2016

Model of mobility demands for future short distance public transport systems

Alexander Sandau
Carl von Ossietzky University of Oldenburg, alexander.sandau@uni-oldenburg.de

Jorge Marx Gómez
Carl von Ossietzky University of Oldenburg, jorge.marx.gomez@uni-oldenburg.de

Daniel Stamer
Carl von Ossietzky University of Oldenburg, daniel.stamer@uni-oldenburg.de

Benjamin Wagner vom Berg
Carl von Ossietzky University of Oldenburg, benjamin.wagnervomberg@uni-oldenburg.de

Jantje Halberstadt
Carl von Ossietzky University of Oldenburg, jantje.halberstadt@leuphana.de

47. Model of mobility demands for future short distance public transport systems

Alexander Sandau, Jorge Marx Gómez,
Daniel Stamer, Benjamin Wagner vom Berg,
Carl von Ossietzky University of Oldenburg
{alexander.sandau, jorge.marx.gomez, daniel.stamer, benjamin.wagnervomberg}@uni-oldenburg.de

Jantje Halberstadt
Leuphana University of Lüneburg
jantje.halberstadt@leuphana.de

Abstract
Short distance public transport faces huge challenges, although it is very important within a sustainable transport system to reduce traffic emissions. Revenues and subsidization are decreasing and especially in rural regions the offer is constantly diminishing. New approaches for public transport systems are strongly needed to avoid traffic infarcts in urban and rural areas to grant a basic offer of mobility services for everyone. In the proposed work a demand centered approach of dynamic public transport planning is introduced which relies on regional traffic data. The approach is based on a demand model which is represented as a dynamic undirected attributed graph. The demands are logged through traffic sensors and sustainability focused traveler information systems.

Keywords
Sustainable mobility, public transport, demand detection, demand model, dynamic undirected attributed graph, municipality information systems, smart city

1. Introduction
The influences and requirements of public transport are changing continuously, thus municipalities and cities are facing huge challenges. Since several years, more and more people are using private cars for their mobility demands, especially in rural regions of Germany. As a result, the ridership and revenue on public transport is heavily decreasing. Simultaneously, the costs of energy and manpower for public transport are increasing rapidly (Kirchhoff and Tsakarestos 2007). In urban areas a similar trend is noticeable which leads to massive challenges for local authorities.

Through this trend the share of public transport in the modal split of Germany decreased from 7.2% in 2002 to 6.9% in 2009 (Federal Environment Agency 2012). The occurred lack of yield from decreasing passenger volume and increasing expenses require new actions and measures from public government as well as from transport companies. Some actions to retain public transport are price hikes but they are very restricted and may lead to a drop in ridership (Kirchhoff and Tsakarestos 2007). Statistically the costs for public transport services increased by 24.6% in the years 2010-2015 regarding the German statistical federal agency (Statistische Bundesamt 2015). Nevertheless the public sector subsidizes the public transport system nearly to 50%. In this way existing supply with public transport services is ensured and payable, especially for low-income inhabitants. A big problem for local authorities is the distribution of the subsidization because the financing is very complex and non-transparent. In general, the subsidy goes strictly from government to the public transport companies, past the regional contracting authority (Werner 2011). Therefore a measurement of efficiency and effectivity and an intervention is not possible for the municipalities. Following these developments, the availability of public transport in rural areas with no counterbalance to the motorized individual car traffic is in danger (Kirchhoff and Tsakarestos 2007). The concatenation of circumstances between lower revenues and raising costs manifests as follows:

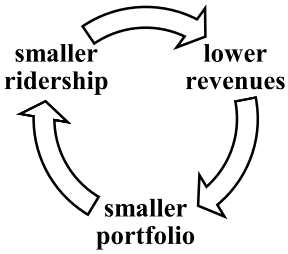

Figure 1: Revenue-cost helix

A further influence is the rising life expectancy of people whereby more people are not able to ensure their mobility of their own anymore. The so called demographic change indicates that in the year 2060 nearly 30% of the inhabitants of Germany are 65 years or older (Bundesministerium des Inneren 2011). Coincidently, the stronger urbanization is a huge challenge for future city authorities to avoid the traffic infarct. This trend can be avoided trough raising costs of fuel and a more attractive public transport services. On a long term perspective the prices for fuel is steadily increasing and a lot of commuters will switch from private cars to public transport (Kirchhoff and Tsakarestos 2007). A simulation of Hautzinger et. al. (Hautzinger, et al. 2005) shows that a rise of fuel prices by 10% will reduce the car traffic by 2.9%. At the same time the share of public transport will rise by 0.4% (Hautzinger, et al. 2005). Furthermore, the European Union and the federal government imposed laws to reduce pollutants in downtown regions and to shift the commuter traffic from cars to public transport, which puts an additional need of actions on the local authorities (Kirchhoff and Tsakarestos 2007).

Unavoidable, an efficient public transport is the only suitable solution for future traffic systems to grant payable and sustainable mobility services for every person. In this context the diffusion of more and more data sources in the public area (e.g. inductive loops or camera sensors) and mobility requests on traveler information systems from citizens via smartphone applications are giving the possibility to predict mobility demands in real time (Di Lorenzo, et al. 2016). The combination of these datasets leads to an accurate reflection of the mobility behavior and performance in a region. Through this understanding it is possible to create a dynamic customer-oriented mobility portfolio tailored to the needs of the people in specific regions in a sustainable way. The most promising approach is the usage of ICT-based solutions to reduce the expenses for resources and reducing harmful environmental impacts. The increasing digitalization and huge distribution of smart phones provide now an optimal basis to establish new planning und steering styles in public transport, c.f. (Di Lorenzo, et al. 2016). The following chapter introduces the different forms of demands and the underlying data sources. Also the needed terms of supply for a dynamic public transport system are introduced. Chapter 3 describes the demand model and the used path finding algorithm.

2. Mobility demands and demand detection

In the first step relevant terms for understanding different forms of demands and offers are defined. In general, *mobility demands* are demands of inhabitants in regions or cities to accomplish a superior objective, e.g. working or shopping. Usually, such individual objectives are gathered through a traveler information system (TIS) and are represented as a request to get from point A to B with several additional parameters, e.g. departure time or via stops. In general, daily mobility demands are mainly region-based.

A *transport demand* is a demand which is generated from mobility demands. This demand is specified as a calculated shortest trip from A to B. This trip is routed over at least 2 (origin, destination) to several (via points) public transport stops.

Fixed offers are conventional public transport routes which are following a fixed schedule with fixed stops and a fixed type of vehicle. For example, a long term offer is a fixed offer.
Dynamic offers are based on the demand model proposed in this work. These offers are changing over time and always fulfill the demands of the inhabitants with direct connections or by using intermodal sections. They are separated in short or middle time dimensions.
Special offers are offers provided by the operating association as i.e. a municipality or city. These offers may be trips to major events or increased demands as e.g. in holiday seasons.
The offers are separated in three time dimensions. *Short term offers* are nearly ad hoc offers which are accomplished by regionally distributed vehicles. These offers have a time limit up to 60 minutes and are served by taxis or call-me-buses. *Middle term offers* are provided by regional transport associations or private companies and have an upper time limit of 24 hours. *Long term offers* are propositions which are equal to conventional public transport services. The trips are not changing for a specific range of time. They are served by the same type of vehicle in a fixed scheduled sequence.
Trip offers are the routes provided for public transport association. They may be dynamic or fixed, short, middle or long term and the type of the vehicle is not specified. So a vehicle may be a big bus, several small buses, or even cars. These offers are provided by public or private mobility providers.

The in Chapter 3 described demand model is based on the following two systems. An analytical system of traffic sensors and a sustainability focused traveler information system. These systems are used to determine the demands of a crowd in a region. The collection of demands is very important to provide a sustainable and reliable future public transport system.

2.1 Mobility demands from traffic sensors and enriched data

The student project group "Regional Analysis and Prediction Platform by In-Memory Data" (RAPID) of the University of Oldenburg, Department Very Large Business Applications developed an analytical platform for traffic flows based on an in-memory system (SAP Hana[1]). Such visual exploration and analytic systems are increasingly demanded by municipalities and cities (Di Lorenzo, et al. 2016).
The first dataset is provided by the municipality and consists of 158 position plans of traffic sensors which generating values at least every 90 seconds. The sensors are classified as follows.

Detector type	**Location of detector**
Normal detectors	On the stop line or 30 meters in front of the stop line to enhance the green phase
Inductive loops	On exits of crossings or on the stop line
Demand buttons for pedestrians and cyclists	Mounted on traffic signals

Table 1: Types of sensors

As second dataset the municipality provided data of the local public transport. The protocols are documenting at which timestamp a specific waypoint was passed by a bus. Unfortunately, there was no real time data of the public transport available thus a simulation of the bus traffic was performed to consider their influence on the traffic system. Delays are not considered in the simulation. The model of the public transport system is represented as an attributed graph (see Chapter 3) whereby a transport stop was stored as a node and a connection between two stops is stored as a relation. Transport stops have attributes like name, number of bus routes and geo-position of the stop. To consider the different time-dependent mobility behaviors of a region the departure dates are clustered in four different types: Monday-Thursday, Friday, Saturday and Sunday/Holidays.

Based on this sensor data the amount of traffic emissions is calculated and predicted. The following paragraph describes the approach in detail.

First, the calculated average carbon dioxide emission for the car-based traffic composition in the observed municipality is 187g CO_2 per kilometer per car. This average is used as basic value for determining local deposits. The average amount of cars on an inductive loop is used and multiplied with carbon dioxide values (Treiber and Kesting 2010). Fabric new vehicles have a limit of 130 grams CO_2 per kilometer. 50 µg/m^3 is set as upper limit for acceptable values. Every value above is considered as harmful. Through this threshold, violations and compliances are easy to determine by an analyst of the municipality. As shown in Figure 2, the

[1] High Performance Analytic Appliance developed by SAP (hana.sap.com)

emissions in a downtown region are very problematic. The city center is a traffic-calmed zone, so there are no traffic sensors. The ring around the city center is equipped with a lot of traffic sensors. The size of the circles are indicating the amount of cars passing a sensor. The color of the circles shows the emission levels caused by the traffic. Red means “very high” and green means “in acceptable range”.

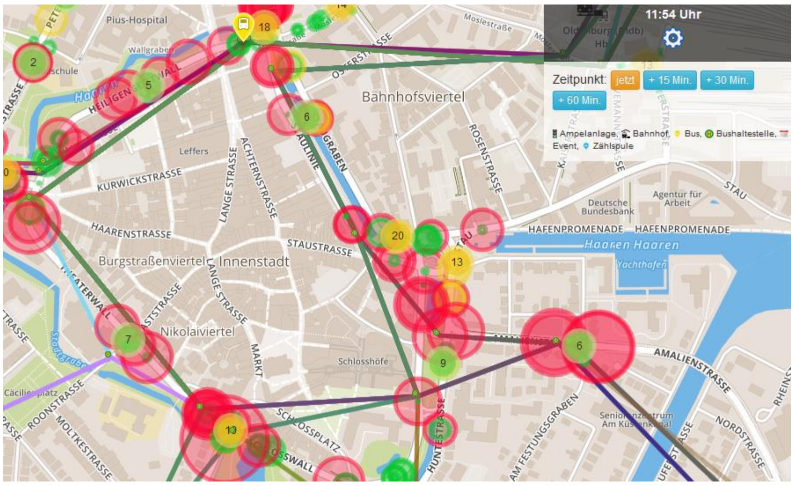

Figure 2: Emissions in a downtown region

The inductive loops are stored as nodes with further information and further relations. The attributes of the nodes are geo-positions, names and types. The relations are storing attributes for the driving directions. These relations are containing the last passed node to get the driving direction (nodeFrom) and the following node to determine the target direction (nodeTo). Additional attributes are the number of counted lanes by an inductive loop and the number of lanes in driving direction of the street. The lane position describes the lane number where a sensor is available. The last attribute is the turn. It describes the possible driving directions of the driver as a number. 100 means only to turn left, 010 to drive straight, 001 to turn right, every direction is 111.

The prediction of the traffic volume was the core task of the project group and was separated in short and long term predictions. The short term predictions build the future dataset for the next 15, 30 and 60 minutes. The long term prediction generates the dataset for any chosen day in the future.

The short term prediction used the data of the previous 15 days. These 15 days have to be in the same day classification as described before because the traffic volume is different on weekdays and weekends. A similar evaluation was given by Roland Chrobok (Chrobok 2005), who observed traffic on highways. To predict the value for the actual time + 15 minutes; all values from the last 15 days for every inductive loop are selected and for each loop an average value is calculated. The same procedure was used for the 30 and 60 minutes intervals. An estimation derived a value of 0.2 for the exponential smoothing parameter A. The value S_t is calculated from the last 15 values with decreasing weighting.

$$S(x_t) = A \sum_{i=0}^{v-1} (1-A)^i x_{t-i} \,; v \cong \#values \qquad \textbf{(1)}$$

A restriction of this approach is that the values for a day classification like Friday and weekend is nearly a week in the past. Thus the last influences are not considered in the prediction. As a result, another prediction approach is used for these groups instead of using the last 15 days while the last 15 values are used to predict.

The used formula is exponential smoothing. The weighting of the values decreases the older the timestamps are. The formula only calculates the first 30 seconds in the future so it was executed 30 times to get the value for 15 minutes. This approach can be used for any point of time but the error rate will increase rapidly for values greater than 15 minutes.

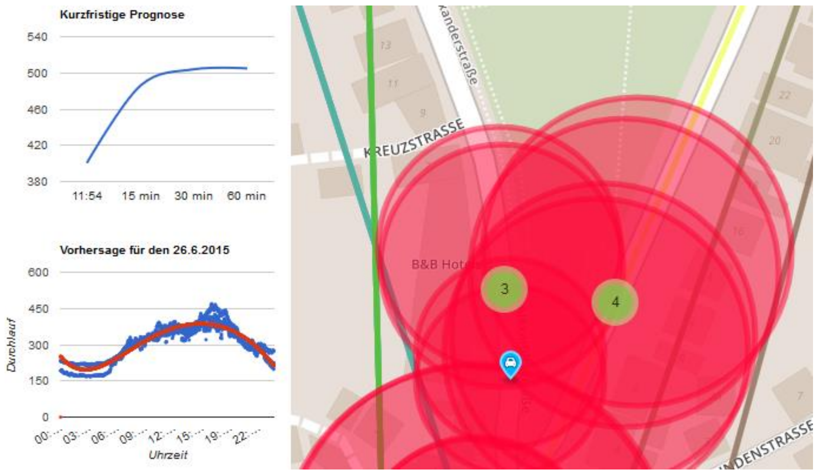

Figure 3: Prediction of traffic volume on inductive loops

By comparison to the short term prediction, the long term prediction is based on a regression model which relies on the described sensor data and additional weather data to calculate the traffic volume for any given day in the future. The predicted date was classified in one of the beforehand described groups and the last 15 days are selected. Afterwards, an average over the values for the whole day in 30-second intervals was built. This leads to a prediction as shown in the upper Figure 3.

$$S(x_t) = \frac{1}{d} \sum_{t=0}^{d-1} x_t \,; d \cong \#days \qquad \textbf{(2)}$$

These short and long term predictions are used to determine the superior traffic flows in a region or city. On these superior traffic flows the dynamic public transport services are aligned to increase their occupancy rates. Beside the alignment, traffic jams, and other incidents can be detected in real time by this tool. It can be used to give a municipality or city the possibility to optimize and control their traffic system more efficiently.

2.2 Mobility demands from traveler information systems

The customer focused demand detection is possible through the usage of traveler information systems. One of these systems is developed in the project *German showcase of electric mobility in Lower Saxony* initiated by the German government (BMWi) in 2012. The project had a duration of three years. The sustainability focused TIS is developed within the sub-project *ICT services* in the work package *customer oriented mobility*, to overcome the lack of sustainable awareness of the traveler. This TIS is enhanced with a Sustainability Customer Relationship Management System (SusCRM) with operative and analytical components (Wagner vom Berg 2015) and a customer centric intermodal mobility service.

The system is able to track modal choices of travelers, analyze and summarize his mobility behavior and deliver reports on the ecological, environmental and social impacts of his travels. By this, the system is able to change the behavior of a traveler to a more sustainable consumption. The user can access the application via a mobile application called *Guyde* which also is a virtual assistant supporting the traveler during the whole trip, if favored. Through this guidance an observation and intervention on a customer level is possible.

The generated data of the sustainable focused TIS consists of conventional models of intermodal trips, with sub-routes and transports. As additional information, specific vehicles are stored on the transport layer and specific restrictions as luggage or buggy are considered. Also, each trip is assessed in terms of costs and sustainability. To nudge users to a more sustainable selection three dimensions are integrated in the assessment process: steering behavior, historic behavior and target behavior of the customer.

As feature of the data warehouse, every trip option and the user choices are comparably stored. Based on this historical door to door requests, a prediction of mobility demands in a region or city can be determined very accurately for individual persons. A similar approach is used by Lathia et al. (Lathia, Froehlich and Capra 2010). The above described data is used to model the customer oriented demands in the following demand model for the observed region.

3. Demand model

The described tools in the sections 2.1 and 2.2 are offering an analytical access for municipalities to local mobility behaviors and can be used as basis for a finer mobility planning and controlling. As next step, these approaches are combined to a regional demand model for a dynamic customer oriented public transport system. The services tailored to the customer demands are depending on different circumstances. Some of these parameters are e.g. peak values of simultaneous passengers on a trip, customer centered demands (bicycle transport, bags and parcels or buggies and wheel chairs) or a short term planning horizon. Derived from this, different transport types are identified. In case of high passenger occurrence figures conventionally articulated buses are used or the passengers are distributed on several normal buses which are serving the same track. If taking a bike, a bus or a car with bike mounting can be used. On a short term planning horizons in a region distributed vehicles are used (e.g. taxi, call-me-bus) to provide ad hoc mobility services. To achieve this, a central demand platform has to be implemented. In the following section such a platform is suggested.

3.1 Architecture of the demand platform

The proposed demand platform includes the demand model for an inhabitant oriented public transport system. At its heart, the demand component contains a transport demand model, which is mainly based on two types of data. On the one hand is the infrastructure data which generally are basic sensors distributed in a city or region (cf. Section 2.1). In the proposed work, this data consists of several data sources, as i.e. inductive loops integrated in the asphalt of the street. Also used are camera sensors mounted on traffic lights for counting cars, trucks, bikes and pedestrians. On the other hand there is customer generated data such as transport requests on an electronic traveler information system (cf. Section 2.2). A further extension of data sources is intended. In this case data from the traveler information system described above is used. Besides these two types of data the municipality or any other operating instance may fill the model with additional fixed or special demands. This data which is not restricted could have the form of conventional regular trips. Also there may be specific trips which are special tours or excursions, trips to major events, or any other irregular event or occurrence. As explained in Chapter 2 there are different types of transport offers as short, middle and long term offers. Each of these offers has to be yield or otherwise the system will not be accepted by the public.

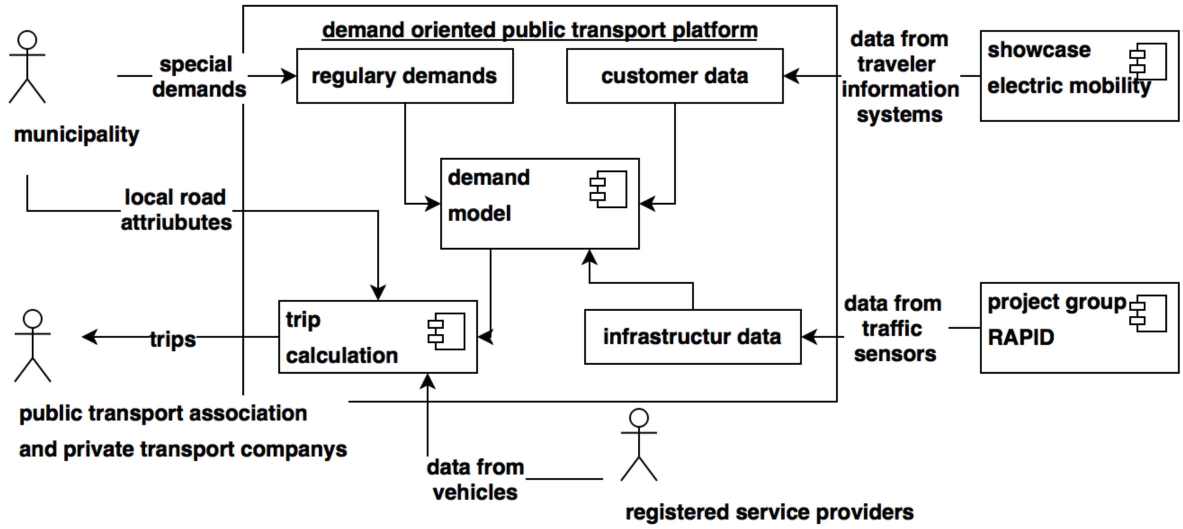

Figure 4: Architecture of demand model with inputs and outputs

Based on these datasets it is possible to identify transport demands in a region which are in line with local laws and sustainability requirements. The infrastructure data is used to determine superior traffic flows but determining demands for a specific customer are not very accurate within this dataset (Section 2.1). Derived from the infrastructure data, general expression for traffic flows on a specific day group and time can be given. Based on this, several regular public transport routes are identified. Also influences like traffic jams and huge load factors on roads can be detected and considered. The demands of the traveler information system are on a customer centered level. In this case we have precise demands from door to door and for any specific customer. These demands are mapped on the model by using public transport routers to determine the shortest way to a destination over one to several transport stops.

Besides the traffic data, data and demands from the municipality are integrated. There are, as described before, special demands like trips to fairs and major events. Additionally, the municipality provides data and maps of an area. For advanced consideration this data includes data of planned road constructions or similar information. Also, data of the street types is used for trip calculation. This data consists of road size and several other circumstances. As last input source, data from distributed vehicles in a region is included. Necessarily, this data is used to distribute demands to specific service providers which are geographically near to the demand request.

Unlike the conventional trip planning in public transport a dynamic trip planning is established. Dynamic trip planning is based on demands gained by the demand model. In a region a set of public transport stops are available which are dynamically served by different public vehicle types. To fulfill demands, it is necessary to know the basic conditions of a region. For example, to calculate dynamic trips a map of the region and the specific road types are essential for planning. Not every type of vehicle is able to drive on small roads or narrow crossings and curves. Also, possible traffic jams have to be considered in calculating trips. The routing component is described in Section 3.3.

3.2 Demand model as a dynamic undirected attributed graph

The demand model is represented as a dynamic undirected attributed graph at a specific point of time. Each node in the graph is a public transport stop.

Let the set of graphs G = {$G_1,\ldots,G_t$} be a sequence of graphs G_i = (V, E, A) with T = {1,…,t} as a set of timestamps. V is the set of vertices and E_i the set of edges that connect vertices of V at time $i \in T$ ($E_i \subseteq V \, x \, V$) and A, the set of attributes that map each vertex-time pair to a real value: $\forall f \in A, f : V \, x \, T \rightarrow \mathbb{R}$ (Pitarch, et al. 2014).

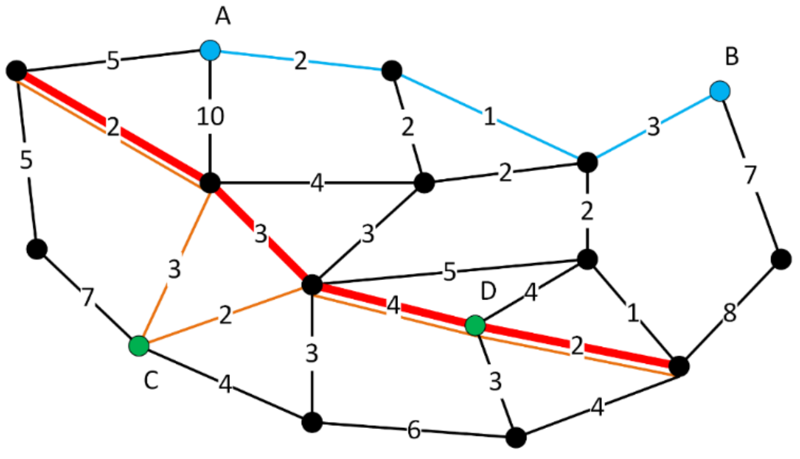

Figure 5: Example of a dynamic undirected attributed graph of mobility demands

The set of graphs G includes different demand requests over time. In Figure 5 a graph G_i for a specific timestamp *i* is shown. The black colored nodes are public transport stops with no transport demand. The nodes A-D are representing demands whereby the demands are A to B and C to D. Each edge is the shortest road-based connection between two stops. The attributes of the edges are distance, transport demand identifier and superior traffic flow. In Figure 5, the shortest connections between two stops are visualized as black edges, two distinct demands are colored in orange or blue (from TIS). The red line in the center of the figure shows the overall traffic flow through an area derived from the infrastructure data.

To achieve a best possible occupancy rate on public transport vehicles trips are approximated to the superior traffic flow. Thus the demand from C to D is fulfilled as trip (orange line) attached to the traffic flow (in red) to boost occupancy rate for this transport service. The demand from A to B is in consideration of economic and sustainable factors not directly linked to the superior traffic flow. By this, a small public transport vehicle can be used as a call-me-bus or a taxi to fulfill the demand request.

3.3 Calculation of optimal paths in graph-based public transport systems

To achieve such a trip planning component, several approaches have to be combined. Koszelew introduces a method for determining optimal paths in public transportation networks (Koszelew 2007). Usually, algorithms are determining the shortest path in a network but they are not time-dependent. As described before, the demand model is time-dependent and can be used in a network model as proposed by Koszelew. An adopted version of the proposed algorithm is used. This version is based on the certain labeling algorithm which is a solution of the K-shortest path problem and covers user preferences. The public transport network is defined as described in Section 3.2. In order to find the optimal path with a best possible occupancy rate further Key Performance Indicators (KPIs) like sustainability and costs for connections between stops have been added on the edges. Upper limits for these two parameters have to be set. The occupancy rate is defined as Min_{oc}, trips with rates smaller than 25% are not offered. Max_{sus} is set as sustainability indicator; its maximum value is equal to conventional public transport network emissions. The in the following paragraph summarized algorithm from Koszelew determines the K-shortest paths for a given public transportation network. The set of input parameters includes additional parameters which have different importance (e.g. transfer time). The preferences are ordered and if the algorithm doesn't determine a route the weakest weighted parameter will be ignored until a route is determined. If two or more routes are resulting the routes are prioritized by the importance of the preferences (travel time, etc.).

The proposed algorithm consists of four main steps (see (Koszelew 2007)). First, it generates paths without changes and a standard breadth-first-search method is applied to construct the shortest path. Then the last kind of paths are determined which are including changes and distances. Then all additional preferences are determined for each path.

Finally, the algorithm divides the set in a set of subsets according to the number of preferences in which they are sorted as best fitting or less fitting (Koszelew 2007). Nevertheless different path optimization algorithms (e.g. Chinese postman) can be implemented but have to be tested within the demand model (c.f. (Lu, et al. 2015)).

Besides the routing, a rerouting is very important to avoid disturbances. Shang et al. have introduced such an unobstructed route planning system (Shang, et al. 2014). Also, route optimization benchmarks may be used to validate trips in public transport system in further steps (Kilic and Gök 2015).

3.4 Restrictions and similar approaches

First, similar demand oriented public transport models are addressed by the German Aerospace Center (DLR) simulation tool SUMO (Krajzewicz, et al. 2012). Further approaches focusing on agent-based demand modelling, as described by (Huynh, et al. 2014). A broad overview for demand centered public transport is provided by Nelson et al. (Nelson, et al. 2010).

The proposed demand model is still at experimental stage. Further tests and developments have to be performed. The model will be evaluated in the interdisciplinary research project "*NEMo – Sustainable fulfillment of mobility demands in rural areas*" funded by the Volkswagen foundation. Besides the technical evaluation, the acceptance on the customer side is also considered.

A problem of this approach may be the cross-financing of public line networks in which productive lines are financing weak lines with low passenger volume. This should be compensated by a more effective public transport system with higher occupancy rates of transport vehicles. A further challenge is the question how to inform the travelers with information about the short term dynamic offers. A possible solution may be a mobile application based approach or intelligent signs at transport stops.

4. Conclusion

The public transport is mainly influenced by two inverse trends: cost pressure and securing the public mobility of the population with public transport services. The basic methods for planning public transport services are outdated and still relying on questionnaires, censuses and rarely requests on traveler information systems or ticket systems (Di Lorenzo, et al. 2016), (Schnieder 2015). Some approaches are aiming to implement new technologies on the vehicles or infrastructure but this is very expensive (cf. (Vassilis 2013)). This results in infrequent adjustments in public transport services because of high expenses.

In this paper a demand model for future public transport systems is proposed to introduce a new steering opportunity for local traffic agents and public transport associations. This demand model is used to achieve a more dynamic customer oriented public transport system to ensure the mobility of the population and at the same time minimizing emissions. In term of Green IS the proposed solution shows new ways to organize and manage public transport systems in a more sustainable way by using ICT based solutions.

The next steps are to enlarge the competition in public transport systems by allocating demand oriented transport orders to private service providers. Enabling the private sector to participate in public transport services leads to a stronger portfolio of transport services and a broader access for society.

References

Bundesministerium des Inneren. Demography Report of the Federal Government. Berlin: Publikationsversand der Bundesregierung, 2011.

Chrobok, Roland. Theory and Application of Advanced Traffic Forecast Methods. Müllheim an der Ruhr, 2005.

Di Lorenzo, G, M Sbodio, F Calabrese, M Berlingerio, F Pinelli, and R Nair. "AllAboard: Visual Exploration of Cellphone Mobility Data to Optimise Public Transport." IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS 2, no. 22 (2016): 1036-1050.

Federal Environment Agency. Ratgeber - Daten zum Verkehr. Berlin: Umweltbundesamt, 2012.

Hautzinger, H, G Haag, M Helms, and J Hugo. "Autofahren um jeden Preis?" Internationales Verkehrswesen (Deutscher Verkehrs), no. 3 (2005): 77-82.

Huynh, Nam N., Vu Cao, Rohan Wickramasuriya Denagamage, Matthew Berryman, and Pascal Perez. "An agent based model for the simulation of road traffic and transport demand in a Sydney metropolitan area." Eighth International Workshop on Agents in Traffic and Transportation, 2014: 1-7.

Kilic, Fatih, and Mustafa Gök. "A Benchmark Proposal for Route-Planning of Urban Bus Service." 4th Eastern European Regional Conference on the Engineering of Computer Based Systems, 2015: 134-137.

Kirchhoff, P., and A. Tsakarestos. Planung des ÖPNV in ländlichen Räumen. Edited by 1. Wiesbaden: Teubner Verlag / GWV Fachverlag GmbH, 2007.

Koszelew, Jolanta. "The Theoretical Framework of the Optimization of Public Transport Travel." In Computer Information Systems and Industrial Management Applications, 65 - 70. Minneapolis, USA: IEEE, 2007.

Krajzewicz, Daniel, Jakob Erdmann, Michael Behrisch, and Laura Bieker. "Recent Development and Applications of SUMO – Simulation of Urban MObility." International Journal on Advances in Systems and Measurements, 2012: 128-138.

Lathia, Neal, Jon Froehlich, and Licia Capra. "Mining Public Transport Usage For Personalised Intelligent Transport Systems." IEEE International Conference on Data Mining. 2010. 887-892.

Lu, Xiaolin, Jie Yu, Xianfeng Yang, Shuliang Pan, and Nan Zou. "Flexible feeder transit route design to enhance service accessibility in urban area." In Journal of Advanced Transportation. 2015.

Nelson, John D., Steve Wright, Brian Masson, Giorgio Ambrosino, and Aristotelis Naniopoulos. "Recent developments in Flexible Transport Services." Reforming Public Transport throughout the World 29, no. 1 (2010): 243-248.

Pitarch, Y, M Plantevit, C Robardet, and M Kaytour. "Triggering Patterns of Topology Changes in Dynamic Graphs." Advances in Social Networks Analysis and Mining (ASONAM), 2014: 158-165.
Schnieder, Lars. Betriebsplanung im öffentlichen Personennahverkehr. Ziele, Methoden, Konzepte. Berlin: Springer Vieweg (VDI-Buch), 2015.
Shang, Shou, Danhuai Guo, Jiajin Liu, and Kuien Liu. "Human Mobility Prediction and Unobstructed Route Planning in Public Transport Networks." IEEE 15th International Conference on Mobile Data Management, 2014: 43-48.
Statistische Bundesamt. "Verbraucherpreisindex: Deutschland, Monate, Klassifikation der Verwendungszwecke des Individualkonsums." 2015. https://www-genesis.destatis.de/genesis/online/ (accessed 12 22, 2015).
Treiber, Martin, and Arne Kesting. Verkehrsdynamik und -simulation. Berlin Heidelberg: Springer, 2010.
Vassilis, Kostakos. "Towards sustainable transport: wireless detection of passenger trips on public transport buses." Personal and Ubiquitous Computing 8, no. 17 (2013): 1807-1816.
Wagner vom Berg, Benjamin. Konzeption eines Sustainability Customer Relationship Management (SusCRM) für Anbieter nachhaltiger Mobilität. Aachen: Shaker Verlag, 2015.
Werner, Jan. Zukunft der ÖPNV-Finanzierung in Deutschland. Berlin: KCW GmbH, 2011.