Artificial Neural Networks for forecasting passenger flows on metro lines

Mariano Gallo, Giuseppina De Luca, Luca D'Acierno, and Marilisa Botte

Abstract—Forecasting users' flows on transportation networks is a fundamental task of *Intelligent Transport Systems* (*ITSs*); indeed, most control and management strategies on transportation systems are based on the knowledge of user flows. For implementing ITS strategies, the forecast of user flows on some network links obtained as a function of user flows on other links (for instance, where the data are available in real-time) may be a significant contribution. In this paper, we propose the use of *Artificial Neural Networks* (*ANNs*) for forecasting metro onboard passenger flows as a function of passenger counts at stations' turnstiles. We assume that metro station turnstiles allow collecting the number of entering passenger by means of an automatic counting system and these are available every some minutes (temporal aggregation); the objective is to estimate on-board passengers on each track section of the line (i.e. between two successive stations) as a function of turnstiles' data collected in the previous periods. The choice of the period length may depend on service schedules. Artificial Neural Networks are trained by using simulation data obtained with a dynamic loading procedure of the rail line; the proposed approach is tested on a real-scale case: the Line 1 of the Naples metro system (Italy). Numerical results show that the proposed approach is able to forecast the flows on metro sections with satisfactory precision.

Keywords—Artificial Neural Networks, metro, transportation, user flow forecast.

M. Gallo is with the University of Sannio, Department of Engineering, Benevento, 82100, Italy (phone: +39 0824 305565; fax: +39 0824 325246; e-mail: gallo@unisannio.it).

G. De Luca is with the University of Sannio, Department of Engineering, Benevento, 82100, Italy (e-mail: pideluca@unisannio.it).

L. D'Acierno is with the Federico II University of Naples, Department of Civil, Architectural and Environmental Engineering, Naples, 80125, Italy, (e-mail: luca.dacierno@unina.it).

M. Botte is with the Federico II University of Naples, Department of Civil, Architectural and Environmental Engineering, Naples, 80125, Italy, (e-mail: marilisa.botte@unina.it).

I. INTRODUCTION

THE knowledge of user flows on transportation systems is crucial for implementing control and management policies. In this context, the monitoring systems assume a central role and are diffused in many road and rail networks: they are one of the most important (and necessary) components of *Intelligent Transport Systems* (*ITSs*).

Monitoring systems are based on sensors (or detectors) that measure some characteristics of flows and transmit them to a control room, where these data are used for implementing control and management strategies. For instance, to know traffic flows on a road network is useful for implementing flow-responsive traffic-signal systems, while the user loads on public transport vehicles can be used for real-time scheduling/rescheduling tasks.

Despite their usefulness, monitoring systems are not always provided on road and rail networks or, sometimes, implemented systems do not have enough sensors to collect the data necessary to control and management strategies. Indeed, the costs of these systems require significant investments from public administrations or public transport firms that, often, are not admittable.

In this paper, we focus on metro lines, where the accesses are controlled with turnstiles, which can count the passengers entering each station, with or without identifying their direction (in most of the existing stations, except the terminals, passengers can board on trains with different directions). These data can be easily collected every some minutes (e.g., fifteen-minute intervals) without installing new sensors. The objective of this paper is to propose a method for estimating the number of passengers on each segment of a metro line, knowing the data at turnstiles.

In the following, we propose to use *Artificial Neural Networks* (*ANNs*) for estimating the onboard passengers of a metro line, using as input data the counts at turnstiles.

The paper is organised as follows: section II examines the background; section III describes the problem to solve and the ANN approach; the method adopted for generating the data used in numerical tests is reported in section IV; section V describes the case study and the results; section VI concludes

and identifies some research prospects.

II. BACKGROUND

A. Artificial Neural Networks

The Artificial Neural Network (ANN) is a mathematical method that is widely used for reproducing several physical phenomena and forecasting the results of some actions on (or variations of) the parameters/variables of the system. ANNs are considered black-boxes since the functions and the relationships between inputs and outputs are hidden, not known and, generally, not interpretable.

Both the strengths and weaknesses of ANNs are related to their black-box approach. ANNs can reproduce a phenomenon or approximate a function without making explicit the parameters; moreover, once trained, they are able to give the results rapidly. On the other hand, the trained ANNs are not extendible even to similar cases and work only if the boundary conditions do not change significantly.

ANNs were introduced in [1]-[3]; other pioneering contributions can be found in [4]-[8]. Some general books are [9]-[14], while some literature reviews can be found in [15]-[21].

B. Transportation flow forecasting and ANN approaches

Two main types of transportation flow forecasting problems can be identified: i) short-term forecasting and ii) traffic data spatial extension. A review can be found in [22].

The first problem aims to forecast the traffic flows (or user flows) that cross a road section (or use a transit line) in a future time interval, using the data measured in the previous time intervals in the same section. This problem is widely studied in the literature and a complete review should deserve a specific paper; hence, we refer to [23], [24] that have reviewed the problem. This problem has been tackled with several approaches, and the ANNs have been widely used too [25]-[44].

The second problem, instead, aims to estimate the traffic flows (or user flows) on some components of a network (e.g., roads links, transit links, etc.), using the data measured on other components. This problem was less studied in the literature [43], [44]; recently, Gallo and De Luca [45] proposed an ANN approach that has given good results on a real-scale road network.

III. PROBLEM DESCRIPTION AND ANN APPROACH

We assume that turnstiles control all accesses to a metro line: each user, entering a station, uses a ticket (or a pass) for crossing the turnstile. Moreover, the turnstiles are able only to count users entering the station without linking the origin of each trip with the corresponding destination. This situation is common in many metro lines, as Line 1 of the Naples metro system (Italy) that will be the object of the real-scale test. Often, indeed, the turnstiles are installed only for facilitating the ticket control/validation and avoiding no-ticket trips, and, in urban contexts, the ticket is the same regardless of the origin-destination pair. In the following, we will consider two cases: a) turnstiles at the station entrance that measure only the entering passengers, without any indication on the direction that they will follow; b) turnstiles at the accesses to the platforms that give information also on the trip direction.

The data collected by turnstiles can be used, with a low technologic investment, for implementing a monitoring system of the whole metro line, generating information about the passengers on each railway section (between two stations). This information can be very useful to metro operators for implementing real-time strategies, such as a frequency increase or reduction, the definition of train composition (number of passenger carriages), the scheduling of additional runs, and so on.

The problem to solve is the estimation of loads on the line starting from turnstile data. For solving this problem, we propose to use feedforward ANNs, which are suitable because a) it is not necessary to explicitly know the relationships between inputs and outputs, b) the results are obtained rapidly, and c) usually, the boundary conditions do not change so much to invalidate the forecasts.

The structure of the ANN provides an input layer with a node for each turnstile datum, an output layer with a node for each convoy load datum, and one or more hidden layers. The best structure of the ANN has to be designed for each specific problem. A crucial point is related to the dynamic nature of the problem; indeed, the train moves along the line and loads and unloads passengers at stations in different time intervals. Therefore, onboard passengers between two stations at time t depends on the passengers loaded and unloaded to the previous stations at different times $< t$. For this reason, the inputs of the ANN have to regard turnstile counts referring to more time intervals preceding the ones under forecast. The number of inputs will depend on the travel time duration between terminals.

The other crucial point is the training phase of ANNs; here we propose to use a supervised learning method, where the example datasets are generated through dynamic simulation models (see section IV).

IV. GENERATION OF TRAINING DATASETS

To generate the training datasets, we use the simulation model proposed in [46]; this model assumes that:

1) platforms can accommodate all passengers (incoming, waiting and outgoing);

2) at each station and for each direction there is only one platform available;

3) the dwell time is constant and independent on the number of passengers alighting and boarding;

4) there is no interaction between alighting, boarding and waiting passengers;

5) the capacity of each train is fixed;

6) passengers are distributed uniformly among the train coaches;

7) there is no interaction in the train between alighting, boarding and onboard passengers.

In our test, we assume that the passengers follow a *FIFO* (*First In-First Out*) rule for boarding the convoy. The analytic details of the model can be found in [46].

Using this model, we generate the training datasets on the case study as follows: a) numerous origin-destination (OD) matrices referring to 15' intervals are randomly generated starting from a base OD matrix; b) four OD matrices, referring to four time intervals, are assigned to the metro line, giving as results the passengers counted at turnstiles, for each interval, and the passengers onboard in each railway section in the next time interval; c) the output data of the problem are the passengers on railway sections, while the input data are the passengers counted at turnstiles in four time intervals, corresponding to the four previous 15' periods (e.g., flows on railway sections between 10:15 and 10:30 are calculated in function of the turnstile counts in the following intervals: 9:15-9:30, 9:30-9:45, 9:45-10:00 and 10:00-10:15). Therefore, the structure of the training datasets is reported in Fig. 1, where the following notations are used:

ds is the number of datasets;

t is the period under analysis;

$c^i_{j,t}$ is the passenger count at turnstile j in period t for dataset i;

$f^i_{k,t}$ is the load on railway section k in period t for dataset i.

Dataset →	1	2	...	*ds*
Period t =	$t_{in\text{-}fin1}$	$t_{in\text{-}fin2}$	...	...
Input data				
Turnstile 1 - Period t-1	$c^1_{1,t\text{-}1}$	$c^2_{1,t\text{-}1}$	...	$c^{ds}_{1,t\text{-}1}$
Turnstile 2 - Period t-1	$c^1_{2,t\text{-}1}$	$c^2_{2,t\text{-}1}$	...	$c^{ds}_{2,t\text{-}1}$
...	...	...	...	...
Turnstile ts - Period t-1	$c^1_{ts,t\text{-}1}$	$c^2_{ts,t\text{-}1}$	...	$c^{ds}_{ts,t\text{-}1}$
Turnstile 1 - Period t-2	$c^1_{1,t\text{-}2}$	$c^2_{1,t\text{-}2}$	...	$c^{ds}_{1,t\text{-}2}$
Turnstile 2 - Period t-2	$c^1_{2,t\text{-}2}$	$c^2_{2,t\text{-}2}$	...	$c^{ds}_{2,t\text{-}2}$
...	...	...	...	...
Turnstile ts - Period t-2	$c^1_{ts,t\text{-}2}$	$c^2_{ts,t\text{-}2}$	...	$c^{ds}_{ts,t\text{-}2}$
Turnstile 1 - Period t-3	$c^1_{1,t\text{-}3}$	$c^2_{1,t\text{-}2}$	...	$c^{ds}_{1,t\text{-}2}$
Turnstile 2 - Period t-3	$c^1_{2,t\text{-}2}$	$c^2_{2,t\text{-}3}$	...	$c^{ds}_{2,t\text{-}3}$
...	...	...	...	...
Turnstile ts - Period t-3	$c^1_{ts,t\text{-}3}$	$c^2_{ts,t\text{-}3}$	...	$c^{ds}_{ts,t\text{-}3}$
Turnstile 1 - Period t-4	$c^1_{1,t\text{-}4}$	$c^2_{1,t\text{-}4}$	...	$c^{ds}_{1,t\text{-}4}$
Turnstile 2 - Period t-4	$c^1_{2,t\text{-}4}$	$c^2_{2,t\text{-}4}$	...	$c^{ds}_{2,t\text{-}4}$
...	...	...	...	...
Turnstile ts - Period t-4	$c^1_{ts,t\text{-}4}$	$c^2_{ts,t\text{-}4}$	...	$c^{ds}_{ts,t\text{-}4}$
Output data				
Railway section 1 - Period t	$f^1_{1,t}$	$f^2_{1,t}$	...	$f^{ds}_{1,t}$
Railway section 2 - Period t	$f^1_{2,t}$	$f^2_{2,t}$	...	$f^{ds}_{2,t}$
...	...	...	...	...
Railway section rs - Period t	$f^1_{rs,t}$	$f^2_{rs,t}$	...	$f^{ds}_{rs,t}$

Fig. 1 Structure of training datasets for period t

V. CASE STUDY AND NUMERICAL RESULTS

The proposed approach has been tested on Line 1 of the Naples metro. This line (see Fig. 2) is long 18 km and has 18 stations; it connects high-density districts of Naples and is a crucial infrastructure for urban mobility.

Considering these characteristics, we have 18 or 34 turnstiles, if we do not divide the passengers in function of the direction or vice versa, and 34 mono-directional railway sections. The main features of the line are summarised in Table I.

The training datasets were obtained by simulating 2,500 OD matrices generated randomly; eliminating some of them because their results were not feasible (too many passengers compared to the actual capacity), we generated 2,279 training datasets. Among them, 2,229 were used for training the ANNs

with the software MatLab, and 50 were used for verifying the results. We have tested six structures of ANNs for both cases: a) turnstiles at the entrance of the station (18 turnstiles), and b) turnstiles at the accesses to the platforms (34 turnstiles). Therefore, we have trained and tested 12 ANNs, as reported in Table II.

Table I Features of Line 1

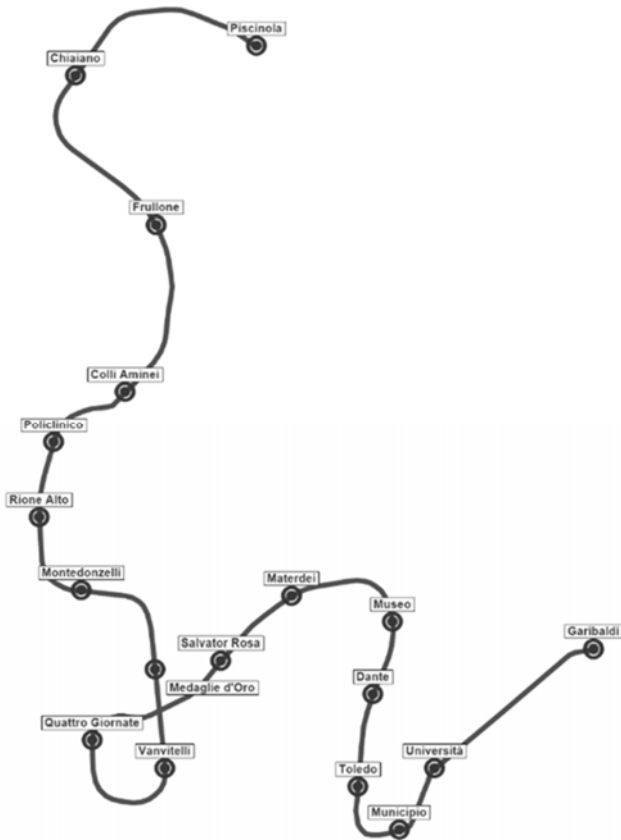| Stations	18
Working day runs	241
Convoy capacity (pax/convoy)	864
Line length (km) (outward/return direction)	18.8/18.6
Headway (min)	8-20

Fig. 2 Line 1 route

Table II Trained and tested ANNs

Case	ANN	Input nodes	Output nodes	Hidden layers	Neurons
a	a_1_6	72	34	1	6
a	a_1_10	72	34	1	10
a	a_1_20	72	34	1	20
a	a_2_6	72	34	2	6/6
a	a_2_10	72	34	2	10/10
a	a_2_20	72	34	2	20/20
b	b_1_6	136	34	1	6
b	b_1_10	136	34	1	10
b	b_1_20	136	34	1	20
b	b_2_6	136	34	2	6/6
b	b_2_10	136	34	2	10/10
b	b_2_20	136	34	2	20/20

The training phase has required computing times from 30 seconds (case a_1_6) to 8 minutes (case b_2_20), with a PC i7-7700HQ, 2,80 GHz, RAM 16 GB. In Table III we report the best and worst coefficients of determination (R^2) for each case, referring to the 50 datasets not used in the training phase, and the corresponding values of average and variance. The datasets for which the R^2 value is lower than 0.9, 0.8, 0.7 and 0.6 are reported in Table IV. In these tables, the best values for each ANN are underlined.

Examining the results reported in Tables III and IV, we may identify as best ANN structures the one with 1 hidden layer and 20 neurons for the case a), and 2 hidden layers and 10 neurons for the case b). The corresponding dispersion diagrams in the cases of best and worst R^2 are reported in Figs. 3 and 4.

Table III Coefficients of determination (R^2)

ANN	Best	Worst	Average	Variance
a_1_6	0.9946	0.5487	0.7984	0.0124
a_1_10	0.9941	0.4990	0.8108	0.0160
a_1_20	0.9931	0.5613	0.8332	0.0157
a_2_6	0.9916	0.5353	0.7949	0.0121
a_2_10	0.9930	0.4638	0.8136	0.0175
a_2_20	0.9933	0.5342	0.8244	0.0162
b_1_6	0.9875	0.5460	0.8016	0.0129
b_1_10	0.9905	0.3505	0.8115	0.0202
b_1_20	0.9882	0.4226	0.8291	0.0160
b_2_6	0.9785	0.5119	0.7775	0.0132
b_2_10	0.9889	0.4935	0.8221	0.0132
b_2_20	0.9852	0.4492	0.8075	0.0245

Table IV Analysis of R^2 values

ANN	$R^2 < 0.9$	$R^2 < 0.8$	$R^2 < 0.7$	$R^2 < 0.6$
Number of datasets				
a_1_6	41	25	9	4
a_1_10	36	22	7	4
a_1_20	33	18	7	3
a_2_6	43	25	10	3
a_2_10	35	21	8	4
a_2_20	34	19	9	5
b_1_6	37	24	10	2
b_1_10	34	23	8	5
b_1_20	32	19	8	3
b_2_6	43	25	10	6
b_2_10	35	20	7	2
b_2_20	30	21	9	7
Percentage of datasets				
a_1_6	82%	50%	18%	8%
a_1_10	72%	44%	14%	8%
a_1_20	66%	36%	14%	6%
a_2_6	86%	50%	20%	6%
a_2_10	70%	42%	16%	8%
a_2_20	68%	38%	18%	10%
b_1_6	74%	48%	20%	4%
b_1_10	68%	46%	16%	10%
b_1_20	64%	38%	16%	6%
b_2_6	86%	50%	20%	12%
b_2_10	70%	40%	14%	4%
b_2_20	60%	42%	18%	14%

VI. CONCLUSIONS AND RESEARCH PROSPECTS

In this paper, we proposed to use ANNs for forecasting passenger flows on railway sections of a metro line starting from counts at turnstiles. We considered two cases: turnstiles at station entrances and turnstiles at platform accesses. For both, we designed and trained some ANNs.
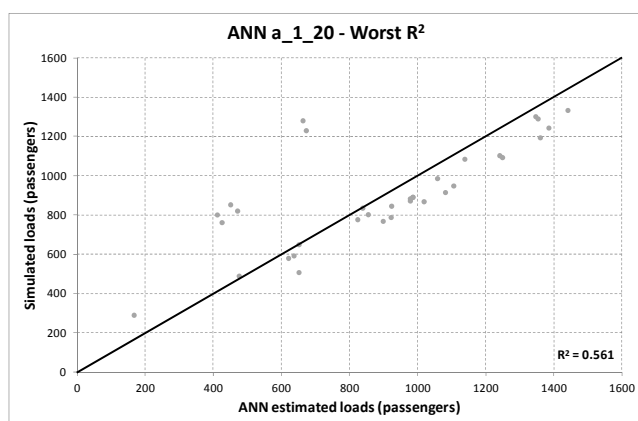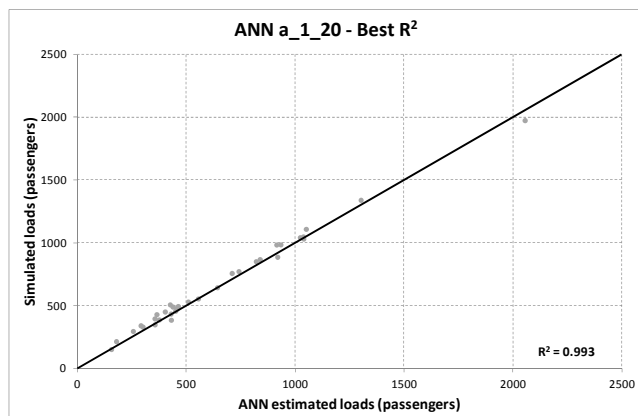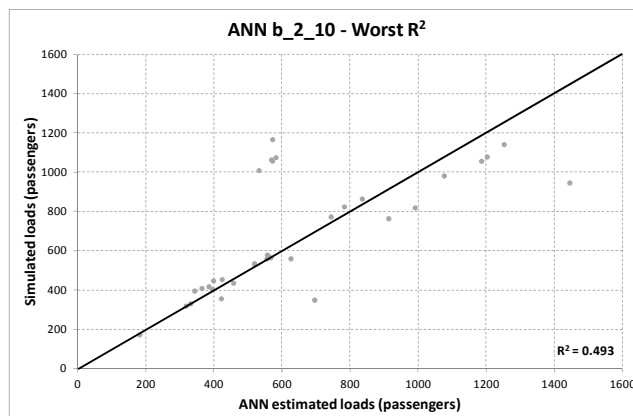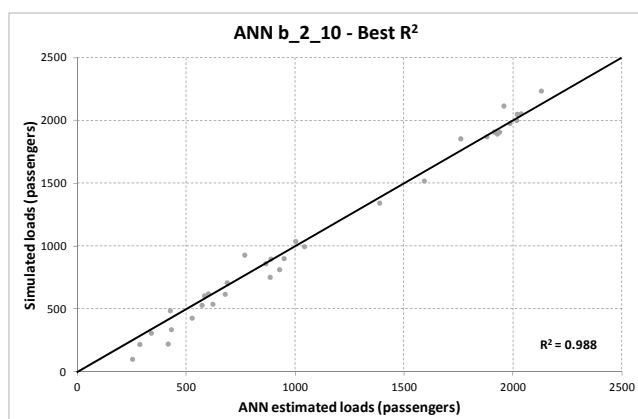
Fig. 4 Dispersion diagrams ANN b_2_10

Fig. 3 Dispersion diagrams ANN a_1_20

The results showed a good capacity of ANNs to forecast the loads on railway sections. Our analysis allowed us to identify the best ANN structure for each case.

However, these results have to be considered only preliminary. Indeed, in future works we propose to: 1) test other ANN structures; 2) train a different ANN for each railway section, considering only some turnstile counts (the ones that forego the section under analysis); 3) propose deep learning approaches.

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