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Optimal infrastructure capacity of automated on-demand rail-bound transit systems

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ABSTRACT

Fully-automated services potentially allow for greater flexibility in operations and lower marginal operational costs. The objective of this study is to determine the capacity requirements of an envisaged automated on-demand rail-bound transit system which offers a direct non-stop service. An optimization model is formulated for determining the optimal track and station platform capacities for an on-demand rail transit system so that passenger, infrastructure and operational costs are minimized. The macroscopic model allows for studying the underlying relations between technological, operational and demand parameters, optimal capacity settings and the obtained cost components. The model is applied to a series of numerical experiments followed by its application to part of the Dutch railway network. The performance is benchmarked against the existing service, suggesting that in-vehicle times can be reduced by 10% in the case study network while the optimal link and station capacity allocation is comparable to those currently available in the case study network. While network geometry and demand distribution are always the underlying determinants of both service frequencies and in-vehicle times, line configuration is only a determinant in the conventional system, whereas the automated on-demand rail service better caters for the prevailing demand relations, resulting in greater variations in service provision. A series of sensitivity analyses are performed to test the consequences of a range of network structures, technological capabilities, operational settings, cost functions and demand scenarios for future automated on-demand rail-bound systems.

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1. Introduction

The rapid advancements in the development of fully-automated vehicles have led to an increasing interest in the concept of automated on-demand transit systems. Automated services can potentially allow for greater flexibility in operations and lower marginal operational costs. The area of application considered hitherto has almost exclusively been limited to road-bound systems. To the best of the authors' knowledge, offering flexible services using heavy rail systems as a substitute to scheduled line-based services has not been considered in literature or practice insofar. This paper presents a first step into the relatively unknown area of automated on-demand rail-bound (ADR) systems.

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In this work, an ADR service designed as a full replacement of scheduled heavy rail for a given (sub-)network is envisaged. The automated rail-bound vehicles offer a direct non-stop service and move in the rail network in response to passenger requests with no pre-defined routes and schedules. Vehicles transport passengers that share the same origin and destination stations. Vehicles can be sized according to the operator's preference, but they are considerably smaller than existing train rolling stock units.

The objective of this study is to determine the capacity requirements of ADR systems. Unlike road-bound demand responsive transit services that operate in rural areas or cater for special user groups, the ADR network is designed to serve a large geographical area with relatively high demand that can result in operations being constrained by congestion and capacity limitations. The strategic planning objective of this study constitutes a major difference from most earlier models such as [Anderson \(1998\)](#) and [Winter et al. \(2016\)](#) which considered microscopic, operational models of flexible transport services with a stochastic passenger arrival. The on-demand routing and scheduling features of the envisaged service also sets it apart from studies for planning transit lines with specific network design features, often in urban settings (e.g. [Saidi et al., 2016](#); [Fielbaum et al., 2016](#)), and methods for designing timetables that better cater for dynamic demand patterns ([Sun et al., 2014](#)).

The development of technological and service concepts that will facilitate ADR systems are still at their early stages. It is therefore not surprising that literature on this service concept is sparse. Automation is a prerequisite for developing such a service given the high costs associated with operating a large fleet of small rail-bound vehicles. An early research identified the challenges of short vehicle headways and limited station capacity in the context of dense urban operations ([Bendix and Hesse, 1972](#)). The vehicle engineering RailCab project developed technical and mechanical solutions for small driverless rail-bound traffic ([Henke et al., 2008](#)). Vehicle design solutions for operating at short headways in an automated guideway transit system were studied by [Choromanski and Kowara \(2011\)](#), while capacity in relation to station layout has been analysed in more detail by [Greenwood et al. \(2011\)](#). According to [UITP \(2016\)](#), there is more than 800 km operated by automated metro and this is expected to quadruple by 2025 based on confirmed projects. [Wang et al. \(2016\)](#) provide a recent overview of trends and issues related to automated metro operations, including increased capacity and reliability. These studies provide preliminary insights into anticipated advanced in-vehicle technologies and their implications. However, there is lack of knowledge on the capacity requirements that such operations inflict on railway network infrastructure and related system performance and level-of-service. Crucially, none of the previous studies have examined the system requirements of network-wide operations of a flexible rail-bound service.

The contributions of this study are: (i) presenting the concept of an automated on-demand rail-bound transit system and its features; (ii) formulating a novel optimization model for determining the optimal track and station platform capacities for such a system so that passenger, infrastructure and operational costs are minimized. The model is formulated as a cost minimization problem with the premise that system-optimum vehicle flow distribution conditions can be attained; (iii) the underlying relations between technological, operational and demand parameters, optimal capacity settings and the obtained cost components are studied through a series of numerical experiments; (iv) the model is applied to part of the Dutch railway network. The performance is benchmarked against the existing service, its sensitivity to various scenarios is assessed and the implications of which are discussed.

The modeling approach along with the formulation of ADR cost functions and the overall cost minimization problem are presented in the following [Section 2](#). Thereafter, details on model implementation and the specification of model parameters are given in [Section 3](#). A series of numerical experiments designed to test ADR performance under a range of network, demand, costs and technological scenarios are performed in [Section 4](#), followed by an application for part of the Dutch railway network reported in [Section 5](#). We conclude with a discussion of model implications and potential extensions in [Section 6](#).

2. Model formulation

2.1. Modeling approach

Current railway models with lines and timetables as their cornerstone are unsuitable for ADR applications. Passenger transport in general, and the railway planning process in particular, includes successive models for line pool generation, scheduling optimization and methods for infrastructure allocation based on traffic models ([Bussieck et al., 1997](#); [Cordeau et al., 1998](#); [Guihaire and Hao, 2008](#)). The main challenge in modelling network-wide long-term planning for ADR is that the model needs to capture flow distribution and capacity constraints without representing system dynamics in microscopic details. Other ADR challenges include the need to handle large numbers of hourly passenger requests, strict routing due to rail infrastructure constraints and highly heterogeneous service characteristics compared to traditional rail systems. The approach taken in this study is to develop a novel macroscopic model by considering ADR as a special case of the network flow problem. This approach allows evaluating a large number of network-wide solutions.

The deterministic and static optimization problem is solved for a given network topology and passenger demand distribution, both are thus exogenous to the model. Other input to the model includes vehicle size, cost units and track and node flow-speed- and delay functions. Model output is the optimal infrastructure capacity per network element – each rail segment and station, vehicle flow distribution and the value of passenger, infrastructure and operational costs.

2.2. Network representation and cost functions

The public transport network is represented by a directed and weighted graph $G(N, A)$, where the node set N represents rail stations, and the set of links $A \subseteq N \times N$ represents rail track segments between stations. s_j is the capacity of station $j \in N$. c_a is the capacity of link $a \in A$ and l_a is the corresponding length. $a_{i \rightarrow j}$ denotes the directed link connecting station i to downstream station j . Travel demand is given in the form of an hourly origin-destination matrix, P , where each entry, P_{od} , denotes passenger demand between a pair of stops o and d , $o, d \in N$. Let $x_{a,od}$ represent the flow on link a that originated at node o and is en-route to destination d . The macroscopic principles governing the traffic regime at links and nodes, i.e. link speed-density function and node delay-density function, are detailed in the following sub-sections.

2.2.1. Link travel times

The speed-density function is assumed to follow a logistic function (Rotoli et al., 2016), albeit with an abrupt transition from free flow to jam conditions which is arguably more suitable for characterizing automated systems. Let v_a and $\hat{v}_a$ be the speed and the free-flow speed, respectively, of vehicles traversing link a . Link travel times are then determined based on link length, free-flow speed and the logistic term with the volume over capacity ratio as follows:

$$t_a = \frac{l_a \cdot \left[1 + e^{-\alpha \cdot \left(\frac{x_a}{\theta \cdot c_a} - \phi \right)} \right]}{\hat{v}_a} \quad (1)$$

The parameters α and ϕ are the scale and shift of the logistic distribution. θ is the maximum number of vehicles per hour per unit of link capacity, here used to convert infrastructure units (i.e. number of tracks) into flow units (i.e. number of vehicles). While volume-over capacity terms are used extensively for modelling car traffic conditions, in the context of rail traffic, the minimum train separation time and distance are commonly used to quantify rail line capacity. In this research, volume to capacity ratio, $x_a/\theta \cdot c_a$, is defined as the deployed number of vehicles per hour over the maximum number of vehicles per hour. In practise this maximum is a result of various factors such as minimum vehicle separation and vehicle driving characteristics, signalling and control system and track switching time. Since these railway traffic properties are not subject of analysis in this study, the maximum number of vehicles per hour is considered an exogenous variable in the proposed model.

2.2.2. Station processing times

Let $x_{j,od}$ denote the number of vehicles that arrive at station j that are en-route connecting a given OD-pair (including vehicles for which this station is an origin or a destination). Vehicle arrivals are assumed to follow the Poisson distribution, implying that service requests of all vehicles can be represented as a joint Poisson process with the summative event rate parameter $\lambda_j = \sum_{o \in N} \sum_{d \in N} x_{j,od}$.

Vehicles either drive through intermediate stations or call at origin and destination stations. Considering each platform as a server and assuming that all vehicles have the same mean service time of $1/\mu_j$ with an exponential service time distribution and all vehicles are permitted to use any platform, the ADR station is characterized as a non-pre-emptive M/M/c system (similarly to metro stations in for example Xu et al., 2014). If the station has more than two platforms, it is assumed that through-going vehicles can overtake dwelling vehicles, otherwise the station is governed by non-prioritized M/M/c queues. The value of μ_j is determined based on the ratio between through-going and dwelling vehicle-times at each station and thus depends on the share of vehicles calling (i.e. originating or destined) at station j out of all vehicles traversing this stations and vehicle dwell time, τ^{dwell} . The expected waiting time in the non-pre-emptive M/M/c queue depends on delay probability Π (Kella and Yechiali, 1985), which is calculated as follows:

$$\Pi_j = \frac{(s_j \cdot \rho_j)^{s_j}}{s_j!} \cdot \frac{1}{\frac{(s_j \cdot \rho_j)^{s_j}}{s_j!} + (1 - \rho_j) \cdot \sum_{m=0}^{s_j-1} \frac{(s_j \cdot \rho_j)^m}{m!}} \cdot \forall j \in N \quad (2)$$

where the density term is defined as:

$$\rho_j = \frac{\sum_{o \in N \setminus j} \sum_{d \in N \setminus j} x_{j,od}}{s_j \cdot \mu_j} + \frac{\sum_{o \in N \setminus j} x_{j,oj} + \sum_{d \in N \setminus j} x_{j,jd}}{s_j \cdot \mu_j} \quad \forall j \in N \quad (3)$$

The numerators in the first and second terms in Eq. (3) correspond to the number of vehicles traversing and calling, respectively, at station j . The corresponding expected delays in prioritized and non-prioritized queuing systems can then be determined according to the formulations provided in Wagner (1997), resulting in the expected delay per station, $E(w_j) = f(\Pi_j)$. This function assigns different values for through-going vehicles and dwelling vehicles at stations where overtaking is possible, whereas otherwise no distinction is made.

2.3. Cost minimization problem formulation

Considering ADR as a special case of the network flow problem, the decision variables are link capacity, node capacity and the share of vehicle flow routed via each route alternative per origin-destination pair. The objective is to minimize

the cumulative value of infrastructure capacity costs, passenger travel time costs and operational costs. The ADR network planning objective is designed to balance between the costs of adding infrastructure capacity and the costs of delay or detours caused by inadequate infrastructure capacity.

The cost minimization problem is then formulated as follows:

$$z = \min \left\{ \beta_1 \cdot \vartheta \cdot \left[\sum_{o \in N} \sum_{d \in N} \sum_{a \in A} (x_{a,od} \cdot t_a) + \sum_{j \in N} (\lambda_j \cdot E(w_j)) \right] + \beta_2 \cdot \sum_{a \in A} c_a \cdot l_a + \beta_3 \cdot \sum_{j \in N} s_j + \beta_4 \cdot \vartheta \cdot \sum_{o \in S} \sum_{d \in S} \sum_{a \in A} (x_{a,od} \cdot l_a) \right\} \quad (4)$$

subject to

$$\sum_{i \in N} x_{a_{i \rightarrow j}, od} \sum_{k \in N} x_{a_{j \rightarrow k}, od} \forall o, d \in N, j \in N \setminus o, d \quad (5)$$

$$\sum_{j \in N} x_{a_{o \rightarrow j}, od} = \frac{P_{od}}{\vartheta} \forall o, d \in N \quad (6)$$

$$\sum_{j \in N} x_{a_{j \rightarrow d}, od} = \frac{P_{od}}{\vartheta} \forall o, d \in N \quad (7)$$

$$x_{a,od} \geq 0 \quad \forall a \in A, \forall o, d \in N \quad (8)$$

$$c_a \geq 0 \quad \forall a \in A \quad (9)$$

$$s_j \in \mathbb{Z}^+ \forall j \in N \quad (10)$$

$$\rho_j \leq 1.0 \quad \forall j \in N \quad (11)$$

In addition, Eqs. (1)–(3) given in the previous section describe how t_a , link travel time, and $E(w_j)$, the expected delay at each station, are calculated. The remaining constraints pertain to demand satisfaction, flow conservation and non-negative decision variables. Eq. (5) ensures flow conservation at all intermediate nodes whereas Eqs. (6) and (7) require demand satisfaction at origins and destinations, respectively. Eqs. (8) and (9) require that link flows and capacities are non-negative. Eq. (10) ensures that station capacity is a positive integer and Eq. (11) determines the upper value of station density. The decision variables are $x_{a,od}$, c_a and s_j . ϑ is the desired vehicle load level (e.g. seat capacity).

The objective function, Eq. (4), is comprised of four terms: (i) passenger travel times calculated over all links and stations; (ii) track capacity investment costs; (iii) station capacity investment costs; (iv) variable operational costs. $\beta_1 \dots \beta_4$ are the monetary costs associated with each of the objective function components: β_1 is passenger value-of-time, β_2 and β_3 are the costs of track infrastructure and station platform capacity units expressed in hourly terms, respectively, β_4 corresponds to the operational costs per seat kilometre. A single arrival rate per station appears in cost component (iii) for simplicity, but different event rates are specified in case different vehicle classes (i.e. through-going and dwelling) need to be considered.

Passenger travel times consist of waiting time and in-vehicle time in the envisaged context of a direct non-stop station-to-station ADR service. Given the on-demand character of the system, passengers are assumed to arrive at stations at random. Passenger average waiting times are then approximated as half the interval between departures of vehicles connecting a given OD-pair. Service frequency is specified in this study as approximately proportional to passenger demand for a given OD pair by rounding the ratio of P_{od} to the desired vehicle load level, ϑ , unless passenger demand is not sufficient to justify a predefined minimum service frequency ($P_{od}\vartheta < \vartheta$). Hence, waiting times are determined in the initialization phase and are independent of the decision variables and can be left out of the analysis of alternative solutions.

The minimization problem formulated in Eq. (4) entails the simultaneous solution of setting the capacity per rail-segment and station and obtaining the corresponding system-optimum solution of network flow distribution while minimizing user, investment and operational costs.

3. Model implementation and specification

Model specification involves setting values for a series of technological and service parameters. In the following, base case values designed to reflect the prevalent conditions in The Netherlands – for which the authors have access to relevant information and the model is later applied – are specified. The values are meant to indicate a rough estimate. Sensitivity of key variables to selected parameter values is assessed as part of the sensitivity analysis performed in subsequent sections.

The speed-density function involves specifying the free-flow speed and track vehicle capacity. The former was set to 100 km/h ($\hat{v}_a = 100 \forall a \in A$) based on the current conditions in the dense Dutch network. Track capacity, θ , is set to 180 vehicles per hour in line with operational people mover systems which operate at 20 s headways. The logistic function scaling

Table 1
Summary of input parameter specification.

Parameter	Value
Free-flow speed, $\hat{v}_a$ [km/h]	100
Track capacity, θ [vehicle/h]	180
Dwell time, τ^{dwell} [s]	20
Mean service time, $1/\mu$ [s]	5 (non-stop), 80 (dwelling)
Vehicle capacity, κ [passengers]	24
Load factor, ψ	0.7
Value of time, β_1 [€/h]	10
Track investment costs, β_2 [€/track-km/h]	190.13
Platform investment costs, β_3 [€/station platform/h]	469.62
Operational costs, β_4 [€/seat-km]	0.02
Scaling parameter of the speed-density function, α	−11.17
Shifting parameter of the speed-density function ϕ	0.88

and shifting parameters, α and ϕ , are set to −11.17 and 0.88, respectively, based on engineering assumptions derived from a combination of the European Commission publication on railway capacity utilization (Rotoli et al., 2016) and literature on traffic flow properties of automated vehicles (see review in Hoogendoorn et al., 2014). These parameters were specified so that the function reproduces the current scheduled running times of the Dutch railway network.

Station platform operation is governed by the queuing servers. Based on observations in an existing automated system (i.e. Rivium Parkshuttle in Rotterdam) dwell time, τ^{dwell} , is set to 20 s. For reference, current sprinter trains are scheduled to dwell for 24 s. Mean service rate, $1/\mu$, is set to 5 s for non-stop vehicles and 80 s for dwelling vehicles. The latter is based on an estimation of the time required for the processes of setting switches, pulling into the station, dwelling and clearing the platform. An estimate of the mean service time may have to be developed when network complexity is such that service time for non-stop vehicles may become an endogenous variable.

The base case vehicle capacity is set to $\kappa = 24$ passengers. Vehicles are designed so that all passengers are seated ($\vartheta = \kappa$). Service frequency per OD-pair is determined so that passenger demand is satisfied with a load factor of at least 0.7. OD-pairs for which demand does not justify at least one departure per hour (i.e. <17 passengers) remain unserved by the ADR service.

Objective function weights are set to $\{\beta_1, \beta_2, \beta_3, \beta_4\} = \{10, 190.13, 469.62, 0.02\}$. The first weight is the Dutch value-of-time expressed in Euros per hour. The second and third are specified based on estimates in the Dutch rail industry and correspond to €50 million per kilometre of track and €123.5 million per station platform. The latter depends on platform length which is specified to accommodate the envisaged vehicle dimensions. Based on current rolling stock specifications, approximately one meter of platform is needed per three vehicle seats. In addition, it is assumed that each platform needs a fixed length component to accommodate low speed switches on both ends, each of which has a length of 15 m. Hence, platforms designed to serve vehicles with 24 seats should be 38 m long. Track and station platform costs are assumed to be depreciated over a 30 years period. Operational cost per seat-km is estimated at €0.02.

The optimization problem is solved in MATLAB using a trust-region method (Byrd et al., 1987). Method deployment involves the computation of a full eigensystem. The computational effort is therefore proportional to several factorizations of the Hessian matrix at the location under consideration. Given the scale of our ADR model, MATLAB uses heuristic approaches to reduce computation time by solving a sequence of approximated minimization problems. The optimization method is designed for breadth followed by depth – starting with a global search process where cumulative constraint values are considered while permitting violations of individual constraints followed by an efficient local convergence. Since the objective function includes factorial terms in the queuing theory waiting time equations, those have been replaced by a Ramanujan's expression, a continuous function for approximating the factorial term. Consequently, all decision variables are continuous when handled by the optimization tool, which is advantageous for reducing running times. Furthermore, the number of decision variables for real-size problems was reduced by replacing $x_{a,od}$ with the determination of passenger flows per OD-pair at the route rather than the link level. For each OD-pair, all routing alternatives that involve free-flow travel times of up to three times those of the shortest path were included. Flow conservation constraints are then removed and substituted by a constraint ensuring that the cumulative route flows correspond to passenger demand per OD-pair.

4. Numerical experiments

The cost minimization model presented in Section 2 was applied to a series of numerical experiments using the specifications detailed in Section 3. The numerical experiments are devised to investigate the generic properties of ADR systems, underlying relations between model variables and the sensitivity of model output to variations in input parameters.

4.1. Experimental set-up

The numerical experiments are performed using two graphs, both of which are composed of 17 nodes and 48 unidirectional links. Two distinct network structures are considered: a grid and a ring/radial structure, as illustrated in Fig. 1. The

Fig. 1. The two network structures considered in the numerical experiments: grid (left) and ring/radial (right). All lines represent bidirectional arcs.

Fig. 2. Optimal track and station capacity and the corresponding utilization level (in color) for the grid network.

base case passenger demand amounts to 34,000 hourly requests distributed over the network based on a gravity model using the Euclidean distance between all origin and destination nodes (an average of 125 trips per OD-pair). The optimization problem formulation for the numerical experiments involves approximately 1000 constraints, most of which are equality constraints. Each optimization problem is solved within 15 s on a standard PC.

A series of sensitivity analyses pertaining to service design, cost parameters, technological capabilities and demand scenarios are performed. In the following, the results for variations in vehicle passenger capacity, track capacity and demand distribution are reported and discussed. In the case of vehicle capacity, it is also varied in conjunction with corresponding changes in operational costs and the minimum service frequency threshold criterion.

4.2. Results and analysis

4.2.1. Scenarios summary

Table 2 summarizes the results of the base case scenario along with the key sensitivity analysis scenarios for both the grid and the ring/radial networks. The base case is set with a vehicle capacity of 24 passengers and track capacity of 180 vehicles per hour – and with the Euclidian gravity demand distribution. The table reports results for other vehicle capacity (VC) and track capacity (TC) scenarios noted with the corresponding value, as well as demand distribution (DD) and demand level (D) scenarios. Scenario labels refer to the input variable differing from the base case scenario and its respective value. For example, scenario “VC_96” corresponds to setting vehicle capacity to 96 passengers, while all other variables remain unchanged (*ceteris paribus*). For each scenario, Table 2 reports the four cost components for the optimal solution expressed in hourly terms (columns 2–5), followed by two indicators of system resources – fleet size and total seat-km offered (columns 6–7) – and the resulting service speed (last column).

Overall, the grid network outperforms the ring/radial network, yielding lower values for all cost components in the optimal solution with the existing demand distribution. A careful investigation reveals that differences primarily stem from the fact that in the grid network flows can often be rerouted at constant mileage, while in the ring/radial network rerouting (almost) always comes at the price of increased travel distance. Consequently, flow rerouting is common in the grid network, whereas all vehicles take the shortest route in the ring/radial scenario.

Fig. 2 depicts the track and station capacity decision variable values as well as their utilization levels. All but four arcs have a single track. Only the middle horizontal axis requires double tracks. Utilization levels are highest on single-track segments located on the horizontal and vertical pivots. Station capacity ranges between 3 and 11 platforms with a perfectly symmetrical allocation as could be expected given the demand distribution. Station utilization levels across the network exhibit a low variability with saturation levels of 76–88% at all stations.

Table 2

Numerical experiments scenario results for grid; ring/radial networks per hour of operation.

Scenario	Passenger costs[€1000]	Link costs[€1000]	Node costs[€1000]	Operation-al costs[€1000]	Fleet size[veh]	Offered seat-km[1000 km]	Service speed[km/h]
Base	47.1; 49.1	31.8; 33.5	46.1; 46.3	9.9; 10.4	370; 386	495.4;521.6	74; 74
VC_12	58.2; 60.3	69.8; 72.9	83.3; 83.2	11.7; 12.2	915; 948	583.5;609.2	70; 71
VC_48	32.4; 36.4	14.0; 13.5	27.0; 26.8	7.0; 7.8	127; 143	348.7;390.1	75; 75
VC_96	26.5; 27.5	8.3; 7.6	18.1; 18.0	5.5; 5.9	52; 54	276.6;294.6	73; 75
TC_30	60.6; 63.3	160.5; 169.0	46.4; 46.3	9.9; 10.4	476; 497	495.4;521.6	57; 58
TC_45	55.6; 58.0	111.0; 116.9	46.4; 46.3	9.9; 10.4	437; 456	495.4;521.6	62; 63
TC_120	48.7; 50.7	45.8; 48.2	46.4; 46.3	9.9; 10.4	382; 399	495.4;521.6	71; 72
DD_CC	80.1; 75.2	57.9; 53.9	52.7; 52.4	18.0; 16.8	630; 591	902.1; 839.4	79; 78
DD_U	78.6; 74.1	56.9; 53.4	49.5; 49.5	17.7; 16.7	618; 582	887.1;832.5	79; 79
D_75	34.2; 36.9	22.5; 24.5	35.1; 34.5	6.9; 7.6	269; 290	347.3;381.6	71; 72
D_125	63.5; 65.8	43.8; 45.9	59.8; 59.7	13.6; 14.3	499; 518	683.1;714.5	75; 76
D_150	77.4; 83.8	54.0; 56.8	72.2; 75.1	16.8; 17.7	608; 659	842.1;884.8	76; 74
D_U_75	73.8; 63.2	51.5; 45.2	30.6; 42.8	15.9; 14. 1	580; 497	794.2;704.2	75; 78
D_U_125	114.7;105.2	77.2; 72.3	49.5; 49.5	23.9; 22.3	901; 827	1192.8;1114.2	73; 74
D_U_150	140.5;113.4	93.3; 82.9	60.9; 75.0	28.8; 25.8	1104; 891	1438.7;1292.3	72; 80

VC (vehicle capacity); TC (track capacity); DD (demand distribution); CC (closeness centrality); U (uniform).

4.2.2. Vehicle capacity, operational costs and minimal service frequency

Solution sensitivity to vehicle capacity was tested for $\kappa = \{12, 24, 48, 96\}$. These capacities correspond to the number of seats ranging from a midi-bus to an intercity train car unit. Station capacity costs were adjusted to correspond to changing platform length requirements. A pronounced trend can be observed for both network structures in the results reported in Table 2 – the smaller the vehicle capacity the higher all cost components become. Reducing vehicle capacity from the base case value of 24 to 12 results in an increase of approximately 120% and 80% in link and node capacity costs, respectively. This increased capacity is required to handle a fleet size that is 2.5 times larger, but nevertheless results with a 25% rise in passenger costs. Part of this difference is attributed to the increasing number of passengers that are not offered a direct ADR service as vehicle size increases. This share increases dramatically from negligible levels to a sizeable minority of passenger demand in the scenario with a capacity of 96. With the exception of the lowest capacity scenario, service speed remains at a relatively constant level.

Smaller rail vehicles are associated with higher operational costs (β_4), because the seat-to-engine ratio is lower. It might therefore be argued that to ensure a fair comparison, a change in vehicle size needs to be accompanied with an opposite change in operational costs. The following scenarios are studied for the grid network: 12 seats at €0.08 per seat kilometre, 24 seats at €0.02 per seat kilometre (base case), 48 seats at €0.015 per seat kilometre and 96 seats at €0.0125 per seat kilometre. We conclude from the results (not included in Table 2) that a change in unit operational costs has no major influence on the decision variables. Differences between the various vehicle size scenarios are in line with the results reported in Table 2.

The risk that low-demand OD pairs will not meet the minimum threshold set for justifying a direct service in the ADR system increases with larger vehicle sizes. To overcome the deficiency of an increasing share of unserved demand when vehicles size increases, the second set of combinatorial scenarios relaxes the minimum service frequency alongside an increase in vehicle capacity for the grid network. The largest vehicle is associated with a frequency threshold of one departure per hour. The threshold values for smaller vehicles are set such that the minimum capacity of 96 seats per hour is obtained in all scenarios: 12 seats and at least 8 departures per hour; 24 seats and 4 hourly departures; 48 seats and 2 hourly departures; and 96 seats with at least 1 departure per hour. In this way, the share of unserved demand is fixed in all cases (12%). While served demand is equal in all scenarios, passenger costs still decrease with increasing vehicle capacity, albeit more modestly (i.e. 46,940 and 40,560 for 12 seats and 96 seats, respectively) than reported in Table 2. Link and node capacity costs are significantly higher in low vehicle capacity scenarios with costs more than five and three times as high for link and node costs, respectively, when comparing 12-seats and 96-seats scenario, yet resulting in a lower operational speed. Notwithstanding, smaller vehicles may still be preferred because they offer higher service frequency and thus a higher level-of-service.

4.2.3. Track capacity

The automated rail track capacity assumed in the base case scenario, $\theta = 180$ vehicles per hour, is very high compared to existing heavy rail systems. In order to test the consequences of technological developments that result in lower values, the model was run with track capacity values of 30, 45 and 120 vehicles per hour. The most conservative value corresponds to the maximum frequency in classical heavy rail with ERTMS signalling. A reference value of 45 is taken from automated metro systems (e.g. Line 14 in Paris). An intermediate value of 120 can be indicative of more limited technological advancements. As can be expected, link costs are most affected by changes in track capacity. In contrast, the impact of track capacity on passenger costs exhibits a logistic relation through the operational speed. Node costs and operational costs remain unaffected. Link costs dominate the cost function for low track capacity values and decrease to levels similar to station capacity and passenger costs for track capacity values of 120 vehicles per hour and is then exceeded by the latter two for $\theta = 180$ (i.e. base case).

4.2.4. Demand distribution

The demand distribution is expected to have profound effects on system performance. Two demand distribution scenarios are considered in addition to the base case where the demand is oriented towards the network's centre of gravity: the opposite case of a uniform demand distribution (DD_U) and an intermediate case where demand is proportional to the node closeness centrality (DD_CC) metric (i.e. average distance to all other nodes). Note that unlike the uniform and gravity distributions, demand distribution in the latter scenario is not independent from network connectivity and hence results with a different OD-matrix for the two network structures.

Unlike the base case, link costs in the optimal solutions for the two alternative demand distribution scenarios surpass station costs. A more uniformly distributed demand requires a larger fleet and leads to higher mileage and thus increased track capacity on a larger number of network links, albeit with lower congestion levels as reflected in the increase in average speed for both network structures. Operational costs are lower for the ring/radial network than for the grid network in the average closeness and uniform scenarios due to its superior connectivity whereas the grid network performs better when demand is concentrated at the centre where it can offer shorter routes around the congested centre node instead of through the centre node.

The availability of rerouting options with constant mileage in the grid network allows for a more efficient vehicle routing and more opportunities for trading-off different cost components. This grid network property is particularly useful when the demand around the central node is the highest. The grid network therefore outperforms the ring/radial in the base case of gravity-based demand distribution. Conversely, in the case of uniform demand distribution, the ring/radial network has the

Fig. 3. Cost component sensitivity to demand level in the grid network.

lowest link-related costs. This is a consequence of the shorter average link length of the ring-radial network (1.28 units of length on average per link in the ring-radial network compared with 1.33 in the grid network structure).

4.2.5. Demand level

We investigated the sensitivity of the solutions yielded under different network saturation levels by varying demand levels. The base case demand profile based on a gravity model as well as the uniform demand profile are uniformly (i) decreased by 25%; (ii) increased by 25%, and; (iii) increased by 50%.

As can be seen in Table 2, the grid network consistently outperforms the ring/radial network in terms of total costs for all demand levels when demand is a function of accessibility and vice-versa in the case of uniform demand distribution, regardless of the demand level. In the case of the base case demand distribution, all cost components increase approximately linearly as demand level rises. In contrast, the marginal cost increase follows a reversed U-shape for link, passenger and operational costs in the case of uniform demand distribution. This can be observed in Fig. 3 where the total passenger-hours do not exhibit a linear relation over the linear increase in passenger demand, but rather an S-shaped curve. This holds for both grid and ring-radial network types. This suggests that systems characterized by demand patterns that are fairly uniformly distributed in space can result with abrupt increases in all cost components due to fewer economy of scale benefits.

Examining the flow distribution and related network performance in the optimal solution reveals that track capacity utilization hovers between 40 and 50% in all demand level and distribution scenarios for both network prototypes. However, station capacity utilization is generally higher, ranging between 60 and 70%, with the exception of the most central nodes. Higher passenger costs are traded-off against lower infrastructure costs in low demand scenarios whereas in high demand networks, there is a tendency to increase infrastructure capacity with the aim to reduce passenger costs. This also explains the slightly higher infrastructure utilization (and hence more infrastructure related delays) in lower demand scenarios.

5. Application

The ADR network capacity allocation optimization problem detailed above was applied to the real-world case study of part of the national Dutch railway network. The case study is described, followed by the results and their analysis.

5.1. Case study description

The case study area constitutes a part of the national Dutch railway network. The area corresponds to the Dutch province of North-Holland, north of the North Sea Canal, shown in Fig. 4. The Dutch capital, Amsterdam, is situated at the south-east corner of the case study network and is connected to the city of Zaandam from which different corridors via Hoorn, Uitgeest and Alkmaar stretch to Enkhuizen (north-east) and Den Helder (north-west). The network consists of 28 stations and is currently served by 8 fixed lines. Each line is operated with a frequency of 1–2 departures per hour but service design is such that the busiest corridors are served by up to 8 trains per hour. This sub-network was selected because it can be assumed to operate relatively independently from the rest of the national railway network yet contains routing alternatives and a network of urban settlements with strong commuting patterns to Amsterdam. The network graph consists of an inner ring with three branches resembling the ring/radial structure but without a central station but rather a central

Fig. 4. Case study network – in relation to the Dutch railway network (left) and zoom-in on the North-Holland subnetwork (right).

Fig. 5. Demand visualization in the case study area during the morning rush hour before (left) and after (right) applying the minimum service frequency threshold of one departure per hour per OD-pair.

ring. Interchanges between the ADR operations within this network and conventional services can be performed at Uitgeest and Amsterdam Central stations.

In analysing the ADR capacity requirements for the case study network, we use the existing passenger demand patterns. Passenger demand is obtained from smartcard data records. An important feature of the Dutch smartcard system is that passengers are required to check in and check out on every single journey for calculating the distance-based fare. An OD matrix is constructed for an average weekday morning rush hour with a total of approximately 7000 passenger trips. Fig. 5 visualizes the demand distribution pattern during the morning rush hour before and after the minimum service frequency threshold of one departure per hour per OD pair has been applied. One station, namely Zaandam Kogerveld, is not served at all because the demand to any other station does not amount to a volume that justifies a direct connection as indicated by the absence of any connecting service arcs in Fig. 5 (right).

Fig. 6. Optimal infrastructure capacity allocation for the North Holland case study network; link thickness and node size and corresponding infrastructure utilization rates shown using the colour scheme.

The set of parameters detailed in Section 3 is used in the base case scenario. Note that the envisaged ADR system is served by vehicles much smaller than current trains (i.e. 24 passengers) and a significantly higher track capacity (i.e. 180 vehicles per hour per single-track). The sensitivity of the results obtained to variations in track capacity for automated vehicles – an important design parameter that at the moment cannot be estimated with certainty – is then analysed. The optimization problem results with 244 constraints in the base case. This substantially lower number than in the numerical experiments (about 1000) stems from the smaller number of non-zero demand OD pairs. The smaller number of routing alternatives also means there are fewer decision variables. Each optimization problem is solved within 30 s on a standard PC.

5.2. Results and analysis

5.2.1. System costs and capacity allocation and utilization

Table 3 presents the cost components and decision variables values for the optimal solution, expressed in hourly terms. Passenger costs are the largest cost component (39%), followed by link (29%) and node (24%) capacity investment costs while operational costs (8%) are considerably lower. Applying the procedure described in Section 2, we found that 191 vehicle trips are required for serving the current passenger demand.

The magnitude of the link and node capacity decision variables are displayed in Fig. 6 (size of nodes and thickness of links) as well as their utilization rate (colour of nodes and links) – expressed in terms of vehicle volume over capacity ratio – of each track segment and station platforms. Most of the stations require either one or two platforms, similar to or fewer than their current capacities. Only the busiest stations are assigned with three (Alkmaar, Hoorn and Zaandam) or five (Amsterdam Centraal and Amsterdam Sloterdijk) platforms in the optimal solution. One might expect the heterogeneity in terms of stopping patterns of the ADR system to require a higher capacity. However, the high share of through-going vehicles to dwelling vehicles allows for efficient infrastructure utilization. Node utilization rates vary between 0.18 and 0.74.

Double track infrastructure is necessary only on the busy corridor between Amsterdam Sloterdijk and Wormerveer (see Fig. 4). This exemplifies the important role that network effects also play in the context of ADR services. Single track (per direction) is sufficient for the remainder of the network. Utilization rates vary between 0.01 for the low-demand branch

Table 3

Case study results expressed in terms of objective function components and related variables.

Variable	Units	Value
Passenger costs	[€1000]	24.32
Link costs	[€1000]	17.94
Node costs	[€1000]	14.61
Operational costs	[€1000]	5.07
Fleet size	[vehicles]	191
Offered seat-km	[1000 km]	253.6
Unserved demand	[-]	4%
Service effectiveness	[km/h]	73
Passenger waiting time	[min]	9.5
Passenger in-vehicle time	[min]	21

leading to Enkhuizen to 0.63 for the 2×2 tracks between the two Amsterdam stations as well as on the link just after the 2×2 corridor due to the (abrupt integer) capacity drop to a single-track per direction.

5.2.2. Level-of-service

In order to assess the performance of the ADR service, we compare the travel time to those offered by the fixed train service. The latter are obtained from the current timetable. Fig. 7 shows the distribution of (nominal) total passenger travel time for the envisaged and the existing services, comprising of passenger in-vehicle and waiting times. Evidently, the distribution of the envisaged service outperforms the existing service for short- and medium-length trips, yielding shorter travel times. The average passenger travel time will decrease from 32.5 min to 30.5 min – saving 2 min of the travel time for each passenger – if the existing system is to be replaced with an automated on-demand service. This amounts to a saving of 230 passenger-hours for a single peak hour in the case study network. The share of passenger trips completed within a certain time budget – a common measure of level-of-service – increases from 11% to 17% for 15 min, from 47% to 49% for 30 min and from 81% to 87% for 45 min.

Passenger travel time savings are the result of differences in-vehicle time only, as waiting times remain on average unchanged. Since free-flow speed was determined based on the timetable travel time between stations, differences in travel time stem from congestion in the ADR network or different routing. System performance is expected to exercise economies of scale as demonstrated in Winter et al. (2018). Notwithstanding the overall time gains, travel times increase with the ADR service compared to the current train timetable for several OD-pairs. In all these cases the underlying cause is that while most vehicles are assigned to the shortest path, a minority of the vehicle flow operating between these OD-pairs is routed via the higher capacity route from Zaandam to Hoorn via Alkmaar (western wing of the ring in Fig. 6), instead of the shortest option via Purmerend (eastern wing). The optimization model has found this routing to be beneficial for attaining system optimum at the cost of prolonging travel times for some of the passengers. The ADR system outperforms the existing service in terms of passenger travel times for short and medium distance trips while no systematic difference is observed for long distance trips.

We further examine the composition of total passenger travel times in the alternative systems. In both systems, 72% of travel time is spent in-vehicle and 28% waiting, the share of in-vehicle/waiting time out of the total travel time varies more in the automated on-demand service than in the existing conventional service. The property can be expected as certain relatively long routes have high demand and correspondingly a high frequency (e.g. Alkmaar–Amsterdam) while the opposite

Fig. 7. Distribution of passenger total travel time with the existing conventional service and the envisaged automated on-demand service.

Fig. 8. Sensitivity of infrastructure costs and passenger hours to changes in track capacity in the case study.

holds as well: short routes with low frequency and hence more waiting time than in-vehicle-time, albeit both are relatively short. Notwithstanding, in general demand for long trips is relatively low in the case study network, thus resulting with lower frequencies than in the existing conventional service and hence longer waiting time. The latter are compensated by reductions in-vehicle time thanks to the direct service and the possibility to route vehicles through less congested parts of the network.

While network geometry and demand distribution are always the underlying determinants of both service frequencies (and thus waiting times) and in-vehicle times, line configuration is only a determinant in the conventional system, whereas the rail ADR service better caters for the prevailing OD demand relations, resulting in greater variations in service provision. Train frequencies per OD-pair range from 1 to 16 departures per hour in the ADR system, compared to 2 to 12 in the existing fixed service system. One segment of the demand that is clearly worse off are passengers travelling between OD-pairs that are associated with a low-demand station that is currently well-served because of network configuration (i.e. happens to be on the way between high demand stations). A total of 4% of the passenger demand is not served by a direct ADR service in this application. For the vast majority of travellers, the ADR service makes therefore the need to transfer and related passenger costs obsolete.

5.2.3. Sensitivity to changes in track capacity

Technological advances that enable increasing the capacity of an automated rail-bound service operated by small vehicles is expected to be crucial to its performance and viability in a large-scale application. The optimization problem is solved for track capacity, θ , values of 30, 60, 90, 120, 150 and 180 vehicles per hour. The objective function cost components values – passenger, link capacity and station capacity – are presented in Fig. 8. It can be seen that the link costs decrease exponentially with increasing track capacity. Track capacity also affects fleet size and vehicle circulation and consequently passenger in-vehicle times. The lower track capacity is the longer passenger travel times become. Compared with the base case scenario of $\theta = 180$, capacities of 150, 120, 90, 60 and 30, yield passenger in-vehicle time increases of 2.6, 3.4, 7.7, 13.4 and 29.2%, respectively. Consequently, passenger costs appear to first decline rapidly, followed by a more modest decrease for $\theta > 90$ vehicles per hour.

A track capacity of 90 is found to be the breakeven value in this case study for obtaining shorter in-vehicle times in the ADR system than in the conventional system on average in this case study. Given the passenger value of time in the case study area, when moving into lower values of θ , the model first tries to limit the increase in travel time at the cost of rising infrastructure costs. Only once the link capacity costs increase sharply, will they be partly traded-off against travel time costs. This is supported by the observation that the average speed is not affected significantly by decreasing track capacity until track capacity becomes smaller than the aforementioned 90 vehicles per hour.

6. Conclusion

This study presents a network cost minimization model for determining the optimal infrastructure capacity and flow distribution of ADR systems. The envisaged system consists of automated vehicles that offer a direct connection between passenger origin and destination stations and is routed so that system flow costs are minimized, yielding system optimum conditions. The results of the numerical experiments and the case study application indicate that similarly to conventional rail systems, stations are often the bottleneck determining the performance of automated ADR systems. Demand for the morning rush hour was used in our analysis, allowing for the dimensioning of the infrastructure (track and station) capacity. Under the base case parameter settings, the optimal track segment and station capacity allocation for the case study network is comparable to those currently available in this heavy rail network.

The need to invest in link capacity strongly depends on vehicle characteristics of minimum headway and the speed-density relation. Trading-off link costs against passenger costs is possible in the form of either inducing longer travel time or reducing service frequency by increasing vehicle capacity. Smaller vehicles offer better service due to shorter waiting times and fewer unserved travel requests (see also [van Engelen et al., 2018](#)) as long as the increase in the number of vehicles does not result with network congestion and thus a lower operational speed. Moreover, system optimum is achieved when the vast majority of passengers are served most effectively while OD pairs with very low demand are unserved. This arises a planning and political dilemma as the system as a whole is better off by making minor market segments worse-off (i.e. not catering for the long tail), compromising the notion of a universal service.

The optimal solution corresponded to the system-optimum flow distribution. Even though model formulation allows for rerouting vehicles to attain global system optimum conditions, only in extreme cases a minority of the vehicle flow is not assigned to the shortest route. In the futuristic scenario that several competing operators can in real-time reroute the automated rail-bound vehicles, system performance may shift away from system optimum conditions. The implications of competing ADR service providers can be studied by adjusting the objective function used in this study to guarantee user-equilibrium conditions.

Since this study is pioneering in the public transport system it envisages, model specification required making a series of assumptions about plausible characteristics of prospective automated rail-ADR systems. A series of sensitivity analyses was performed to test the impacts of even extreme deviations from the assumed values on model outputs. Future developments are expected to allow finer specifications of technological and service features such as the link speed-density function, the station platforms queuing regime and related assumptions, including the consideration of a heterogeneous fleet composition. Modelling fleet size as a decision variable rather than determining it endogenously will allow explicitly investigating its impact on passenger travel time. Furthermore, changes in service performance should be examined in relation to temporal dynamics of the demand level and distribution patterns. Once considering stochastic demand patterns – which are higher at the OD level than at the more aggregate directional demand in conventional systems – the risk of denied boarding due to binding vehicle capacity limits also becomes relevant.

Future research may investigate whether the results attained in this study hold for a large variety of network structure designs and the potential breakeven point in terms of service performance and overall system costs in relation to existing fixed scheduled services. While the value of network redundancy for rail system performance under disruptions has been established ([Jenelius and Cats, 2015](#)), our findings suggest that in the context of on-demand transport, network redundancy is an important determinant of system efficiency under normal operations. Furthermore, infrastructure utilization can be further increased by allowing for a more flexible on-demand service, including ride-matching capabilities that involve detours. Assessing the potential of such a service concept requires developing a model which can capture the potential shareification among different OD pairs.

This study examined the long-term planning consequences of offering a new transportation technology and service concept. In order to test its potential to substitute the existing rail service, current demand levels were tested in the application. Future behavioural research is needed to assess traveller's perceptions and preferences towards such services and potential changes in demand patterns that may be caused by the introduction of ADR services. This will potentially allow considering passenger demand as an endogenous variable in the optimisation model. For example, the service might have consequences for station attractiveness due to the increased correlation between service frequency and demand for specific connections. This may also have ramifications for network structure design and service availability.

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Supplementary materials

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