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A HIGH PERFORMANCE MULTI-MODAL TRAFFIC SIMULATION PLATFORM AND ITS CASE STUDY WITH THE DUBLIN CITY

Toyotaro Suzumura

IBM T.J. Watson Research Center

University College Dublin / JST

New York, USA

Gavin McArdle

IBM Research Smarter Cities
Technology Center
Maynooth University
Damastown Industrial Estate
Mulhuddart Dublin 15, IRELAND

Hiroki Kanezashi

Graduate School of Information Science and Engineering,
Tokyo Institute of Technology

2-12-1 Oo-okayama
Meguro Tokyo, JAPAN

ABSTRACT

This paper describes a highly scalable multi-modal traffic simulation platform and its case study in Dublin city. By leveraging various sources of open and administrative data for the Greater Dublin Region, we have built a city operating system like platform that simulates not only private cars but also public buses and trains. Our performance study demonstrates that our simulator is highly scalable by achieving 15.5 times faster than real-world time with 12 parallel threads. This is the first effort that has provided a high-performance and high-scalability traffic simulation on a distributed-memory environment and demonstrated the validity of the approach using real data sets.

1 INTRODUCTION

Traffic congestion is one of the most common problems facing city authorities. Reducing traffic jams brings higher efficiency of human mobility – which eventually leads to better quality of life and an improved economic environment. To reduce traffic jams, many solutions have been proposed, such as reducing private cars as much as possible by introducing new policies (higher toll rates, car pools, park & ride, incentives for using public transport or bicycles), optimizing signal controls and expanding road capacity by introducing additional roads and lanes. Each city in the world has different problems and constraints. For example, public transport in the capital city of Ireland, Dublin is dominated by buses. Thus optimizing bus routes, schedules, and fares are important. Although most roads leading to the city centre have dedicated bus lanes, some public bus routes consistently have delays mainly affected by roads which do not have bus lanes. Given some constraints (time, space, and financial cost), realistic solutions are required. Unpredictable events such as natural disasters, car accidents and flooding add to traffic congestion problems. Additionally, these unpredictable and sudden events give tremendous impacts to the society, so disaster management is also important. By producing accurate simulations of current conditions, the effects of such adverse conditions and the introduction of interventions can be forecast and studied. The challenge is to rapidly produce reliable models which can accommodate the dynamic conditions of cities and urban areas .

Several efforts provide a microscopic traffic simulation to tackle the previously mentioned problems, but there are few simulation platforms that incorporate multi-modal transportation entities such as public buses, trains, pedestrians, etc., as well as making the simulation platform runnable in a high-performance manner. Little research has examined performance optimization of such simulations using a real data set. Since time-step based traffic simulations run in a synchronous manner, it is important to minimize the elapsed time of each step. Also if more threads and nodes are involved in processing, the overhead of synchronizing all the threads is a critical component of the simulation process. To demonstrate any improvements to the efficiency of such simulations, it is important to use real-world data.

To date, performing optimization tests with such real-world data has been a challenge because access to good quality and reliable information regarding individual mobility has not been widely available. While quality road network data from the crowd sourced Open Street Map project, and public transport data from transit operators are now typically accessible, data relating to individual movements is not widely available. For this research, we obtained a set of Origin-Destination (OD) data derived from the National Census for Ireland. The data set contains OD data for over 2 million individuals which improves significantly on our previous work which relied on grid-like traffic demand.

The contribution of this paper is to apply our high performance multi-modal traffic simulator in the context of a real city, Dublin in Ireland, and to show the validity of the high performance platform by validating the results of the simulation.

This paper is organized in 6 sections. Section 2 is a system overview of our scalable multi-modal traffic simulation platform. Section 3 describes the case study with Dublin city and how we can apply our simulator to the real city. Then Section 4 shows the evaluation of the simulation results. Section 5 reviews relevant work, mainly focusing on multi-modal traffic simulations, and finally Section 6 describes possible future directions for the research with some concluding remarks.

2 HIGH PERFORMANCE MULTI-MODAL TRAFFIC SIMULATOR

In our prior work, we proposed the preliminary design and implementation of a high-performance multi-modal traffic simulation platform for parallel and distributed systems (Suzumura et al. 2014). Using this approach we can simulate a wide variety of transportation modes including public buses, trains, or private cars on a municipal or national scale.

The overall system architecture of our simulator is divided into 3 components, the simulation input dataset, the simulation platform itself, and the simulation output. For the simulation input, a series of trips or individual travel trajectories are provided or generated by a modular external component called a journey planner. The input for the journey planner could be coarse-grained traffic flows from certain parts of the city to other parts that are often provided by census data. If the OD (Origin-Destination) data includes home and work locations, then our journey planner computes the path or trajectory from the origin to the destination. Our current implementation uses basic functions to compute the routes that minimize the total distance or total time with specified transportation modes such as only using public transportation systems or only using private cars. For the input data, we need networks for multi-modal simulations, such as public buses, trains, and private cars. The timetables for public transportation are also crucial data. The simulation platform reads the input data including the routes, networks, and timetables for public transportation, and then moves all the agents representing the people, private cars, and public transportation vehicles according to their behavior models and the underlying transport network.

The simulation platform outputs low-level data for each simulation step, which includes all of each agents' properties such as location, status, speed, and number of passengers for public transportation. By analyzing the low-level data, it is be possible to obtain higher-level results such as the length of each traffic jam, the average travel time, CO_2 emissions and cost.

3 THE CASE STUDY WITH THE DUBLIN CITY

In this section we describe the input data used to create the multi-modal traffic simulation for Dublin. The data is used with the traffic simulator to produce estimates of the morning peak traffic volumes and travel times.

The road network for Dublin, along with the major roads in the rest of Ireland were extracted from Open Street Map (OSM) and converted into a comma separated format for processing by our multi-modal traffic simulator. This created 61341 links and 19261 cross points. The road network is shown in Figure 1. Dublin consists of 3 main modes of public transport: commuter rail, light rail and bus. The bus network consists of approximately 4700 bus stops and 121 routes. The light rail network consists of 2 routes and 54 stations while the train network has approximately 16 routes and approximately 50 stations. The data for each of these modes were extracted from a General Transport Feed Specification (GTFS) file provided by the National Transport Authority in Ireland. Bus routes were merged with the road network, respecting situations where the bus has its own traffic lane, while new networks were created for the light and commuter rail systems. Further detail on the preparation of these data for use in the simulation platform along with details of OD data are provided in the sections below.

3.1 Road Network

A road network was extracted from Open Street Map, and converted to the network data format required by the multi-modal traffic simulator. It is critical to obtain a high-quality road network to construct a simulated road network structure that is equivalent to the real city. For instance, the number of lanes and varying speed limits are important factors that affect the simulated agents' behavior. Fortunately, the quality of the road network obtained for Dublin is high, which is the case for most capital cities in Europe. Crowd sourced data can commonly contain some errors and anomalies. For the Dublin network, several issues, such as missing segments and inaccurate speed limits were discovered using geovisual analysis. These issues were rectified prior to running the simulation.

3.2 Public Transport Network

A bus network was obtained from the GTFS (General Transit Feed Specification) for Dublin. The GTFS provides the unique id and location of each bus stop in the city. Using the spatial coordinate information for each stop, we developed a component that locate the nearest cross point (road intersection) in the above road network. The GTFS also provides details of the routes which operate in the city. Route information contains a unique route identifier and details the roads which are associated with the route. These data were also merged with the road network for Dublin.

In Dublin, public transportation is dominated by buses, and Dublin city have introduced a number of bus lanes to provide priority for public buses and taxis. This policy has been introduced to reduce private car use by promoting faster travel times for public bus users. Despite this, there are cases were a dedicated bus lane is not possible and so busses face the same delay and congestion problems as other road uses.

Similar information, such as commuter train and light rail station locations and the routes of the train tracks in the city are also available from the GTFS for Dublin. The train network operates independently of the road network and so there is little interaction between the two modes. Therefore, for the purpose of simulation, the commuter and light rail train services can operate in a deterministic manner according to their timetable.

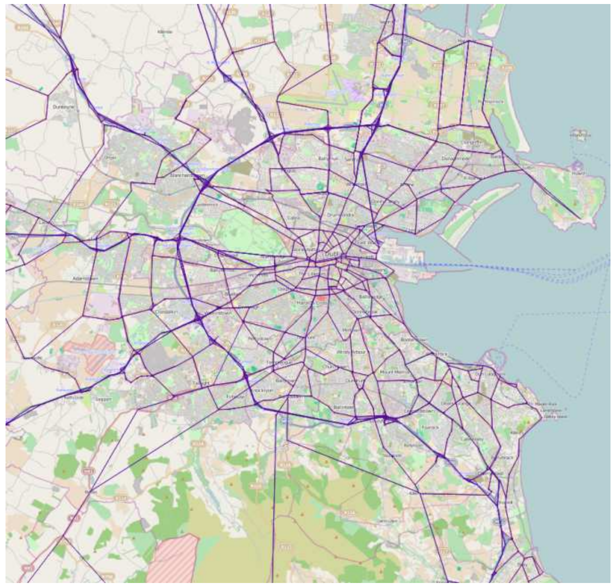


Figure 1: A section of the road network used for the Dublin Scenario.

3.3 Population

The focus of this study was to simulate multi-modal transport for the morning commute in Dublin. The section of the population of interest is individuals that use the transport network of Dublin to travel to work. The Irish Central Statistics Office produces a subset of the census results which describe commuting data. The dataset, called Place of Work, School Census of Anonymised Records (POWSCAR), consists of a home location, work, school or college location, departure times, transport mode preference as well as other socio-economic data about individuals in Ireland. The home and work locations are described by an aggregated statistical unit which consists of a polygon containing 100-150 households. The departure times are described by 30 minute discrete units and the mode choice includes car, passenger in car, bus, pedestrian, bike, motor cycle and train.

POWSCAR provides data for individuals in Ireland while our simulation is for the Dublin region, we therefore those individuals whose place of work or home is in Dublin were extracted. Next, only those who drive, or use public transport were selected. This produced a population of 384,167, with 242,740 car drivers and 141,427 public transport users. Finally, a high resolution OD matrix was generated by translating the home and work locations from a polygon to randomly selected point within that polygon to represent the home (Figure 2) and work/school places (Figure 3) of individuals. Furthermore, to create a realistic departure time series, a random departure time within a 30 minute window centered at the time declared in POWSCAR was used.

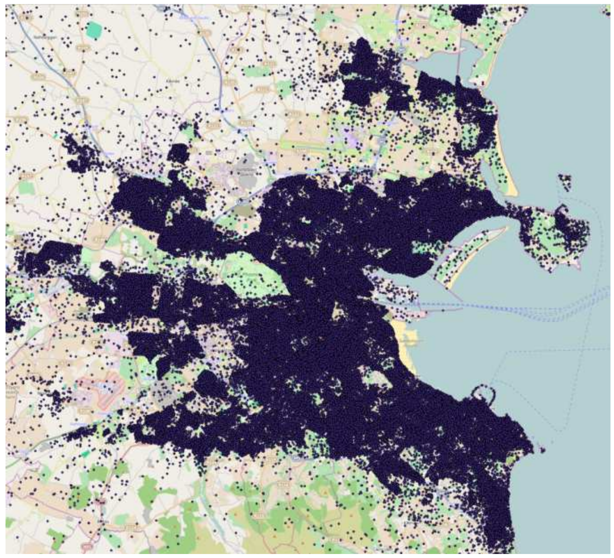


Figure 2: The distribution of home locations in the Greater Dublin Region derived from POWSCAR.

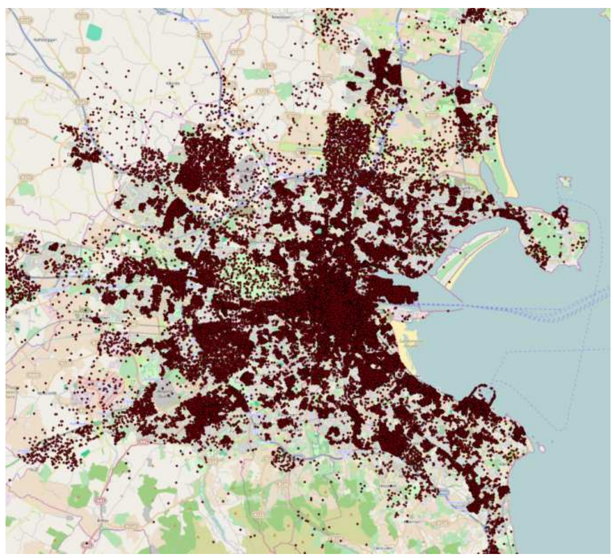


Figure 3: The distribution of work locations in the Greater Dublin Region derived from POWSCAR.

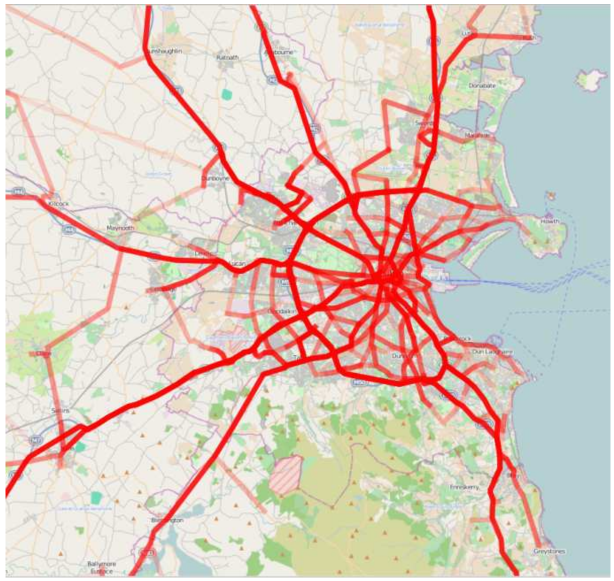


Figure 4: The density of a sample of trajectories using the road network in Dublin.

3.4 Travel Demand

The high resolution OD matrix which contains the mode choice, departure time and home and work locations was used as an input to a journey planning module of our multi-modal traffic simulator to produce the travel demand on the transport network. The journey planner computes a trajectory through the transport network for individuals based on their origin, destination and preferred transport mode. In the case of private cars, the Dijkstra method (Dijkstra 1959) is used to determine a route which minimizes total travel time from the home to work location. The generated route consists of a series of cross points through the road network. Figure 4 shows the density trajectories created for a sample of 1000 agents in the Dublin scenario. The trajectories are overlaid, so a darker color indicates more individuals using that route.

To generate the public transport demand, our approach relies on an external public transport routing tool called Dynamic Optimization for City Intermodal Transportation (DOCIT) (Botea et al. 2014). DOCIT uses public transit information extracted from General Transit Feed Specification (GTFS) files to generate a multi-modal path, via public transport, from an origin to a destination at a given time. The high resolution OD plans with public transport as the modal preference are passed to the DOCIT service for processing. DOCIT produces routes which are then translated into cross points of the road of our multi-modal traffic simulator, bus and rail networks. The travel demand is used to simulate the movements of individuals through the transport network of Dublin.

4 EVALUATION WITH THE DUBLIN CASE

This section describes the evaluation of the validation framework as well as the performance evaluation by using the real data set described in the previous section with the simulator described in Section 2.

The validation includes the accuracy of the simulation. We have mainly conducted the validation on travel time of private cars and also the Dublin buses.

4.1 Dublin Simulation Setting

Since the census data only details the time that individuals leave their home location to travel to their work location in the morning, we conducted a 4-hours simulation starting at 6 am and finishing at 10 am.

Furthermore, for the purpose of simulation we assume that the data represent the travel patterns in Dublin on a typical Monday morning. The simulation consists of 14400 steps.

The total number of private vehicles is 242,740, and 241,196 of them can reach to their destination during the simulation period. There are 16,777 public buses in total during the day.

4.2 Travel Time for Private Cars

In addition to the departure time, the census data also contains a self declared travel time for each individual. We compared this data with the results produced by the simulation platform for private vehicles. There are approximately 240k private vehicles, so the Figure 5 shows the distribution of the absolute travel time. The fitness confirmation here is defined as (Actual travel time – simulated travel time) / (Actual travel time), so it means that if the value of the fitness confirmation is closer to zero, the simulation accuracy is better. The Figure 6 shows the histogram of the fitness confirmation for all private vehicles. The average value is 0.49, and the median value is 0.61.

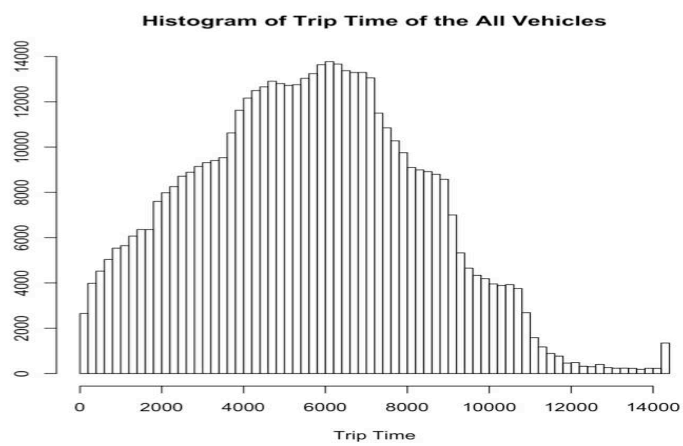


Figure 5: Absolute journey time of private cars.

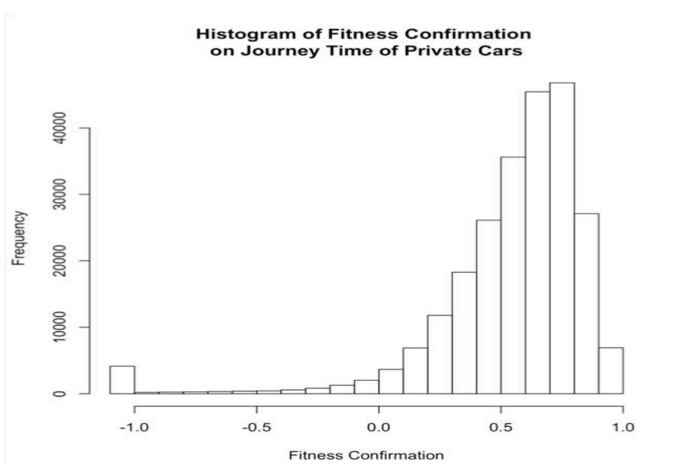
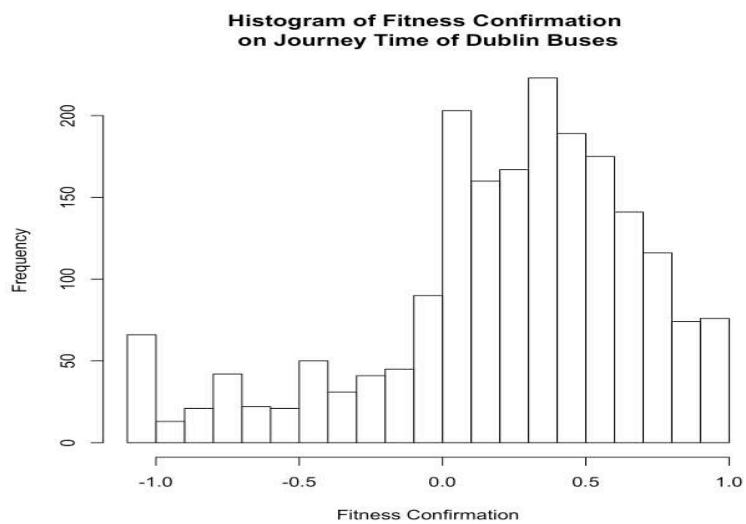


Figure 6: Fitness confirmation on journey time of private cars.

The results indicate that the travel times of the simulated vehicles is faster than the actual time. There are various factors that affect this precision, but at first, since the travel time described in the census is estimated by individuals to the nearest 5 minute, its granularity is not as fine-grained as the simulation output. Furthermore, since the census only provides OD information, our simulator computes a trajectory that minimizes the travel time, which is not necessarily how individuals make route decisions. Finally, although the data is rich, it only contains private vehicles of people commuting to work. Other travelers on the road such as retirees or unemployed are not included. Similarly, commercial traffic such as taxis, vans and trucks is also missing. Including these modes in the simulation would obviously increase tavel time for all travelers. At this moment, no calibration model is included in the simulation, so the calibration could help improve the precision..

4.3 Travel Time for Dublin Buses

Since a sample of fine-grained GPS data for Dublin buses are available as open data from a web site of dublinked.ie, it was possible to compute the real-world average travel time of buses on all routes and compare this to the data produced by the simulation. Figure 7 shows the histogram of accuracy in the same metric used for private cars in Section 4.2, which is the fitness confirmation. There are approximately 2000 buses that complete their routes during the simulation interval of 6 am to 10 am on a weekday morning. The average value is 0.21 and the medium value is 0.31. The validation results show that the precision was better than private cars. This can be attributed to the simulation program ensuring that buses wait at bus stops according to the timetable and the simulated buses follow the precise route of their real-work counterpart.. The faster travel time can be caused by the missing traffic on the road



network(commercial vehicles and non-worker trips).

Figure 7: Fitness confirmation on journey time of Dublin buses.

4.4 Performance Evaluation for the Dublin City

Given the complexity of routing the population of city, There has been little research evaluating the performance of multi-modal traffic simulation using real-world city data in a distributed-memory environment.

We firstly show the result on 1 node of shared-memory and multi-thread environment. Figure 8 shows the performance speed-ups by varying the number of threads from 1 to 12. The Y-axis on the left shows the elapsed time for running the 14400 simulation steps that corresponds to 4 hours. The Y-axis on the right shows the speed-up ratio of multiple threads versus a single thread. In terms of the absolute time, it takes 3886 seconds for 4 hours simulation. The speed-up is saturated with 10 threads, reaching up to 4.18 times faster than 1 thread, and the absolute time is 929 seconds for 4 hours simulation. It means that the Dublin simulation can complete 15.5 times faster than the real-world clock.

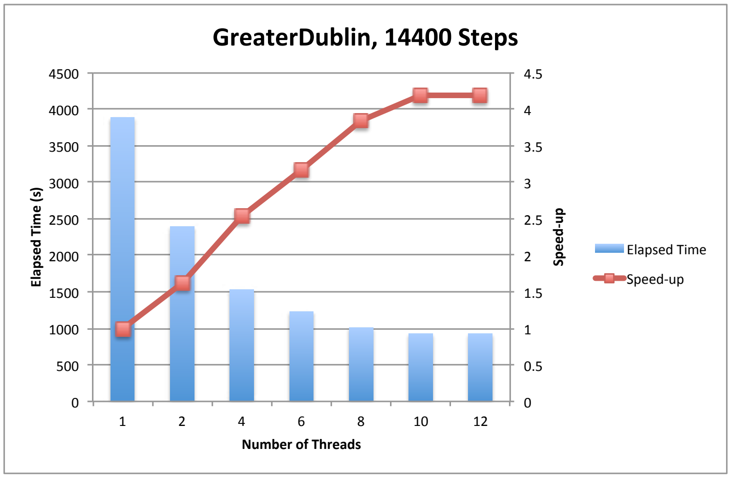


Figure 8: Performance improvements by the number of threads.

5 RELATED WORK

As the population in urban areas increases rapidly (Heilig, 2012), cities are seeking to improve the efficiency and sustainability of their infrastructure. Practitioners generally use traffic modelling and traffic assignment techniques to simulate current conditions, forecast urban mobility and investigate the impact of interventions, such as road closures and new modal choices, on the transport network. Traffic forecasting is an established research field with well defined theories and models for simulating traffic flow.

Traditional Trip-Based Models (TBM), such as the 4-step model (McNally 2008), apply a static deterministic approach to an OD matrix to estimate traffic movement at an aggregate zone level (Gao et al. 2010). An alternative approach shifts the emphasis from trips to activities resulting in so called Activity-Based Models (ABM) which assume that travel results from the need to complete activities (working, shopping, eating, etc.). Within this context, agent-based micro-simulations are often used to produce disaggregate, person level estimates of mobility. The use and adoption of agent-based micro-simulations is increasing and Gao et al. (2010) have shown that an ABM can outperform the TBM approach for simulating traffic.

Several open source and commercial software toolkits have been developed to facilitate agent-based micro-simulations. MatSim (Horni et al. 2009), SUMO (Behrisch et al. 2011), MITSim (Ben-Akiva et al. 2010),VISSIM (Fellendorf 1994) and Megaffic (Osogami et al. 2013) are examples. In these approaches, the transport network, the population and the travel demand for the study area are defined as input to the simulation. Each individual in the population is considered an agent. The simulation tool uses routing algorithms to move the agents through the transport network according to the travel demand, which consists of an activity chain for each agent. Different techniques for predicting the location of activities, routing and scheduling can be applied. Generally, the simulation has several iterations in which parameters such as the route or departure times for a section of the population are altered. After each iteration individual travel times are scored by a utility function. The iterations continue until the model reaches a stable state where new changes have little impact on the utility function. Other parameters can be introduced to improve traffic estimation results. For example, traffic count data and probe car data can be used to influence how traffic is routed though the network to better reflect observed traffic conditions (Osogami et al. 2013).

These software tools have been used in a variety of scenarios at different spatial scales. Meister et al. (2010) developed a large scale multi-modal transport simulation for Switzerland. Very detailed census, land use and travel survey data were used to create activity chains for 6 million agents. Location choice decisions for secondary activities such as shopping and leisure trips were derived using a local search method. Gao et al. (2010) developed a simulation for the Greater Toronto and Hamilton area in Canada using a 5.8% sample of the households in the region. The availability of detailed trip data removed the requirement for a location choice model. McArdle et al. (2014) implemented a 24 hour traffic simulation for Dublin in Ireland. For this scenario, the population and travel demand were derived from census results and travel surveys. A new location choice model was implemented by adapting the radiation model for determining the locations for secondary activities. Zhuge et al. (2014) developed a simulation for the city of Baoding in China based on census results and a small travel survey. The simulation consisted of approximately 1 million agents. Like the work of Meister et al. (2010), location choice for secondary activities was determined using a local search method. Nicolai at al. (2011) incorporated a multi-agent traffic simulation with an urban simulation tool (UrbanSim) to study the effects on house prices after construction of a new bridge in the Seattle region in the United States. A 1% sample of the 3.2 million population was used in the travel simulation. Furthermore, only commuting traffic was considered with no information on secondary trips provided. Smaller spatial scales are also simulated using micro-simulations; Toledo et al. (2003) developed a model for simulating the traffic on motorways in Northern Stockholm in Sweden. The OD matrix was generated using the volume of vehicles entering and exiting the motorway junctions.

Generally, the accuracy of a simulation, and the impact of altering parameters, such as the routing algorithm or the location choice model, is assessed by benchmarking the simulation output against observed ground truth. Travel time, traffic volume and traffic speed are commonly used metrics for this. Obtaining reliable observation data is challenging and due to a lack of data, rigorous validation does not take place in all studies (Morias & Digiampietri, 2012). In the simulation of Switzerland, Meister et al. (2010) compare the observed traffic counts on individual roads with the output from the simulation and also aggregate these values to evaluate accuracy for different regions. McArdle et al. (2014) compare the simulation output to hourly counts at 6 locations on motorways on the periphery of Dublin. Similarly, Zhuge et al. (2014) compare aggregated volume data in this way for the morning peak in traffic from 6 count stations. Toledo et al. (2003) provide a very detailed evaluation of their results, examining the accuracy of traffic volume at key locations. Travel time and queue lengths are also evaluated using previously collected probe car data. Gao et al. (2010) evaluate the Toronto simulation by comparing volume and speed outputs from the simulation with observed data. Generally, relative errors are used with these metrics to produce an overall score for the accuracy of the simulation.

In the work by (Suzumura and Kanezashi 2014), they evaluated the performance of their proposed multi-modal traffic simulator using the road and public transport network for Dublin The travel demand and population were estimated using a random spatial distribution of an OD matrix. In this paper, we build a detailed case study using real multi-modal travel demand for Dublin derived from the Irish Census. Unlike, the previous multi-agent simulation for Dublin, described in McArdle et al. (2014) we use a multi-modal approach.

6 CONCLUSIONS

In this paper, we have described a high-performance and highly scalable multi-modal traffic simulation platform on a parallel and distributed system. The utility of the application is demonstrated using Dublin City in Ireland as a case study. The results show that the simulation produced results in terms of aggregated travel times for private and public transport.

Future work includes more improvement on the simulation accuracy by calibrating models of agents and introducing time-dependent shortest path. In terms of the software architecture of this kind of simulation, we could employ spatio-time based database since a simulation essentially just updates the status of each agent that could be stored, and a series of analytics over simulation analytics would become simpler by sending spatio-temporal query to the database.

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AUTHOR BIOGRAPHIES

TOYOTARO SUZUMURA is a research staff member at IBM T.J. Watson Research Center in the U.S. as well as a visiting associate professor of University College Dublin in Ireland. He received his Ph.D. in Computer Science from Tokyo Institute of Technology in 2004. He joined IBM Research - Tokyo in 2004 and had involved with several projects such as high performance XML processing, the PHP scripting language, large-scale stream computing, the X10 programming language and so forth. Since 2010, he has started to develop an X10-based agent simulation platform and its application to large-scale traffic simulation. He had served as a visiting associate professor at the Graduate School of Information Science and Engineering of Tokyo Institute of Technology since April 2009 until October, 2013 and explores research on high performance computing and large-scale graph analytics. In October 2013, he joined the Smarter Cities Technology Center of IBM Research located in Dublin, Ireland and in April 2015 he has joined IBM T.J. Watson Research Center in the U.S as a research staff member. His e-mail address is suzumura@acm.org.

GAVIN MCARDLE is a Research Fellow in the National Centre for Geocomputation in Maynooth University and an SFI funded Industry Research fellow at IBM Smarter Technologies Research Centre in Dublin. He is currently working on the ERC funded Programmable City Project where he is designing and developing accessible dashboards for real-time and near real-time city data. The Dublin Dashboard is a tangible output of this research effort and was launched in September 2014. The dashboard provides an interface for data about the population, economy, environment and infrastructure of Dublin. Through his collaboration with IBM, Gavin is examining techniques to analyze, simulate and understand human mobility in urban environments which will lead to improved transport and communication infrastructure. His e-mail address is gavin.mcardle@nuim.ie.

HIROKI KANEZASHI is a Ph.D. student at the Graduate School of Information Science and Engineering of the Tokyo Institute of Technology. He graduated from the Tokyo Institute of Technology Computer Science Department in March 2015. He has been researching large-scale data processing in high-performance computing environments. The main research objects is performance optimization of traffic simulation application and agent-based framework in parallel distributed computation nodes. He has also researched precision evaluation of the result of the simulation by open GIS data analysis.His current research interests from Ph.D. course include machine learning, especially deep learning in supercomputers. His email address is kanezashi.h.aa@m.titech.ac.jp.