kalman filter algorithms. In general, the Kalman filter is a linear recursive predictive update algorithm used to estimate the parameters of a process model. Starting with initial estimates, the Kalman filter allows the parameters of the model to be predicted and adjusted with each new measurement. Its ability to combine the effects of noise on both the process and the measurements, in addition to its computationally tractable algorithms, has made it very popular in many research fields and applications, particularly in the areas of autonomous and assisted navigation. The main assumption used in developing Kalman filters is that the patterns of link traversal times and passenger arrival rates at stops are cyclic for a specific period of the day. Historical data used as input to the Kalman filter is collected from the previous three days and from previous bus runs on that same day. The main drawback of the method presented in this paper is that the Kalman filter process receives as input only short term historical data, which may not be representative.

For performance evaluation purposes, Shalaby and Farhan (2004) compared their proposed method to three previously developed models for the same route. They included an historical average model, a regression model and an artificial neural network (specifically, the Time Lag Recurrent Network - TLRN). These models are all static in nature, in that the model parameters are not updated with new available data. The Kalman filter model exhibited the best predictive performance in the simulated scenarios. In particular, it showed performance that was markedly superior to the other models in the special event and lane closure scenarios. The results from Shalaby and Farhan (2004) also suggested superior performance of the Kalman filter model compared with other prediction models in terms of relative error. Their results also demonstrate how this model can capture dynamic changes due to different characteristics of bus operation. In addition to its highly accurate performance in dynamic environments, the model has the advantage of capturing the effects of control strategies, such as holding and expressing at upstream bus stops. For example, if the bus is currently at a time point where it will be held for an additional one minute in order to conform to its timetable, the model appropriately captures the effect of this extra time on the arrival time at the next bus stop together with the dwell time at that stop (which is a function of the number of passengers waiting at that bus stop when the bus is predicted to arrive) and so forth for the prediction of arrival and dwell times at subsequent stops. The research presented in the reference (Shalaby and Farhan, 2004) deals mainly with irregularities in bus operations caused by traffic accidents and varying numbers of passengers boarding and leaving the vehicle at certain designated stops. All these influences are short term in nature. In this paper, we focus on parameters that impact irregularities in bus operating procedures over longer periods of time.

The widespread use of packet data transfer services offered by cellular network operators as a telecommunications channel for transferring positional data between vehicles and the control centre has led to concerns about security issues. These can be particularly problematic when data acquired from AVL systems are used in security or management and planning scenarios. Xenakis and Merakos (2004) investigated the security requirements imposed by the different types of packet data traffic and by the different players involved (mobile users, serving networks and service providers)
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

in their paper. The authors identify and analyse critical points in the 3G security architecture that may cause network and service vulnerability. User mobility and universal network access certainly provoke additional security threats. Furthermore, complex network topologies and the heterogeneity of the technologies involved only accentuate reliability concerns.

3. TRAFFIC CHARACTERISTICS IN CITY-BASED PUBLIC BUS CONTEXTS

A prerequisite for starting work on analysis and prediction algorithms is a detailed analysis of the characteristics of public bus trajectories in a city. It is necessary to understand relevant limitations and the patterns that vehicle trajectories exhibit on a day-to-day basis.

Today, the most efficient and most frequently implemented vehicle locating method is satellite based, almost exclusively GPS (Ramjattan and Cross, 1995). Its most notable advantages are reliability and excellent availability. Any other locating method (Radio frequency identification - RFID beacons placed at bus stations, for example) would require a monitoring service and, most importantly, the maintenance of an entire network of sensors and power supplies at even the most remote bus stations. These reasons alone are enough to make most city public transport authorities reluctant to implement custom sensor networks. The limited usability of GPS in so-called “urban canyons” is becoming less of a problem with the development of more sensitive receivers. AVL output is an array of points in time and two dimensional space. This form of location data is well suited for vehicle location visualisation on a map or for analysis of whether the vehicle is following the assigned route. The problem of vehicle arrival time prediction is essentially two dimensional (time and one spatial dimension) (Jeong, 2004). For the greater part of the day, buses in a public transport system run along predefined routes (lines). This assumption excludes trajectories that the AVL system records while the vehicles are in transit, travelling to/from a garage, starting or ending operation on the route and other situations when a vehicle is operating outside the service route. The AVL subsystem alone is unable to distinguish between these various situations, and differentiation between buses operating on the line and buses travelling freely must be performed in real-time by map-matching of positional updates to predefined bus routes. Coordinates georeferenced to a certain coordinate system are streamed from the AVL for each vehicle. These data first have to be converted into distance along the assigned line. Also, positional updates are available at regular time intervals. They are usually spaced with insufficient frequency to completely model every aspect of the real-life motion of the vehicle. The principle is shown in Figure 1.

All city bus lines are cyclic in nature and can be categorised as either unidirectional or bidirectional. It is not necessary to include both types of bus lines in the model. Bidirectional bus lines can be generalised as unidirectional with a start station and end station that are geographically identical and by allowing some of the middle stations to appear more than once in this “unfolded” line representation, since these stations belong to both line directions. One extreme is that direction B contains all the stations of direction A in reverse order. The other extreme is that direction B contains a completely different set of stations from direction A. The second case represents the line that is truly unidirectional. For the problem of bus arrival time predictions for a certain station on the line, the distance covered by the transit vehicle along that line can be used as the main predictive parameter.

Bus arrival time prediction based solely on current motion parameters as detected by AVL systems (speed, direction) is unsuitable for city traffic conditions and will generate only very approximate results (Dailey et al, 2000). Not only would this estimation be a weak approximation, but it would also be unstable and could change dramatically over short periods of time. The reasons for this effect are city traffic characteristics such as rush hours, traffic congestion, frequent and
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

irregular stops, frequent and large changes in speed, etc. For all these reasons, conventional arrival time estimation would be precise enough only immediately before the vehicle would arrive, and all long-term predictions would be too imprecise and unstable to be of real use to passengers.

Therefore, it is necessary to use data streamed from the AVL subsystem to record the characteristics of vehicle movement along the line over time during different (representative) time frames (the whole day, rush hour, weekends, public holidays, etc.). An example of recorded data for one line is shown in Figure 2. Ignoring certain irregularities, we note repeating patterns in the distribution of recorded positional data during certain times of the day. The graph shows the distance the vehicle has covered along the line as a function of time. Fourteen instances of line runs are shown from several different vehicles, since the runs are overlapping in time. Since public transport buses are allocated privileged lanes in most city streets, no congestion caused by other, private vehicles is apparent from the data shown in Figure 2. Accumulation of positional updates at
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

This information, stored as a transit profile, can be used for much more stable long-term estimates of bus arrival time. The recorded characteristics of bus advancement along the line are classified according to the period during which they were recorded. Statistical analyses of current bus movements that are mapped against previously formed profiles allow for much more precise estimates. More importantly, these estimates should exhibit much greater stability over longer periods of time.

4. PREDICTION IMPLEMENTATION IN THE IMPLEMENTED PUBLIC TRANSPORT MANAGEMENT SYSTEM

The predominant method today for determining vehicle location and transferring that information to the AVL control centre is a combination of GPS sensors and a GPRS modem. The main reasons for this lie in the excellent availability of cheap and reliable GPS sensors and the ubiquity of packet data transfer services offered by mobile operators. Therefore, AVL systems are not dependent on custom and costly independent telecommunication networks and sensors. Vehicle positions are detected periodically, and updates are transferred to the server located in the control centre. The devices installed in each bus include a microcontroller to synchronise operations and manage local...
memory for the storage of positional updates. This memory is used in the case of restricted GPRS network coverage to prevent data loss. A component deployment view of the implemented system is shown in Figure 3.

The first step in real time analyses of AVL positional data requires matching buses to routes. This step is necessary because bus operators are not obliged to permanently allocate certain vehicles to certain lines. This option provides bus operators with additional flexibility but presents the prediction algorithm with an additional challenge. In the case of the system we have implemented, the system keeps track of the last 100 stops at predefined bus stops for each of the operating vehicles. Arrival of the vehicle at a bus stop is detected if a single positional update for that vehicle is detected inside a predefined circular proximity of the station and the detected vehicle speed is lower than a predefined upper threshold. The reason for such defined conditions is the nature of streamed positional data. The more natural and precise condition would be two consecutive detected positional updates within a defined proximity of the station with speed 0km/h. Unfortunately, this method would require much more frequent positional updates, unnecessarily straining the system and making GPRS costs unacceptably high. Instead, we chose to set up our tracking devices to send updates every 15 seconds. This frequency is low enough to minimise costs but still sufficient to ensure at least one positional update in the proximity of the bus station with the vehicle speed below the threshold if the stop occurs. If multiple bus stops fulfil the defined condition (parallel stops on

Figure 3: Comparison of the city bus public transport tracking system
the same line but in different directions), the closer stop is selected. The array formed by the last 100 detected stops is matched against stop arrays for both directions for the lines on which the operator is running buses. The matching problem is somewhat constrained, since every bus operator has a known predefined list of lines on which it operates. Because the GPS positioning system is less reliable in “urban canyon” conditions, the matching algorithm allows for up to one stop to be skipped during matching (Shalaby and Farhan, 2004). This approach is consistent with the practice of some of the operators to designate request stops in their networks; if no passengers are waiting at a certain stop, and no passenger on the bus wishes to disembark at that stop, then the bus will simply continue on its route. For each line that is matched against a maintained array of the last 100 stops, a probability is calculated depending on the number and order of the matched stops. The line detected with the highest probability is identified as the line on which the bus must be operating. There is also a watchdog feature that designates the bus as being “in the garage” if no stops at designated pick-up points are detected for 30 minutes.

In order to perform bus station arrival time prediction, it is necessary to extract instances of line rides (Cathey and Dailey, 2003) from the streamed AVL positional data. A single instance of a line ride consists of all positional updates for a single vehicle received after bus departure from the starting stop to the last stop in direction A and all updates in direction B back to the starting stop. After that, a new ride for that line is initiated. In order to compensate for different traffic conditions during different periods of the day, the time period during which the ride was recorded is assigned to each ride recording. This information is important and is used later during arrival estimation in order to assign relevance weight factors to each calculated estimation solution. Naturally, rides recorded during similar periods of the day are more relevant than others (Wall and Daily, 1999). After each instance of the ride has been detected and extracted, it is stored in an array of rides that is associated with each of the lines. The last N rides from different time periods for each of the lines are always available for use by the estimation algorithm. This step of the algorithm assembles all the data necessary for the estimation.

From here, the estimation algorithm proceeds as follows. For each of the bus stops that are included in the estimation calculation (Spr), a list of lines that include that station is extracted. Then, for each of the extracted lines, a list of vehicles currently operating on that line is created. For each of these vehicles, the last (previous) station (Spz) at which it stopped and the time when that stop occurred (tpz) are known. Knowing these two pieces of information, it is possible to identify the correct instance of the bus station Spr in every one of the 10 rides from the history associated with that line. The algorithm reports the time (tpz) when the vehicle that recorded that particular ride in the history was at the station in question (Spr). In all 10 rides, the algorithm also notes the time (tpzv) when the vehicle that recorded the ride arrived at the previous station (Spz). The arrival time for that particular vehicle at the bus stop (Spr) is given as:

\[
    t_p = (t_{pz} - t_{pzv}) - (<\text{current\ time}> - t_{pz})
\]

The final estimated arrival time consists of multiple members, where each member is an arrival time estimation based on a single ride from historical data. Based on the time period during which the estimate is being calculated and the time period during which each of the member rides from history participating in final estimation calculations was recorded, each of the partial member estimates contributes to the final estimate with a certain weight factor. This weight factor (wi) models the relevance of the partial estimated time in terms of how it contributes to the final estimation. Hence, if the estimation is performed during a weekend, previous rides recorded at weekends will be more relevant than others.
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

The final estimate, taking into account the relevance of individual partial estimates, is calculated as:

\[ t_f = \sum_{i=1}^{10} w_i \cdot t_{pi} \]  \hspace{1cm} (2)

Furthermore, the number of rides taken from historical data as well as the values of weight factors give operators the flexibility to specifically tailor the performance of the prediction algorithm and react to unforeseen circumstances such as certain streets being closed for some period of time. In practice, during operation of the implemented system, this characteristic proved to be invaluable since the system was able to adapt to temporary rerouting of the bus lines due to a less than ideal operating environment including construction works and rush hours. The system even demonstrated the ability to retain full functionality in terms of arrival time prediction when the rerouted portion of a line represented less than 30% of the line length. This self adaptation required no manual intervention. More significant changes in lines geometry would require operator’s action.

Graphical representation of the previously described prediction algorithm is shown in Figure 4. The estimated arrival time is displayed and periodically refreshed at the information displays installed at the busiest bus stops. Once estimated arrival times are available in the system, this information is also distributed to the passengers (end users) on demand, using SMS, or published on the city’s website or WAP portal (Repenning and Ioannidou, 2006). Relevant data flows are shown in Figure 5.

The data source is an AVL subsystem producing a stream of periodic position updates for vehicles. The transformation of data contained in these updates depends on its subsequent use in the system. For example, before any further transformation, raw positional data must be stored in the database for subsequent replay and statistical analysis, as the authors propose in Lin and Zeng (1999). Also, the current locations of buses are displayed on the map based on this raw data (Petkovic, Djordjevic-Kajan, Mitrovic and Stoimenov, 1998; Petkovic, Djordjevic-Kajan, Mitrovic and Stoimenov, 1998; Petkovic, Djordjevic-Kajan, Mitrovic and Stoimenov, 1998).
Ordinarily, the city public transport service is more interested in daily and monthly reports than in real-time bus tracking. Therefore, in order to produce these reports, raw positions must be transformed, buses must be assigned to the lines they are running on, bus stops must be detected and instances of line runs must be extracted. Based on all this post-processed data, it is possible to issue reports on mileage, bus stop schedules, number of active vehicles, etc. This sort of information is important to city transport managers.

The information generated by the described post-processing can also be of interest to passengers. The estimated arrival time of the next bus can be presented on information displays attached to bus stops (Dzeikan and Kottenhoff, 2007). Passengers waiting for a bus on some specific line can access real-time information concerning buses that are operating on that particular line (Maclean and Dailey, 2002).
5. EXPERIMENTAL RESULTS

In order to verify the assumptions presented in previous sections, an experiment was performed. The preliminary results were published in Predic, Stojanovic, Djordjevic-Kajan, Milosavljevic and Rancic (2007). The experimental test bed consists of a server running in a city bus service monitoring centre that was programmed to accept positional updates from the vehicles, before storing this data in the database and running analysis algorithms (matching vehicles to routes, detecting bus stops and making arrival/travel time predictions). At this stage of system implementation, 150 buses had tracking devices installed. For the purpose of bus arrival time prediction, Bus Stop 045 was selected and equipped with an information display. The information display is a scrolling-capable LED matrix. It contains microcontroller logic and a GPRS modem that is used to connect to the central server and transfer data about the estimated times to be displayed.

Our chosen bus stop is located in the city centre, at the busy intersection of a majority of bus routes. Indeed, 12 routes pass through Stop 045 (Routes 6, 13, 1, 2, 5, 38, 18, 21, 20, 22, 23 and 37).

The hardware was installed in the monitoring centre and fed with real data acquired from vehicles throughout the city. Because the prediction algorithm relies on a number of data structures, the server was left running for 24 hours before the log files were extracted for analysis.

Predicted arrival times were stored and later compared against actual arrival times to assess the algorithm’s performance. Arrival times for various buses were recorded for Bus Stops 011 through 045 (011, 164, 165, 067, 070, 072, 091 and 045). Without loss of generality, this section presents data concerning Route 5. Table 1 shows the recorded bus stop times along Route 5 for the analysed bus stops.

Since the proposed algorithm periodically outputs estimated times for the next bus arrival at Station 045, a full history of arrival times was calculated to rate algorithmic output quality. This was possible because the algorithm in debug mode reported a full log of all events and the times at which they occurred. The graph in Figure 6 shows the times needed for the bus to travel from different consecutive stations to station 045. The graph shows values for eight consecutive rides performed by different vehicles.

During the recording of the data shown in Figure 6, the algorithm gave estimates of the arrival time of the next bus at station 045 in real time. For easier algorithm performance evaluation, Figure 7 shows graphs of the averages and weighted averages of recorded arrival times and for the estimates outputted during recording.

<table>
<thead>
<tr>
<th>Ride</th>
<th>Stop 011</th>
<th>Stop 164</th>
<th>Stop 165</th>
<th>Stop 067</th>
<th>Stop 070</th>
<th>Stop 072</th>
<th>Stop 091</th>
<th>Stop 045</th>
</tr>
</thead>
</table>

Table 1: Recorded bus stops during analysis period
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

Figure 6: Recorded times needed for buses to travel from selected stops to Stop 045

Figure 7: Average, weighted average and real-time arrival time estimates
The trend from Table 1 was also detected on other routes stopping at Bus Stop 045. Therefore, we believe that the presented results are representative and show that the proposed algorithm for arrival time estimation in a city public transport system is sufficiently precise to be used in traveller information services.

In order to verify the public’s response to the availability of predicted arrival times, public information displays were installed at the busiest bus stops, and a WAP interface was made available to the general public, as shown in Figure 8.

6. SECURITY ISSUES IN AVL SYSTEMS BASED ON GPS/GPRS

General Packet Radio Service (GPRS) is a network architecture for data transfer that is integrated into existing GSM networks, allowing mobile subscribers to use packet data transfer to connect with corporate networks or the Internet. The GPRS Tunnelling Protocol (GTP) is used by GSM or UMTS mobile operators to convert radio signals received from mobile subscribers into data packets that are then transported along the operator’s unencrypted tunnels. GTP itself does not offer an acceptable security level when transferring sensitive information such as vehicles’ locations analyzed in this paper. Figure 9 illustrates the principle of a mobile subscriber (MS) accessing packet data transfer services offered by the operator.

The mobile subscriber (MS) logically connects to a Serving GPRS Support Node (SGSN) whose basic function is to offer the subscriber packet data transfer service. SGSN is further logically connected to a Gateway GPRS Support Node (GGSN) via the GTP protocol. A GTP connection within a PLMN (Public Land Mobile Network) operator’s network is called a Gn interface. A connection between two PLMN networks, which are typically used to offer roaming services, is called a Gp interface. GGSN offers a gateway to external networks, including the Internet, through a Gi interface. GTP encapsulates data and initiates, moves and disconnects tunnels between SGSN and GGSN. Finally, the interface connecting the internal operator’s billing network is called a Ga interface.
Gp and Gi interfaces are primary connection points between an operator’s network and external networks. These two interfaces are the primary security concern when a public GPRS network is used to transfer sensitive information, as is the case in the proposed traffic management system. Security services can be classified as follows:

- **Integrity** – ensuring that data being transferred cannot be altered by a third party
- **Confidentiality** – preventing a third party from accessing the data
- **Authentication** – providing dependable identification of the parties involved in data transfer
- **Authorisation** – limiting data access and manipulation rights to authorised personnel
- **Availability** – ensuring that services are available to the intended parties to be used in an adequate manner

In order to secure data transfer using a GPRS network, it is first necessary to identify classes of services traversing previously identified interfaces and analysing threats to these services. A Gp interface is a logical connection between PLMN networks. GTP is used to connect the local SGSN and GGSN. Generally speaking, interface Gp has to allow the following types of traffic: GTP, BGP (routing data between operators) and DNS (determining subscriber’s APN).

A Gi interface is used by a mobile subscriber to access the Internet or corporate network. The network traffic being sent by GGSN over the Gi interface to the mobile subscriber is very diverse, and it is practically impossible to filter it.
Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management

Security threats to a Gp interface are usually of the denial of service (DOS) type. One example would be the saturation of a Border Gateway with traffic created by some peer operator, with the result that legitimate data traffic will be suppressed. Furthermore, GGSN and SGSN nodes can be flooded by unauthorised DNS or GTP traffic and therefore overloaded and the processing capabilities of these nodes exhausted. GTP flooding can prevent mobile subscribers from connecting to a GPRS network at all. Security vulnerabilities in a Gp interface are usually addressed by implementing some sort of packet filtering and traffic shaping. One of the possible solutions is the implementation of IPSec tunnels between operators.

A Gi interface is a connection point between a GPRS network and the Internet or a corporate network. End users can use any type of application and generate various types of traffic. End user in the case addressed in this paper is GPS/GPRS tracking device installed in buses. As a result of that freedom, end users are subject to all the kinds of attacks that are common today on the Internet, such as worms, viruses and DOS attacks. Attacks on service availability at a Gi interface, similarly to a Gp interface, are mostly of the DOS type. That includes Gi interface bandwidth saturation or

Figure 10: Security solution applied to Gi interface
mobile subscriber flooding. MS flooding is particularly important because of the significant bandwidth difference between the Gi interface and the mobile subscriber. Constant data flow toward the IP address of one particular mobile subscriber will completely prevent that user from using packet data transfer service or, in extreme cases, will prevent the user from connecting to a GPRS network at all. Data confidentiality at the application level is left to the user and usually requires implementation of encrypted tunnels at network layers 2 or 3.

Most security solutions that address Gi interfaces include:

- Creation of logical tunnels between GGSN and corporate networks. In the use case analysed by this paper, logical tunnels would allow only registered tracking devices to send positional data to the control centre, filtering out any false identity tracker devices and simulators. If a connection to the corporate network were realised using the Internet, IPSec could be used to connect the GGSN to the corporate network.
- Limiting traffic volume. One approach would be to use separate dedicated physical interfaces to connect to the corporate network. Otherwise, IPSec traffic directed toward the corporate network should be prioritised.
- State-based packet inspection. Implementation of security policies to allow only authorised MS (tracking devices) to initiate connection with the public network and not allowing MS to see traffic initiated by the public network. This approach would prevent third parties from externally connecting to a tracking device and reconfiguring it.
- Incoming and outgoing packet filtering. This measure can prevent false MS (tracking devices) from blocking legal traffic by duplicating the IP addresses assigned to authorised tracking devices.

The security solution applied to the Gi interface uses the tunnelling concept to separate traffic directed toward different corporate networks and toward the Internet. Besides IPSec tunnelling, 802.1q VLAN technologies are also used. This approach is illustrated in Figure 10.

7. APPLICATION-LEVEL SECURITY ISSUES IN AVL CONTEXTS
The previous chapter analysed security issues concerning GPRS data transfer between tracking devices installed inside vehicles and servers at the control centre. Other security issues that should also be addressed include:

- Control centre hardware and software failures
- Failsafe operation of tracking devices in areas not covered by GPRS
- Eavesdropping on data communicated by tracking devices
- Injection of false position data of existing vehicles or connections from non-existent vehicles

Control centre hardware or software failure is the most severe system defect; it leaves the system without the database to store vehicles’ positions. This type of failure can bring down system services that are providing users with real time traffic information. Users include city services monitoring public bus traffic in real time, passengers requesting information using SMS or WAP or independent information displays installed at bus stops. To prevent such catastrophic occurrences, hardware redundancy is provided at the control centre. Instead of a single failure point, there are two identical servers operating in parallel. The backup server is configured to perform transaction based database replication, as shown in Figure 3. Each server is powered by an uninterruptible power supply to minimise downtime in case of a power failure. In case of primary server failure, the backup server takes over the role of the primary server. The backup server has an identical software configuration and can replace the main server almost instantaneously, so that the system retains full functionality.
The functionality of tracking devices installed inside vehicles in areas with sparse GPRS coverage should also be uninterrupted. Tracking devices are equipped with non-volatile memory that is used to store positional updates that the device is unable to send because of a lack of GPRS coverage or a cellular network outage. Local non-volatile random access memory (NVRAM) is cleared and positional updates from that vehicle are sent to the control centre when the network becomes available. The amount of NVRAM installed and the small size of each positional update allows the tracking device to store positions recorded over several days of normal operation. That is more than a sufficient amount of time, since cellular network outages are usually much shorter in duration.

Eavesdropping on data exchanges between tracking devices and the control centre is prevented at both the network and the application levels. A dedicated VPN tunnel is created and is used by each mobile operator to transport data from the trackers to the control centre server. Furthermore, the application level protocol used by the tracking devices is binary and the payload is encrypted using a combination of the vehicle ID, manufacturer’s device ID and mobile subscriber’s number as a pre-shared key. This two layer protection approach renders eavesdropping almost impossible.

Preventing the injection of false positional updates is another important security priority. A pre-shared key encryption approach with MD5 hashing enables the service to reject all messages received from unauthorised tracking devices. The system stores positions linked to vehicles independently from the tracking devices. This approach allows tracking devices to be dynamically registered and deleted from the system and reattached to the appropriate vehicle (Rancic, Predic and Mihajlovic, 2008). In case of tracker malfunction, substitution is seamless in spite of the fact that the newly introduced tracker device has a different manufacturer’s ID and possibly a different mobile subscriber’s number. Dependable AVL data that is acquired from secure sources can be used as valuable information in the process of public bus transport network planning, as confirmed by numerous research projects (Nigel, Wilson and Rahbee, 2009).

8. CONCLUSION
AVL systems offer various functionalities to deal with spatiotemporal data acquired from point-type moving objects. The core components of such systems are tasked with calculating the geographical location of the vehicle and transferring this information to the control centre using wireless telecommunication technology. The systems in use today almost exclusively use satellite based positioning (GPS) for determining vehicle position and packet data transfer using cellular networks (GPRS, EDGE, UMTS...) to transfer that data to the control centre. This approach has proved to be the most reliable and cost effective. This paper focused on specific properties and requirements for an AVL system applied to monitoring and managing a public transport service. The reliability, ubiquity and cost effectiveness of GPS/GPRS technologies have motivated many local authorities to implement AVL solutions in managing and planning public transport systems and improving their traveller information services. The test case this paper presents is somewhat unique in terms of restrictions. In comparison with other similar systems worldwide, it does not require any special sensor network (RFID or similar) or a highly structured public bus transport system (rarely changing bus line assignment, etc.). These restrictions were mainly imposed by local regulations in the city of Nis, Serbia. Also, the manner in which public bus transport is operated by particular local operators had no lesser impact on the work presented in this paper than aforementioned local regulations.

An important part of the system presented in this paper is a vehicle arrival time prediction module. In comparison to prediction systems used in other general purpose AVL systems, which mainly rely on some modification of the Kalman filter and thus base their predictions on an
immediate history of positional and motion data sent by vehicles, in this paper we present a prediction system based on analysis of historical data acquired over longer periods of time, which ultimately leads to much more stable predictions in an environment with numerous and rapid speed variations. Further research in this field could investigate combining some sort of traditional, Kalman filter based prediction method for short term predictions (when vehicle arrival is imminent) together with the long term prediction method proposed in this paper.

Preliminary results show that this minimal configuration of sensor and telecommunication network devices provides a sufficient volume of data to allow for accurate analysis of bus traffic in public transport and to yield accurate predictions of bus arrival times. This information allows a planning service to identify possible future problems such as less than adequate line coverage, vehicle congestion and slowdown on certain parts of lines, etc., in a timely manner. Additional beneficiaries are the citizens who use public bus transport, since accurate information about the dynamics of bus traffic is always available.

The system described in this paper has now been fully operational in the city of Nis, Serbia for three years. Its round-the-clock operation without any significant downtime illustrates that this cost effective approach with a combination of GPS/GPRS technologies is stable and sufficiently mature to provide continuous service.

REFERENCES


JEONG, R.H. (2004): The prediction of bus arrival time using automatic vehicle location systems data Ph.D. thesis, Texas A&M University, College Station, TX, USA.


Impacts of Applying Automated Vehicle Location Systems to Public Bus Transport Management


BIOGRAPHICAL NOTES

Bratislav Predic is a research assistant on the Faculty of Electronic Engineering, University of Nis, Serbia. His research interests are mobile geographic information systems, mobile and ubiquitous computing, context-aware software and geospatial databases. He obtained his MSc degree at the Faculty of Electronic Engineering in 2008. He has published more than 30 papers in refereed conference proceedings and international journals, as well as one book chapter related to these research areas.

Dejan Rancic is an assistant professor at the Faculty of Electronic Engineering, University of Nis, Serbia. His research interests are geographic information systems, mobile applications, C4I, intelligent transport systems, computer graphics and virtual reality. He obtained his PhD from the Faculty of Electronic Engineering, University of Nis in 2004. He has published more than 80 papers in refereed conference proceedings and international journals, as well as book chapters related to these research areas.

Aleksandar Milosavljevic is a research assistant at the Faculty of Electronic Engineering, University of Nis, Serbia. His research interests are geographic information systems, C4I systems, artificial intelligence and fuzzy neural networks. He obtained his MSc from the Faculty of Electronic Engineering, University of Nis in 2006. He has published more than 30 papers in refereed conference proceedings and international journals, as well as one book chapter related to these research areas.