

## Article

# Modelling and Forecasting Passenger Rail Demand in Slovakia Under Crisis Conditions with NARX Neural Networks

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## Abstract

Transportation systems are particularly vulnerable to disruptions such as pandemics, which create significant challenges for maintaining efficiency, safety, and service quality. This study focuses on rail passenger transport in the Slovak Republic and develops a simulation framework to evaluate system performance under crisis conditions. Weekly data from the national rail operator for the period 2019–2021 were combined with information on governmental restrictions, standardized into a five-level framework. A nonlinear autoregressive model with exogenous inputs (NARX), implemented and validated in MATLAB R2021b (MathWorks, Natick, MA, USA), was applied to simulate the impact of restrictive measures on passenger demand. The results revealed a strong relationship between the severity of measures and ridership levels, with the most significant effects observed in education, workplace access, movement limitations, and retail. For instance, during complete school closures, passenger volumes declined by up to 75% relative to the pre-pandemic baseline. Based on the simulation outcomes, recommendations were formulated for adapting railway operations, including dynamic adjustments of transport capacity (10–40%) according to restriction levels. The proposed modelling and simulation approach offers transport authorities a cost-effective tool for scenario testing, disruption management, and the design of resilient passenger rail systems capable of adapting to crises and uncertainties.

**Keywords:** railway passenger transport; pandemic; disruption management; NARX neural network; mobility modelling; sustainable and resilient transportation



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## 1. Introduction

Population mobility is one of the key determinants of economic and social development. In a globalized world, where frequent movement of people at regional, national, and international levels is expected, societies have also become increasingly vulnerable to various crisis situations [1]. Among the most significant of these was the COVID-19 pandemic, which profoundly affected the functioning of transport systems and exposed their weaknesses in terms of flexibility and preparedness to respond to unforeseen circumstances [2].

Given today's high levels of mobility, it is reasonable to expect that crisis situations caused by epidemics will continue to emerge [3,4], whether at global, continental, national,

or regional scales [5,6]. It is therefore crucial for transport authorities to respond effectively to ensure safe and high-quality mobility for the population, while at the same time considering the economic sustainability of transport services [7,8]. A sound forecast of transport demand development is fundamental for such decision-making. In this research, data from the COVID-19 pandemic were used to develop a model for predicting mobility in rail transport, with a specific focus on the regional dimension of epidemic situations.

In rail passenger transport, which plays a crucial role in ensuring the daily mobility of the population, pandemic restrictions resulted in a dramatic decline in travel demand [9–12]. Measures affecting education, workplace access, free movement, and retail substantially reduced passenger numbers, with significant economic consequences for railway operators as well as for the state [13,14]. At the same time, it became evident that traditional approaches to transport planning and organization are insufficient to cope with crisis situations of this scale. Although numerous studies have investigated the impact of the COVID-19 pandemic on transport demand, most focus on countries with railway networks, mobility patterns, and policy frameworks that differ from those of Central and Eastern Europe. For the Slovak Republic, where long-distance commuting and a strong regional dimension are key features, no comprehensive, data-driven simulation of passenger rail demand under crisis conditions has yet been published. This study addresses this gap by developing and validating a neural network-based NARX model tailored to Slovak regional data and pandemic measures. The approach not only quantifies the relationship between restrictions and rail ridership but also provides practical recommendations for adaptive capacity management—a perspective missing in existing European research.

Accurate forecasting of transport demand during a pandemic or other extraordinary situation is therefore an essential prerequisite for effective decision-making by transport authorities. Modelling population mobility while accounting for the dynamics of restrictive measures not only provides deeper insights into passenger behaviour [15] but also enables the design of interventions aimed at reducing social costs and optimizing the operation of the transport system [16,17].

Particular attention in this study is devoted to the regional perspective, as movements between neighbouring regions and districts were heavily restricted during the pandemic. The objective is to ensure that the proposed model can also be applied in crisis situations of a more local character.

The development of the rail transport model was divided into several partial steps:

- A review of the scientific literature addressing the modelling of pandemic impacts on mobility (passenger numbers, capacity utilization, etc.);
- An analysis of adopted pandemic measures and their transformation into a form suitable for model development;
- Collection and processing of passenger mobility data in rail transport;
- Model creation;
- Evaluation of model results.

Based on the constructed data-driven model, which predicts the evolution of rail passenger mobility according to the severity of implemented measures, recommendations were subsequently formulated for adjusting technological processes in rail transport and for adapting railway operations to regional, national, and international conditions.

The aim of this study is therefore to analyse the demand for rail passenger transport in the Slovak Republic during the COVID-19 pandemic and based on empirical data, to develop a modelling framework capable of predicting mobility dynamics under different levels of restrictions. Although the primary analysis uses national-level patterns, the approach is designed to capture potential regional differences and remains applicable to region-specific crisis scenarios. The findings are intended to contribute to more effective

transport policy planning, improved capacity management for rail operators, and enhanced resilience of the transport system to future crises.

This study contributes to the broader field of transportation system modelling and simulation by demonstrating how machine learning techniques can be applied to evaluate system performance under disruption. The proposed framework not only captures the nonlinear relationship between restrictive measures and passenger demand but also enables scenario testing, supporting decision-makers in planning adaptive and cost-effective transport operations. In line with the objectives of this Special Issue, the findings highlight how simulation-based approaches can enhance resilience, optimize resource allocation, and reduce the vulnerability of transportation systems to future crises.

## 2. Literature Review

The issue of modelling the impact of the COVID-19 pandemic on population mobility has been the subject of intensive scientific research since 2020. Recent research confirms that modelling and simulation have become indispensable tools for assessing the resilience and performance of transportation systems under disruptive conditions such as the COVID-19 pandemic. Beyond quantifying passenger losses, these approaches enable scenario testing, provide insights into behavioural responses, and help decision-makers design adaptive strategies for crisis management. Against this backdrop, the present literature review summarizes the diversity of methods employed internationally and highlights the gap for studies focused on rail passenger transport in Central and Eastern Europe, particularly under regional conditions. Table 1 provides a concise overview of several studies [18–37] of the modelling approaches used to examine the effects of the COVID-19 pandemic on mobility, categorized by author and the country for which the model was developed.

**Table 1.** Modelling the impact of COVID-19 on transport—literature review.

Author	Case Study	Domain	Dependent Variable	Explanatory Variable	Modelling Approach
Singh et al. (2023) [18]	Netherlands	Rail passenger travel	Number of train passengers, overcrowding level, delay schedule, departure time	Overcrowding, occupancy, delay, fare discount	Latent class cluster model
Deplomo et al. (2021) [19]	Philippines	Passenger transport	Number of passengers	–	Polynomial regression
Lei et al. (2020) [20]	China	Rail passenger travel	Number of train passengers	–	Spreading model
Elias and Zatmeh-Kanj (2021) [21]	Israel	Travel risk and decisions	Travel risk and decision to use rail	Frequency, socio-economic characteristics, demographic factors	Structural equation model
Ferreira et al. (2022) [22]	Germany	Travel demand	Number of trips	Frequency	Conditional logit model
Zhang et al. (2021) [23]	Australia, Canada, Japan, New Zealand, UK, USA	Policy impacts on mobility	Political measures, passenger movements	–	Dynamic Bayesian multilevel generalized structural equation model
Guo et al. (2021) [24]	Honolulu (Hawaii)	Public transport ridership	Number of passengers	Frequency	Negative binomial models, Pearson correlation
Bian et al. (2021) [25]	New York, Seattle (USA)	Policy delays and mobility	Infections, vehicle volume, passenger volume, bicycle counts	Policy delay variables	Odds ratio, regression structure, Bayesian change-point detection

Table 1. Cont.

Author	Case Study	Domain	Dependent Variable	Explanatory Variable	Modelling Approach
Tan and Ma (2020) [26]	China	Selected rail transport	Travel characteristics	Fare attributes, COVID-19 perception	Logit model, binary logistic regression
Molin and Kroesen (2022) [27]	Netherlands	Travel behaviour and safety	Infection risk perception, referendum voting	Political measures	Latent class choice model, mediation model, linear regression, binary logistic regression
Ding and Zhang (2021) [28]	Japan	Policy making	Behavioural changes of respondents	–	Dynamic structural equation model
Carteni et al. (2021) [29]	Italy	Accessibility	Transport accessibility	Socio-economic, territorial and environmental factors	Multiplicative linear regression
Coppola and De Fabiis (2021) [30]	Italy	Rail demand	Boarding and alighting	Timetables, vehicles, onboard layout	Demand forecasting model
Ding et al. (2023) [31]	Shanghai (China)	Passenger experience	Regular services, pandemic prevention, psychological distancing, safety perception, satisfaction	–	Structural equation model
Haque and Hamid (2022) [32]	India	Capacity allocation	Seat assignment	Capacity utilization	Mixed-integer linear programming
Vichiensan et al. (2021) [33]	Bangkok (Thailand)	Trust and awareness	Trust, awareness, distancing, health measures, contact-tracing app	–	Factor analysis, structural equation model
Navarrete-Hernandez et al. (2023) [34]	London (UK), Milan (Italy), Santiago (Chile)	Perceptions of infection risk	Perceived risk	Government measures	Photo-simulation approach in randomized controlled trial
Thaithatkul et al. (2023) [35]	Bangkok (Thailand)	Travel frequency	Frequency of trips	Online activities, socio-economic factors, COVID-19-related behaviours and attitudes	Random effects models, WBRE
Haque and Hamid (2023) [36]	India	Train capacity planning	Distance, urban planning, boarding and alighting	Train capacity	Mixed-integer programming (MIP), integrated MILP
Abdullah et al. (2021) [37]	Pakistan	Mode choice	Mode preference	Mode of transport	Exploratory factor analysis (EFA)

While several studies have used machine learning to analyse pandemic-related changes in travel demand, most focused on aggregated urban mobility or road traffic and rarely addressed national or regional passenger rail. Only a few works experimented with neural networks, but they typically used simple architectures (feedforward or LSTM) without explicit integration of government intervention indicators. Our approach differs by (i) applying a nonlinear autoregressive model with exogenous inputs (NARX) tailored to rail demand, (ii) directly encoding the intensity of restriction measures as explanatory variables, and (iii) testing applicability in a small, highly centralized railway system such as Slovakia. This extends previous machine-learning applications beyond descriptive analysis and towards actionable demand forecasting under crisis conditions. The literature review (Table 1) shows that most studies focused on quantifying the decline in passenger numbers in rail or urban public transport in relation to the introduction of pandemic restrictions. A significant share of research analysed the impact of these measures on travel behaviour, trip frequency, or passengers' risk perception. Studies such as [18,27,38] examined factors

influencing passenger decision-making, highlighting the key role of overcrowding and the subjective perception of safety. Other studies [19,20,39,40] concentrated on predicting passenger volumes through regression or spreading models.

A specific strand of research has been the evaluation of the effectiveness of policy and organizational measures. Studies such as [23,34] point out that the type and timing of restrictions significantly shape mobility levels, with public trust playing an important role. Similarly, the studies [29,41] emphasized that transport accessibility and territorial characteristics are decisive factors in both the spread of the virus and the subsequent decline in mobility.

The literature also demonstrates that the pandemic's impact was not homogeneous. Regional differences, as documented in studies such as [24] for Honolulu or [25] for New York and Seattle, indicate that local conditions and transport infrastructure strongly influence passenger behaviour. Equally important is the psychological dimension, addressed by [28], who argue that changes in population behaviour are crucial in shaping transport policy during crises.

As shown in Table 1, existing studies predominantly analyse pandemic-related changes in passenger transport at a national or aggregated urban level and rarely address the specific conditions of Central and Eastern Europe. None of the reviewed works explicitly modelled the Slovak passenger rail system, which features a strongly centralized network and high regional commuting flows, nor did they integrate governmental restriction measures into a nonlinear predictive framework. Our study addresses this gap by developing a regionally applicable, data-driven NARX neural network model tailored to Slovak pandemic conditions and evaluating its potential for adaptive railway capacity management.

Previous studies have thus provided a wide range of methodological approaches and empirical evidence on the impact of the pandemic on mobility. However, most of this research has been carried out in countries with transport systems and mobility structures that differ from those of the Slovak Republic. This highlights the need to develop a model reflecting the specific regional and national conditions, one that can not only analyse the impacts of the pandemic but also propose measures for more effective management of rail transport in future crisis situations.

### 3. Data and Research Methodology

A high-quality database is a fundamental prerequisite for developing a reliable model of rail passenger transport demand under crisis conditions. In our research, we worked with two main types of data:

- Qualitative data, representing government measures introduced to contain the spread of COVID-19;
- Quantitative data, capturing passenger mobility in rail transport.

These two sources of information had to be aligned to analyse the relationship between the dynamics of implemented measures and changes in passenger volumes. At the same time, it was necessary to transform and harmonize the data into a unified structure suitable for processing in the modelling environment.

We worked with weekly data, which represent an appropriate compromise between detail and statistical stability. While daily data would provide higher resolution, they are characterized by substantial variability caused by seasonality and short-term fluctuations. Monthly data, on the other hand, would not allow us to capture passengers' rapid responses to changing pandemic measures.

On the quantitative side, we used a comprehensive database provided by the national rail operator (ZSSK), which accounts for more than 97% of passenger rail services in the Slovak Republic. This ensures that the data are sufficiently representative for the entire

country. On the qualitative side, we drew from official government sources, primarily the COVID automat, which specified the type and severity of restrictions during different periods. The resulting integrated database provides the foundation for linking adopted measures with changes in rail mobility, thus forming the basis of the modelling framework.

The methodological approach of this study integrates the systematic collection and transformation of data with advanced time-series modelling techniques. First, qualitative and quantitative data on rail passenger mobility and pandemic measures were gathered and harmonized into a unified database. Then, seasonality was analysed and removed to obtain stable input variables. These prepared datasets were subsequently applied to a Nonlinear Autoregressive model with Exogenous Inputs (NARX), a neural network-based technique well-suited for forecasting non-stationary and nonlinear time series. This process ensured that the modelling framework is robust, data-driven, and capable of reflecting the dynamic effects of government restrictions on passenger demand.

### 3.1. COVID Automat Data—Slovak Republic

During the COVID-19 pandemic, several nationwide measures were introduced in the Slovak Republic to limit the spread of the virus. Since 2021, the so-called COVID automat (it is a government traffic-light system defining the intensity of restrictions based on the epidemiological situation in individual districts) was applied. This tool represented the primary source of qualitative data for our research.

The COVID automat was modified several times during the observation period. From January to August 2021, it operated in a seven-level version, while from August until the end of November 2021, it was transformed into a five-level system. For modelling purposes, it was necessary to harmonize these differences; therefore, the original seven-level system was consolidated into a unified five-level framework, as shown in Table 2.

**Table 2.** COVID automat in the Slovak Republic.

7-Level COVID Automat	5-Level COVID Automat	Colour
Monitoring	Monitoring	Green
First level of vigilance	Vigilance	Orange
Second level of vigilance		
First level of warning	First level of threat	Red
Second level of warning		
Third level of warning	Second level of threat	Burgundy
Fourth level of warning	Third level of threat	Black

This transformation ensured data consistency and enabled comparability across different periods. The framework incorporated measures in key areas that most significantly influenced passenger mobility, in particular:

- Restriction of movement;
- Entry into employment;
- Limiting the operating hours of non-essential operations and services;
- Education;
- Mass events;
- Shops;
- Services;
- Shopping centres;
- Restaurants;
- Accommodation (hotels, pensions, etc.);
- Taxi services.

The data was processed on a weekly basis for all measures using MS Excel spreadsheets. An example of data processing for schools is illustrated in Figure 1.

Region	Number of the week in 2021										
	37	38	39	40	41	42	43	44	45	46	47
Bratislava	0	1	1	1	1	2	2	3	3	3	4
Tnava	2	3	3	3	3	3	3	3	3	3	4
Trenčín	2	2	2	2	2	2	2	3	3	3	4
Nitra	1	2	2	2	2	2	2	4	4	4	4
Žilina	2	2	2	3	3	4	4	4	4	4	4
Banská Bystrica	2	3	3	3	3	3	3	4	4	4	4
Prešov	2	3	3	3	3	4	4	4	4	4	4
Košice	2	3	3	3	3	3	4	4	4	4	4
Daily cases	351	548	888	1207	1607	1942	2438	3646	5302	9103	10,780
Hospitalized pacienti	126	203	329	453	708	824	966	1223	1774	2904	3188
Revenues to hospitals	77	141	249	376	544	675	736	854	1454	x	x

Figure 1. Illustration processing of measures to prevent the spread of the COVID virus for schools in the Slovak Republic.

The data were processed in weekly intervals for all regions of Slovakia. Sources included the Epidemiological Information System (EPIS) and records from the Public Health Authority of the Slovak Republic, which provided continuous updates on the development of the pandemic situation at the district level [42].

The processing of data involved coding the measures into numerical values according to their severity. This step was necessary to enable their integration as input variables into the modelling framework. A graphical representation of the processing (for the education sector—Figure 1) illustrates how the measures were systematically transformed into the database. The resulting set of qualitative data forms the foundation for analysing the relationship between the intensity of measures and the number of passengers transported in individual regions of the Slovak Republic.

### 3.2. Data on the Mobility of Rail Passenger Transport

Many authors addressing similar issues have relied on freely available data sources (for example Google Mobility Reports). While such datasets provide useful insights into general mobility trends, they do not allow for identifying which specific mode of transport was used. Since the objective of our research is to propose technological and policy measures in the transport sector for future epidemics or pandemics, mode-specific data were required.

On the quantitative side, we used a database provided by the national rail operator, Železničná spoločnosť Slovensko (ZSSK), which accounts for more than 97% of passenger rail services in the country. For this reason, the dataset is sufficiently representative both at the national and regional levels.

The data were supplied in weekly intervals for the period 2019–2021 and structured as follows:

- The start of validity of the travel document (week of the given year);
- Origin region;
- Destination region.

Thus, we had at our disposal a comprehensive database covering passenger transport between regions as well as within individual regions. The territory of the Slovak Republic is divided into eight higher territorial units/self-governing regions (HTUs). Figure 2 shows the territorial division of the Slovak Republic together with railway lines.



Figure 2. Territorial division of the Slovak Republic.

The national rail passenger carrier provided a database covering three years, with 52 weeks recorded in 2019 and 2021 and 53 weeks in 2020. We had at our disposal a dataset capturing passenger transport flows from each region to every other region, as well as within individual regions. Each week, it was possible to monitor 64 combinations (variations with repetition) between the regions. The resulting database contained more than 10,000 records. An example of the database structure is presented in Table 3.

Table 3. Structure of the database of the number of passengers transported.

Starting Region	Beginning of the Document Validity		Destination Region	Number of Passengers
	Week	Year		
Bratislava	1	2019	Košice	...
Bratislava	2	2019	Košice	...
Bratislava	...	2019	Košice	...
Bratislava	52	2019	Košice	...
Bratislava	1	2019	Prešov	...
Bratislava	2	2019	Prešov	...
Bratislava	...	2019	Prešov	...
Bratislava	52	2019	Prešov	...
...	...	...	...	...

From a mathematical perspective, these combinations represent variations with repetition, which can be expressed by the Formula (1):

$$V'_k(n) = n^k \tag{1}$$

where:

- $n$  number of elements (number of HTUs),
- $k$   $k$ -element variation (in this case, from one HTU to another;  $k = 2$ ).

The number of data entries for one week is 64, which means that we had a total database of 10,048 records available. When processing the data, it was necessary to consider the actual geography of the routes. For example, if a journey occurred between the Bratislava and Košice regions, we assumed the use of the main railway corridor via Trnava,

Trenčín, Žilina, and Prešov. This approach was based on empirical data from ZSSK, which showed that the alternative route via Nitra and Banská Bystrica accounted for less than 5% of all trips. Other combinations between regions were processed in an analogous way, with the assignment methodology ensuring that each trip was allocated to all regions it passed through.

The results of data processing showed that the development of passenger volumes was similar in most regions. This trend was related to the fact that, during 2020, measures were implemented predominantly at the national level. Regional differences began to appear only in 2021, when the COVID automat introduced differentiated measures according to the epidemiological situation in individual districts. However, differences between regions remained relatively small. The resulting database thus provided a robust foundation for further processing and subsequent modelling of the relationship between pandemic measures and passenger mobility in rail transport. The database in Excel is available from the authors. Since the dataset is subject to trade secrecy, it will be provided upon request only for the purpose of verifying the validity of the data, while ensuring the integrity of the trade secret.

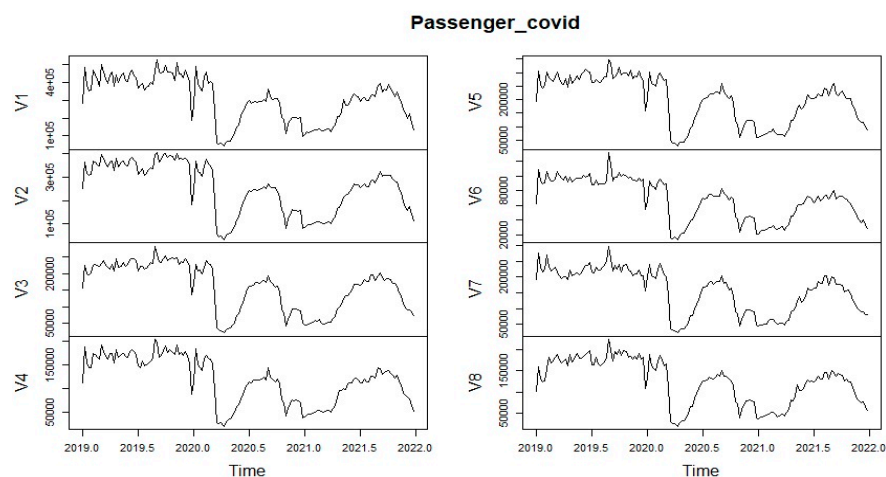
### 3.3. Adaptation of the Data for the Model

Considering that our goal was to examine how measures to prevent the spread of the virus on mobility are reflected in individual regions, we had to adjust the data obtained to know the mobility in each region by individual weeks. For example, if we had data on traffic between the Bratislava and Žilina regions (Figure 2)—we had to assign these passengers to the Trnava and Trenčín regions as well. To address this issue, we applied a methodology of allocating passengers to all regions that the journey would realistically pass through from a geographical perspective. This ensured that not only the origin and destination were considered, but also the intermediate regions traversed by the route. For instance, in the case of the Trenčín region, the weekly data included the following combinations of starting and destination regions, where Trenčín was either the origin, destination, or a transit region along the route.

- Starting region—Bratislava; destination regions—Trnava, Žilina, Prešov, Košice;
- Starting region—Trnava; destination regions—Trenčín, Žilina, Prešov, Košice;
- Starting region—Trenčín; destination regions—Bratislava, Trnava, Nitra, Trenčín, Banská Bystrica, Žilina, Prešov, Košice;
- Starting region—Nitra; destination regions—Trenčín, Žilina;
- Starting region—Banská Bystrica; destination regions—Trenčín, Trnava;
- Starting region—Prešov; destination regions—Trenčín, Trnava, Bratislava;
- Starting region—Košice; destination regions—Trenčín, Trnava, Bratislava.

If the passenger flow occurred between the Bratislava and Košice regions, or in the opposite direction, we assumed that most passengers would travel along the main corridor passing through Trnava, Trenčín, Žilina, and Prešov. This assumption was based on empirical data from ZSSK, which confirmed that the alternative route through Nitra and Banská Bystrica accounted for less than 5% of total trips.

This methodological adjustment ensured that the resulting database reflects not only the origin and destination of trips, but also the intermediate regions realistically traversed by passengers. Such an approach was essential for making the model usable at the regional level, and not merely at the national scale. The development of passenger volumes across individual regions is shown in Figure 3.



**Figure 3.** Number of passengers by region.

The number of passengers showed a similar trend across individual regions (V1—Bratislava, V2—Trnava, V3—Trenčín, V4—Nitra, V5—Žilina, V6—Banská Bystrica, V7—Prešov, V8—Košice). This was primarily because, from the beginning of the pandemic, identical measures were introduced nationwide. Only from 2021 onward were measures applied at the regional level, and even then, the differences between regions remained very small. In this form, the adapted database provided a robust foundation for modelling the relationship between pandemic-related measures and the development of mobility in rail passenger transport.

#### 4. Modelling Framework

The objective of the modelling was to investigate the relationship between the number of passengers transported by rail and the measures introduced during the COVID-19 pandemic. Since the data were available on a weekly basis, it was necessary to apply time series methods, eliminate seasonal effects, and subsequently propose an appropriate model. Traditional econometric approaches such as regression or autoregressive integrated moving average (ARIMA) models are often suitable for capturing linear dependencies in transport data. However, the extraordinary circumstances of the pandemic introduced strong nonlinearities and abrupt shifts in passenger behaviour, caused by the dynamic implementation of government measures. These conditions required a more flexible modelling framework capable of capturing complex relationships and delayed effects. For this reason, we applied a nonlinear autoregressive model with exogenous inputs (NARX) implemented through a neural network architecture. The NARX approach has proven effective in previous mobility studies, as it allows the incorporation of external inputs (in this case, the severity of pandemic measures) and is well-suited for forecasting nonlinear and nonstationary time series. This choice ensured that the model could realistically reflect the interplay between policy interventions and passenger demand, while maintaining sufficient accuracy for scenario testing and policy evaluation.

##### 4.1. Decomposition of Passenger Transportation Time Series

The evolution of the number of passengers revealed the presence of seasonal components that could distort the modelling results. Therefore, the original time series were decomposed into three parts: trend, seasonal, and random components. A simple seasonal variation model was applied to eliminate the seasonal effect.

The use of ARMA/ARIMA models was not feasible, as the stationarity test (Figure 4) confirmed the non-stationary character of the data. Specifically, the null hypothesis of

stationarity was rejected ( $p < 0.05$ ), which indicated that the dataset contained significant structural changes that standard autoregressive models could not properly capture.

```

> tseries::adf.test(Passenger_covid[,1])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 1]
Dickey-Fuller = -3.0116, Lag order = 5, p-value = 0.1546
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,2])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 2]
Dickey-Fuller = -2.7334, Lag order = 5, p-value = 0.2706
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,3])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 3]
Dickey-Fuller = -2.6809, Lag order = 5, p-value = 0.2925
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,4])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 4]
Dickey-Fuller = -2.7423, Lag order = 5, p-value = 0.2669
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,5])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 5]
Dickey-Fuller = -2.8704, Lag order = 5, p-value = 0.2135
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,6])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 6]
Dickey-Fuller = -2.7329, Lag order = 5, p-value = 0.2708
alternative hypothesis: stationary

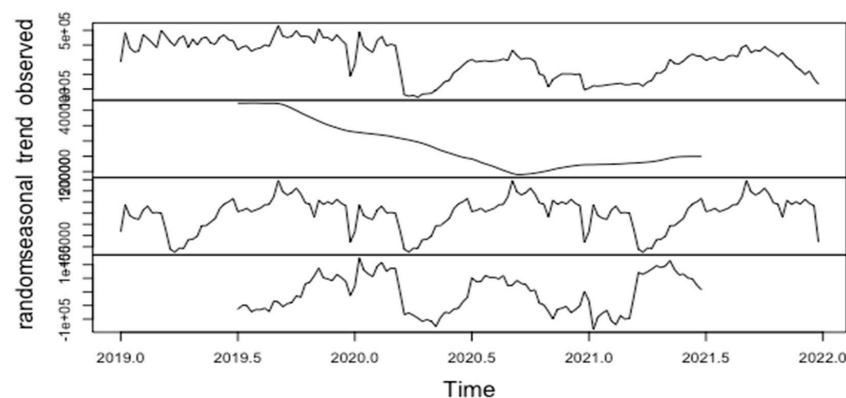
> tseries::adf.test(Passenger_covid[,7])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 7]
Dickey-Fuller = -2.9363, Lag order = 5, p-value = 0.186
alternative hypothesis: stationary

> tseries::adf.test(Passenger_covid[,8])
Augmented Dickey-Fuller Test
data: Passenger_covid[, 8]
Dickey-Fuller = -2.9545, Lag order = 5, p-value = 0.1785
alternative hypothesis: stationary

```

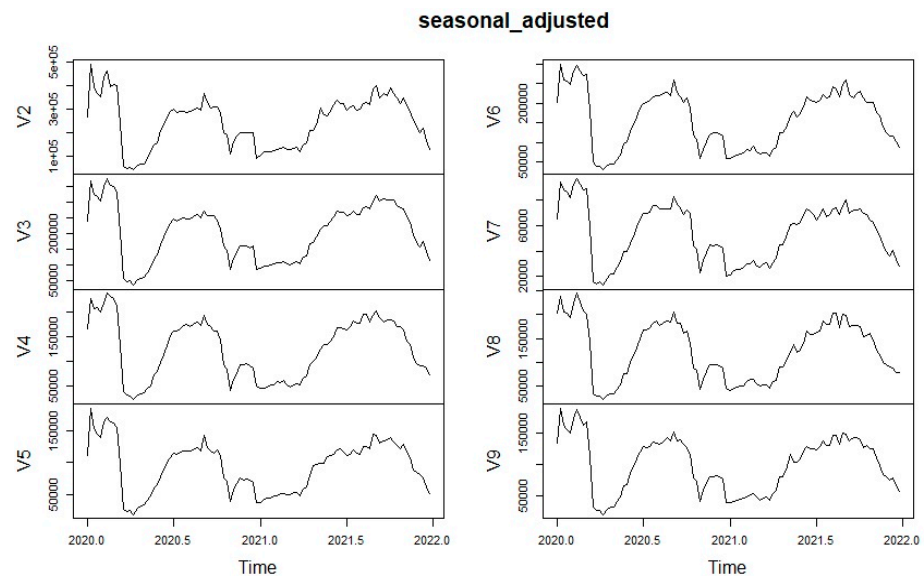
**Figure 4.** Test of stationarity of the passenger transport time series by individual region.

As shown by the results of the stationarity test,  $p < 0.05$ , and therefore the null hypothesis was rejected ( $H_0$ : the time series is stationary). This confirmed the non-stationary nature of the dataset, further justifying the need for decomposition prior to modelling. Figure 5 presents the decomposition of the passenger transport time series into its individual components for the Bratislava region, illustrating the separation into trend, seasonal, and random parts.



**Figure 5.** Decomposition of passenger transport time series—Bratislava region.

Figure 5 shows the components of the time series from top to bottom—original data, trend, seasonal component, and random component. Analogous decompositions of the time series were carried out for all regions. Figure 6 presents the seasonally adjusted passenger transport data, which remove recurring seasonal effects and allow a clearer comparison of mobility trends across regions.



**Figure 6.** Seasonally adjusted data on mobility in rail passenger transport.

As illustrated in Figure 6, the trend in the development of mobility in rail passenger transport during the COVID-19 pandemic (2020–2021) was very similar across individual regions of the Slovak Republic (V2—Bratislava, V3—Trnava, V4—Trenčín, V5—Nitra, V6—Žilina, V7—Banská Bystrica, V8—Prešov, V9—Košice).

#### 4.2. Model Creation

In mathematics and statistics, the Levenberg–Marquardt algorithm (LMA or simply LM), also known as damped least squares (DLS), is widely used to solve nonlinear least squares problems [43]. This algorithm was selected for training the neural network due to its efficiency, robustness, and widespread application in nonlinear regression tasks. The general equation of the neuron model can be expressed as Formula (2):

$$y(t) = f(x(t-1), \dots, x(t-d), y(t-1), \dots, y(t-d)) \quad (2)$$

To construct the model, we employed a Nonlinear Autoregressive model with Exogenous Inputs (NARX) neural network, as this framework allows the capture of nonlinear dependencies between past values of the output variable and external input factors. Such an approach is particularly well suited for transport demand data, which are strongly affected by sudden external shocks such as pandemic measures.

The input to the model consisted of seasonally adjusted passenger transport data (Figure 6) and the set of measures introduced in individual policy areas. Since these measures (education, mass events, entry into employment, etc.) differed not only in time (nationwide measures versus the COVID automat), but also in severity across areas, it was necessary to transform them into a binary variable for modelling purposes, as follows:

- Variable “0” if there was no change in the measure in the given week compared to the previous week, or if the measure was relaxed;
- Variable “1” if the degree of the measure was tightened according to the COVID automat in the given week compared to the previous week.

A model was developed in MATLAB using a neural network based on the seasonally adjusted time series of the number of passengers transported in individual regions. The NARX neural network was implemented in MATLAB using the following steps:

- Import time series of weekly passenger counts and exogenous inputs representing government measures.

- Pre-process data by removing seasonality and normalizing values.
- Define a NARX architecture with one hidden layer of 10 neurons and time delays of 1–4 weeks.
- Split the dataset into training (70%), validation (15%), and testing (15%) sets.
- Train the network using the Levenberg–Marquardt backpropagation algorithm.
- Evaluate performance using R and MSE on validation and test sets.

In this study, model performance was evaluated using the coefficient of determination (R) and mean squared error (MSE) for training, validation, and test sets. While these metrics provide a first indication of predictive quality, further robustness checks such as k-fold cross-validation, sensitivity analysis to input variables, and benchmarking against simpler models (for example ARIMA, multiple regression) were not performed in the current version. This will be an important part of future research to better substantiate the selection of NARX for this type of demand modelling. Figure 7 shows workflow of the NARX modelling process.



Figure 7. Workflow of the NARX modelling process.

The diagram summarizes the main steps used to build and validate the nonlinear autoregressive network with exogenous inputs (NARX) for forecasting passenger rail demand. Raw weekly passenger counts, and government restriction indicators are first collected and pre-processed (seasonality removal, normalization). The dataset is then split into training, validation, and testing subsets. A NARX network architecture with selected time delays and hidden neurons is configured and trained using the Levenberg–Marquardt backpropagation algorithm. Finally, the model performance is evaluated on validation and test sets and applied to scenario-based demand forecasting.

This standard division of data ensured that the model was not only fitted to the training subset but also validated and tested for predictive accuracy, thereby increasing the reliability and generalizability of the results. Prior to the creation of the final model, we verified the distribution of random errors (Figure 8) and the autocorrelation of residuals (Figure 9), to confirm that the neural network’s outputs met the basic assumptions of randomness and independence of errors.

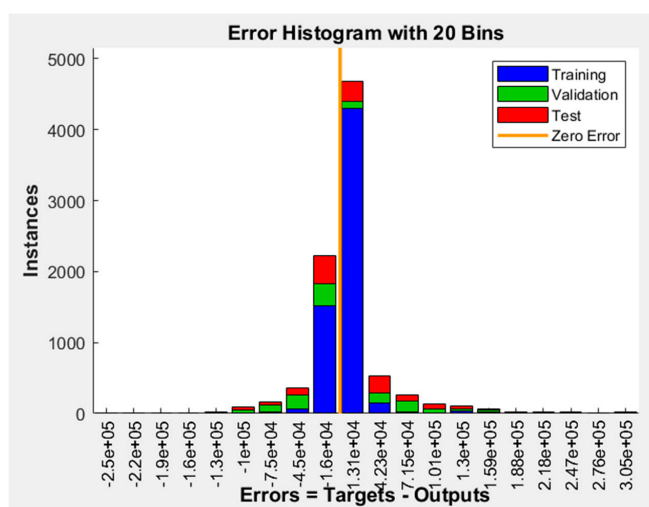
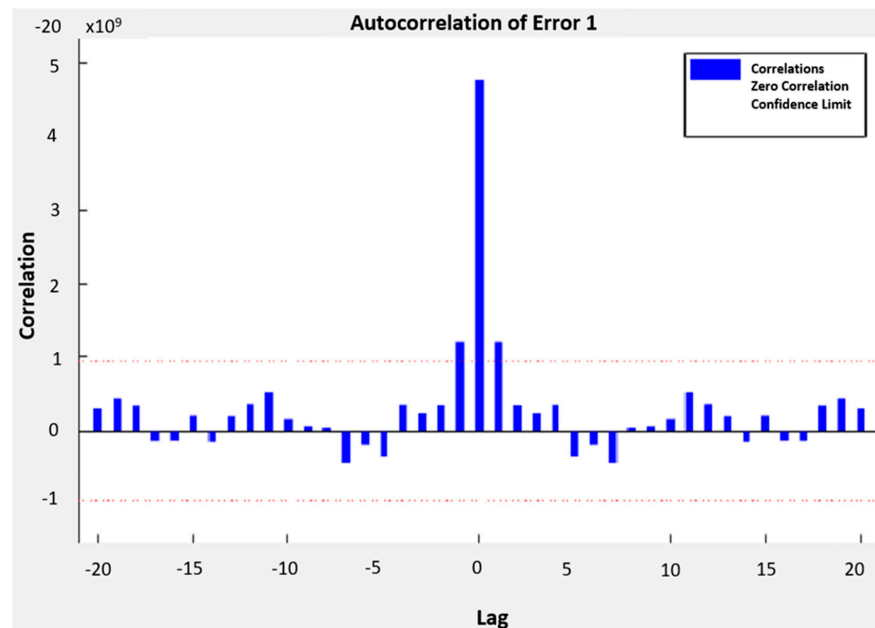


Figure 8. Randomness distribution of the errors.



**Figure 9.** Autocorrelation of the random errors.

The distribution of residual errors corresponded approximately to a normal (Gaussian) probability distribution, and the autocorrelation values obtained from network training did not exceed the critical thresholds. These diagnostics confirmed that the proposed model can be reliably used to investigate the relationship between the number of transported passengers and the degree of measures introduced. The main advantage of the proposed NARX neural network model lies in its ability to flexibly adapt to nonlinear changes in passenger demand under varying levels of restrictions. Nevertheless, a limitation of this approach is the occasional occurrence of extreme predicted values, which naturally result from the neural network methodology when multiple measures are applied simultaneously.

## 5. Results

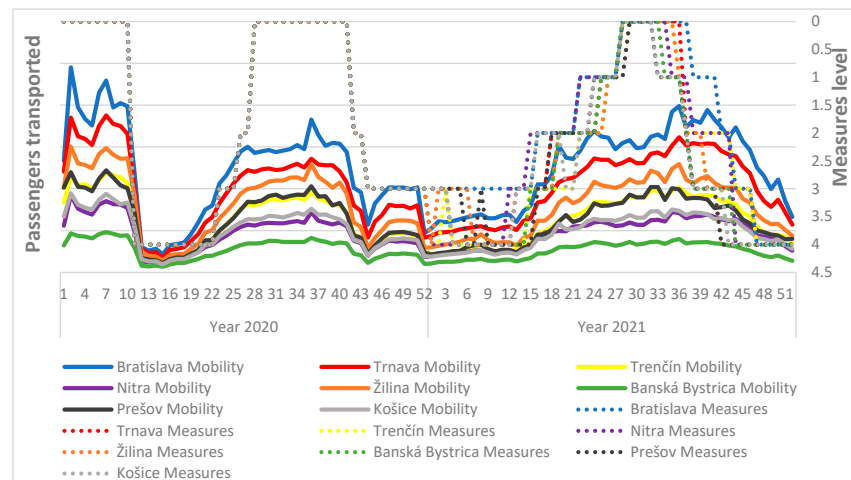
This section presents the outcomes of the data-driven analysis and the NARX neural network model applied to rail passenger transport in the Slovak Republic. First, the relationship between pandemic measures and passenger mobility is described and illustrated using comparative graphs for selected policy areas. Then, the predictive performance of the model is evaluated, and the regression outputs are presented. Finally, the results are broken down by individual regions and key measures (education, workplace entry, restrictions on movement, and retail), providing a basis for formulating recommendations for railway capacity management during crisis conditions.

### 5.1. Comparison of Measures and Mobility Data in Rail Passenger Transport

Based on the development of the number of passengers transported in individual regions, comparative graphs were constructed according to the levels of restrictions in areas assumed to influence rail passenger transport. These included measures related to:

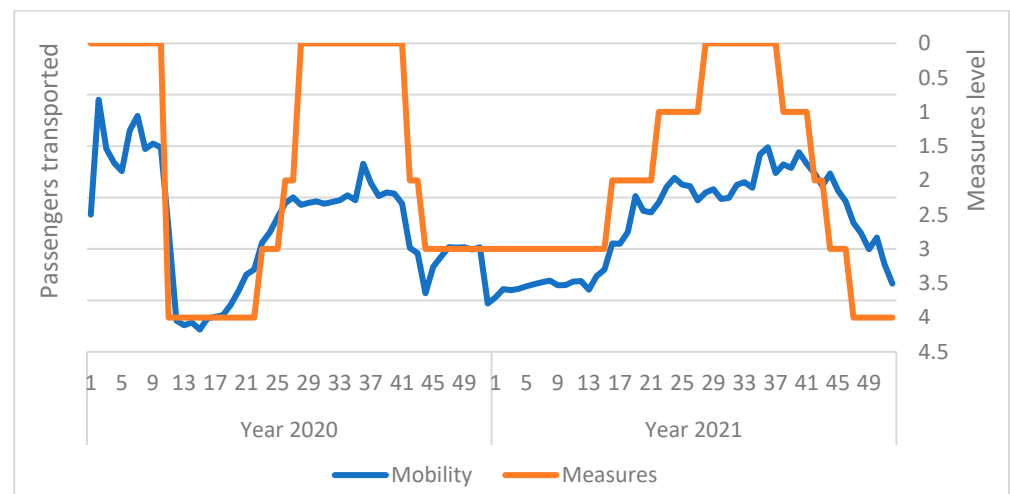
- Schools (education sector);
- Entry into employment (workplace entry);
- Restriction of movement (limitation of movement);
- Shops;
- Accommodation facilities.

Figure 10 shows that education restrictions had the most significant impact on rail demand, with complete school closures reducing passenger numbers by about 75% compared to pre-crisis levels.



**Figure 10.** Comparison of rail passenger mobility according to the levels of restrictions in the education sector.

Although Figures 10–19 may appear visually similar at first glance, each plot represents a distinct government measure and its specific relationship to passenger rail demand. Subtle differences in slopes, turning points, and temporal responses reveal how individual interventions, such as school closures, workplace restrictions, retail limitations, and mobility bans, influenced demand dynamics. Education-related restrictions produced the steepest and most immediate declines in passenger volumes, confirming the major impact of student commuting on rail travel. Workplace access limitations caused a slower but persistent decrease in demand, consistent with the gradual adoption of remote work. Mobility bans triggered sharp drops followed by rapid rebounds once restrictions were lifted, indicating a high latent demand for travel. Retail and leisure closures had more moderate, short-term effects. These patterns suggest that future capacity planning must pay special attention to school and workplace policy signals, as they drive the most pronounced fluctuations in ridership.



**Figure 11.** Comparison of rail passenger mobility and the levels of restrictions in the education sector for the Bratislava region.

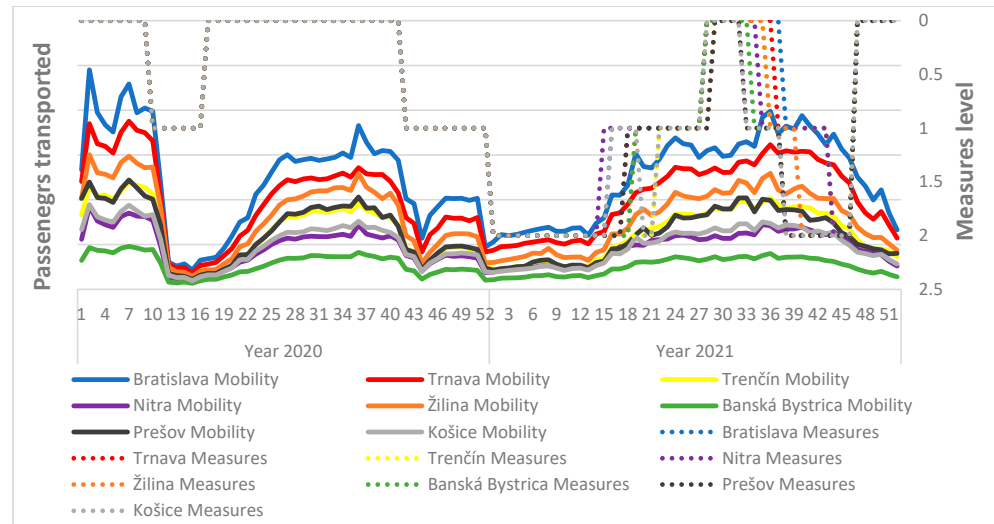


Figure 12. Comparison of rail passenger mobility according to the levels of restrictions on workplace entry.

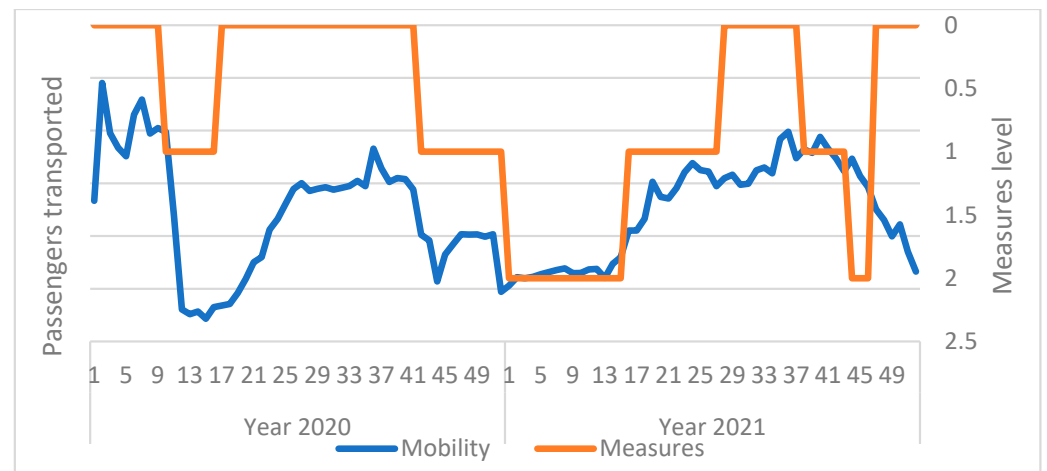


Figure 13. Comparison of rail passenger mobility and the levels of restrictions on workplace entry in the Bratislava region.

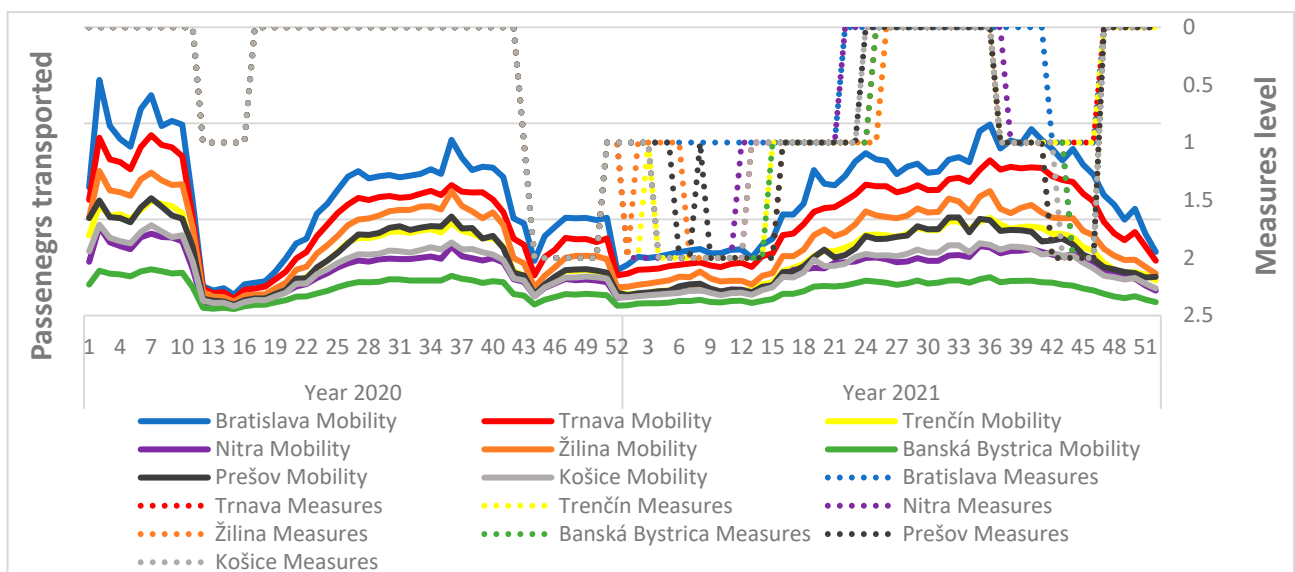
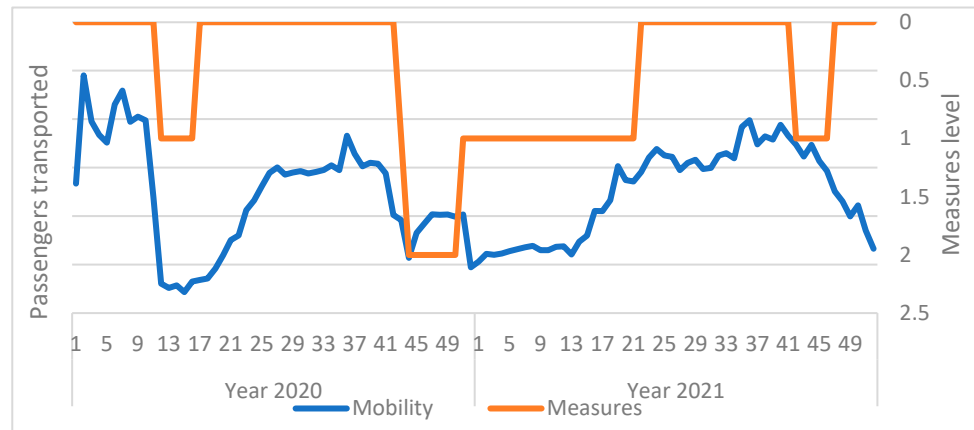
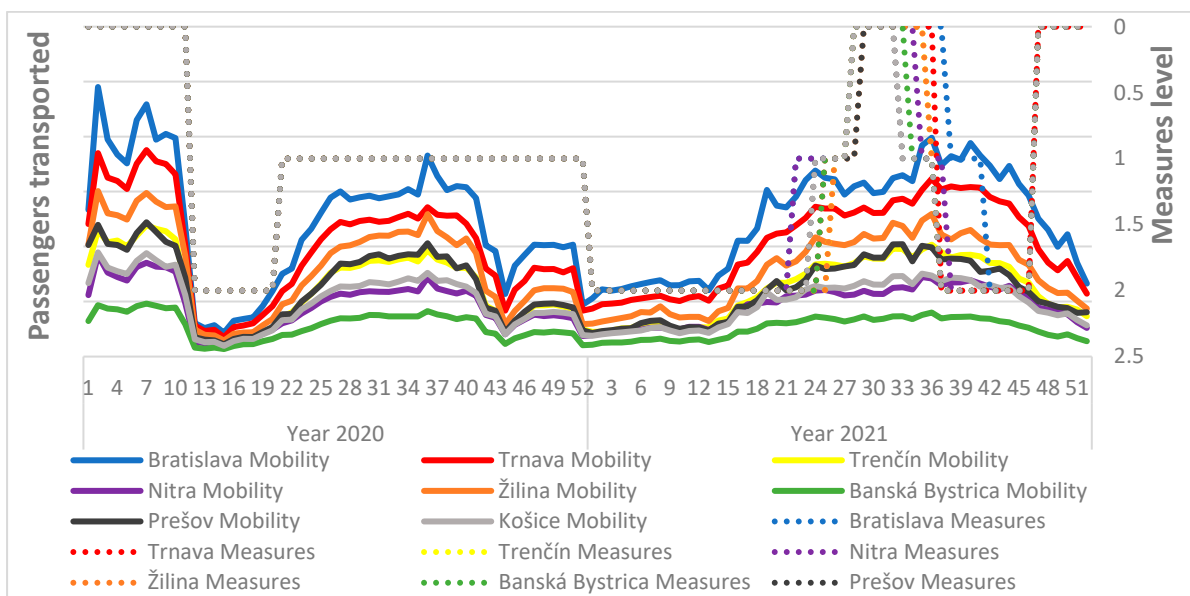


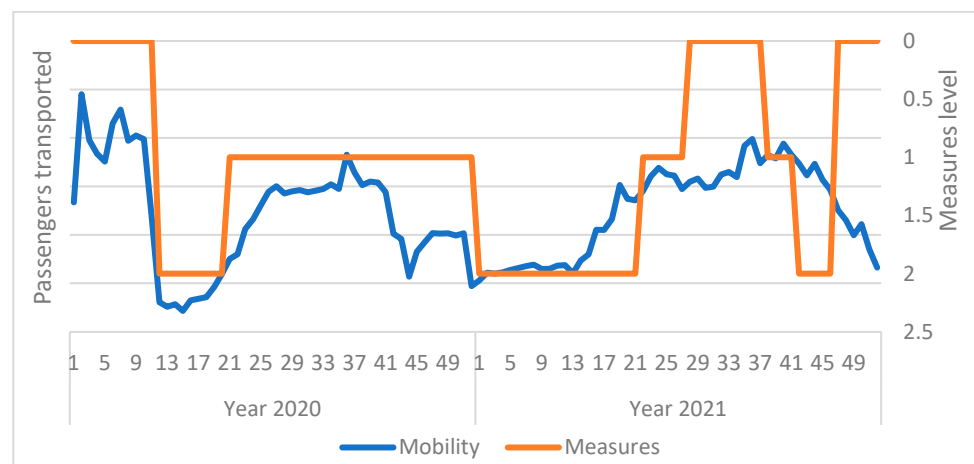
Figure 14. Comparison of rail passenger mobility according to the levels of restrictions on movement.



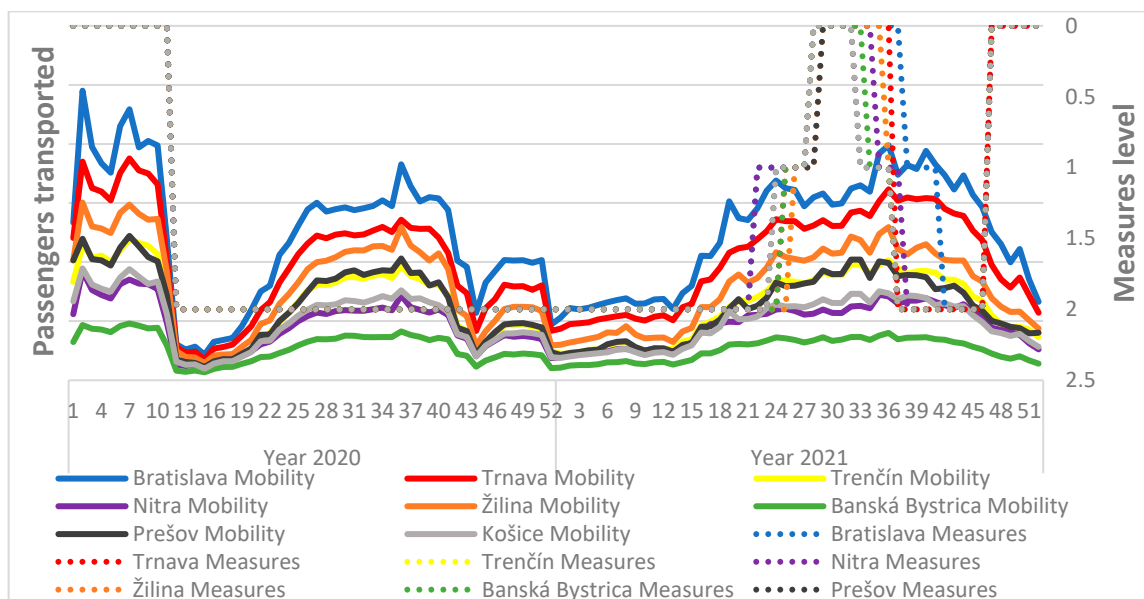
**Figure 15.** Comparison of rail passenger mobility and the levels of restrictions on movement in the Bratislava region.



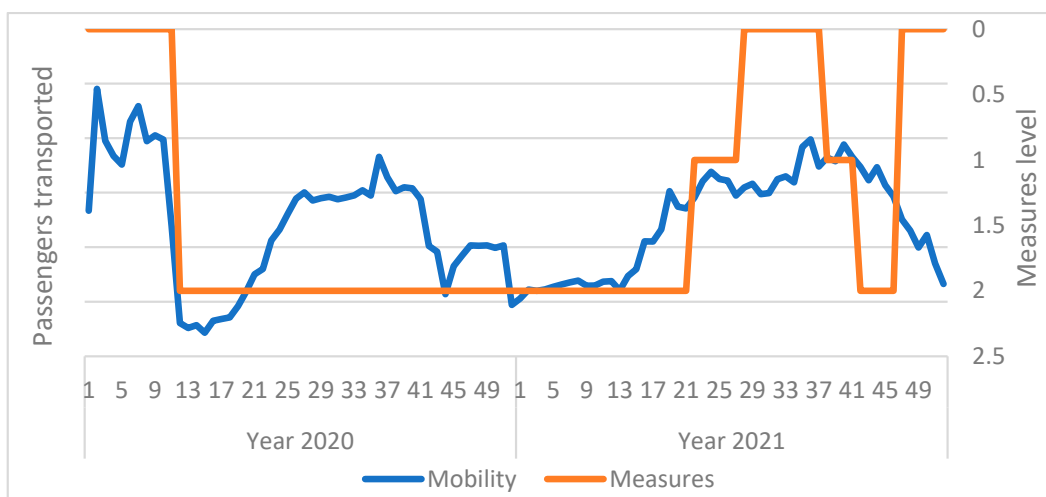
**Figure 16.** Comparison of rail passenger mobility according to the levels of restrictions on shops.



**Figure 17.** Comparison of rail passenger mobility and the levels of restrictions on shops in the Bratislava region.



**Figure 18.** Comparison of rail passenger mobility according to the levels of restrictions in accommodation facilities.



**Figure 19.** Comparison of rail passenger mobility and the levels of restrictions in accommodation facilities in the Bratislava region.

Restriction levels were nearly identical across regions in 2020 due to nationwide measures. The Bratislava region is shown in Figure 11 as a representative example.

Across all eight regions of Slovakia, a consistent pattern was observed between the number of passengers transported and the levels of restrictions. As the severity of measures increased, rail passenger mobility declined, and vice versa. The differences between regions were only minimal. This finding underlines the fact that, during the initial phase of the pandemic, the nationwide character of restrictions overshadowed regional specificities, which only began to emerge later with the introduction of the COVID automat. Passenger transport in railways was also strongly influenced by the daily commuting of residents to employment. Figure 12 illustrates the comparison between restrictions on entering workplaces and the number of passengers transported across all regions of Slovakia.

When comparing the development of rail passenger mobility and the levels of restrictions on employment, certain categories of measures were merged for analytical purposes. Specifically, the level of vigilance was combined with the first level of threat, and the second

and third levels of threat were also merged, since the imposed measures were identical. For example, at both the second and third levels of vigilance, home-office was mandated wherever possible, with exceptions allowed under the OTP (vaccinated, tested, recovered) regime. This reflects the gradual shift to remote work. Patterns across regions remained similar, again dominated by national policies (Figure 13).

Workplace-related restrictions showed similar nationwide patterns, with demand falling as measures tightened.

These deviations underscore the significant role of long-distance connections, which can introduce discrepancies into otherwise homogeneous regional trends. Another divergence was observed across all regions in the final weeks of 2021, primarily due to seasonal effects, such as the reduction in travel during the Christmas holidays. Figure 14 illustrates the development of rail passenger mobility and the corresponding levels of restrictions related to the limitation of movement.

Like the workplace entry measures, the levels of restrictions for movement were merged for analytical purposes. Specifically, monitoring and vigilance were combined, as well as the first and second levels of threat, since the applied measures were identical in these categories.

To provide a clearer picture of these relationships, Figure 15 presents the comparison of rail passenger mobility and the levels of movement restrictions in the Bratislava region.

In the case of movement restrictions, a trend analogous to workplace entry measures was observed. Mobility decreased with increasing severity of restrictions, and vice versa. In some regions, particularly Prešov and Košice, anomalies were again identified, caused primarily by long-distance commuting from other parts of the country. Restrictions on shops caused moderate, short-term decreases in ridership (Figures 16 and 17). Toward the end of 2021, seasonal effects such as the Christmas period partly masked policy impacts.

The development of passenger transport in relation to shop-related restrictions displayed a similar pattern across all regions. As the severity of restrictions increased, the number of passengers declined. However, an opposite trend was again recorded in the final weeks of 2021, primarily due to seasonal effects. These results confirm that rail passenger mobility is directly influenced by restrictions on economic activity and that the impact of seasonality may temporarily overshadow the effects of governmental measures.

Measures affecting accommodation produced minimal changes in rail demand (Figures 18 and 19), suggesting that recreational and leisure travel is mostly undertaken by individual transport rather than rail.

The comparison of rail passenger mobility and the restrictions introduced in accommodation facilities shows an almost identical pattern across all regions. Figures 18 and 19 indicate that, despite the introduction of stricter measures in accommodation facilities, there was no significant change in the number of passengers transported by rail. This finding suggests that travel related to recreational or sports activities is predominantly carried out by individual transport, which explains why the restrictions in accommodation facilities had only a limited impact on rail mobility.

Moreover, when examined at a higher level of detail (in our case, weekly data), the development of rail passenger transport clearly exhibits seasonal characteristics. Therefore, prior to the construction of the model, it was necessary to decompose the time series of the observed data into its individual components and to exclude the seasonal effect.

## 5.2. Model Performance

The outputs of the model are presented in Table 4 and Figure 20.

Table 4. Model outputs.

Calculation Process	Performance	Regression
Training	$6.557107629351653 \times 10^8$	0.9598
Validation	$5.067852971757998 \times 10^9$	0.6541
Testing	$4.393849062438726 \times 10^9$	0.7389

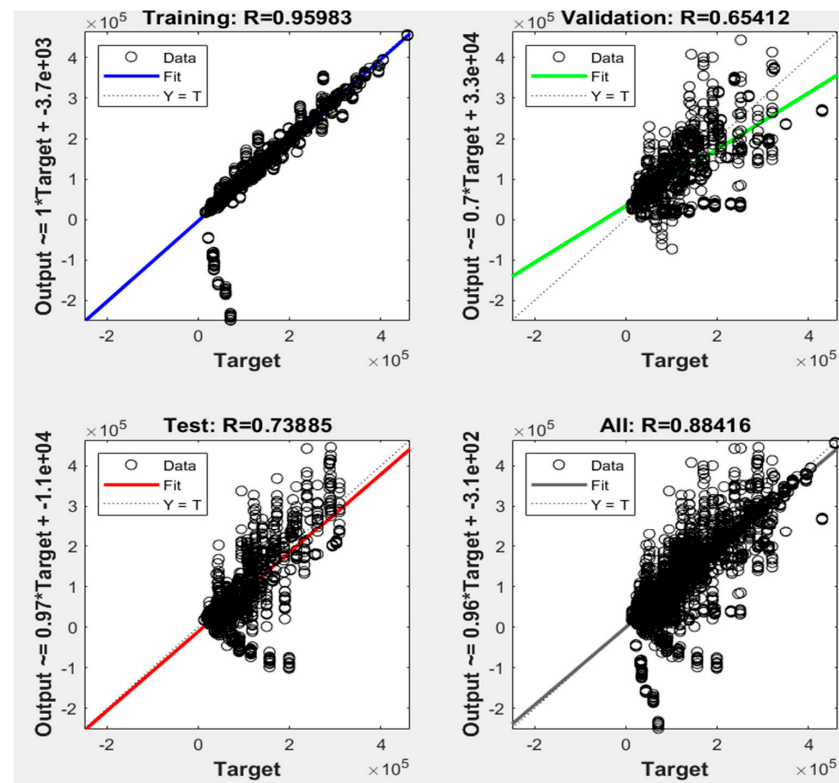


Figure 20. Regression results of the NARX model.

The results confirm the existence of regression for the training, validation, and testing phases, thereby demonstrating that the model adequately captured the relationship between the applied measures and passenger mobility. Figure 20 shows the regression results of the NARX model.

Figure 20 presents the regression results of the NARX model, including the functions and corresponding regression coefficients for training, validation, and testing. An important outcome is the overall regression coefficient ( $R = 0.88416$ ), which confirms the dependence between the measures introduced to limit the spread of COVID-19 in the individual regions and rail passenger mobility.

The  $R$  value close to 0.96 for the training set confirms a very good model fit. The lower values for the validation set (0.65) and the testing set (0.74) indicate that, although the predictive ability of the model is satisfactory, there remains a degree of variability not fully captured. Nevertheless, the overall regression coefficient ( $R = 0.88416$ ) demonstrates a strong correlation between the severity of restrictions and the development of passenger mobility. These results show that the proposed NARX model is capable of adequately capturing the relationships between the input variables (measures) and the output variable (mobility). The model thus provides a reliable basis for further analysis and for formulating recommendations for railway transport management during crisis situations.

The proposal of measures for rail transport is based on the constructed and validated model. The model was developed using all available data (passenger transport across all

regions and measures in all areas), while its results can also be applied individually to specific regions and particular types of measures. For this reason, this chapter is further divided into two parts: (i) the presentation of modelling results for individual regions, which illustrates regional specificities in mobility trends, and (ii) the proposal of measures for rail transport, which builds on the identified relationships and provides recommendations for practice.

### 5.2.1. Results of Modelling Data for Individual Regions

The analysis revealed that the main areas influencing the development of passenger transport in railways are education, entry into employment, restrictions on movement, and retail. For this reason, the model results are presented for these four areas (Figures 21–24). At the same time, the model enables the evaluation of changes in passenger transport according to changes in measures across all areas and within individual regions. Figure 21 shows the modelled time series (forecast) of changes in passenger mobility (number of passengers) in rail transport between individual weeks under the implemented measures.

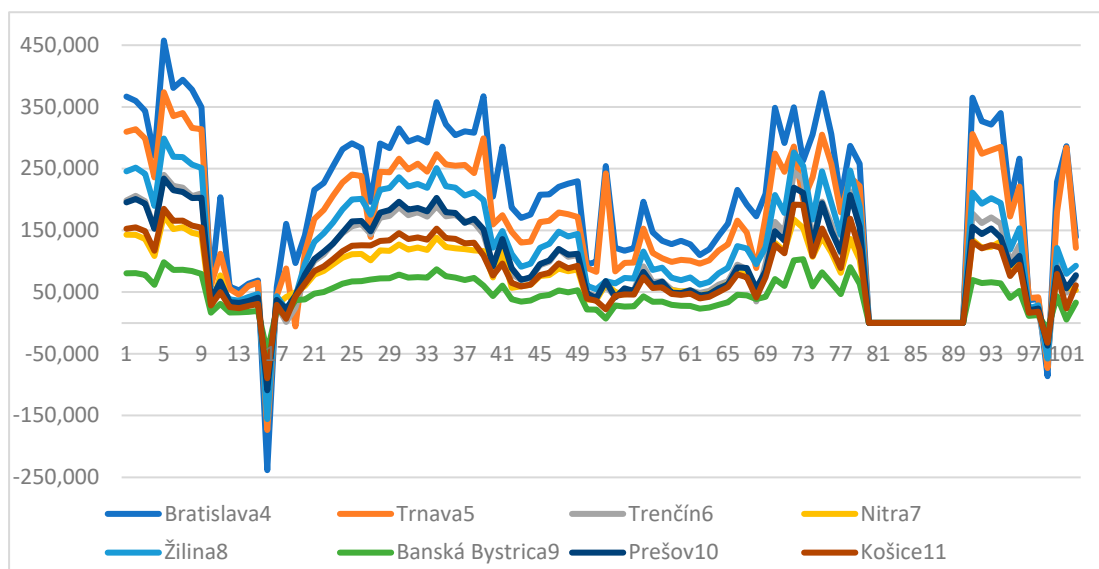


Figure 21. Model results for the measure Education sector.

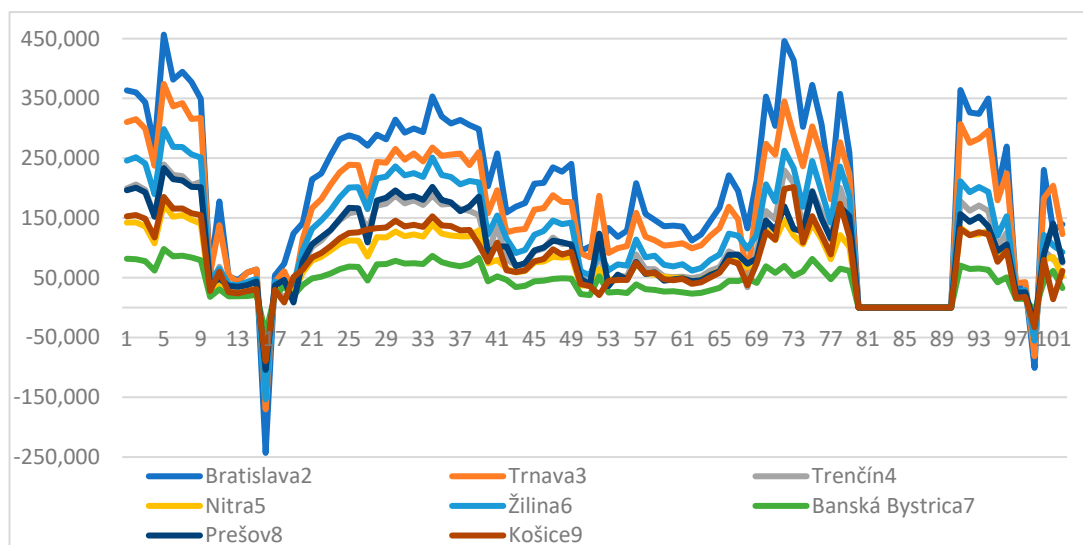


Figure 22. Model results for the measure Workplace entry.

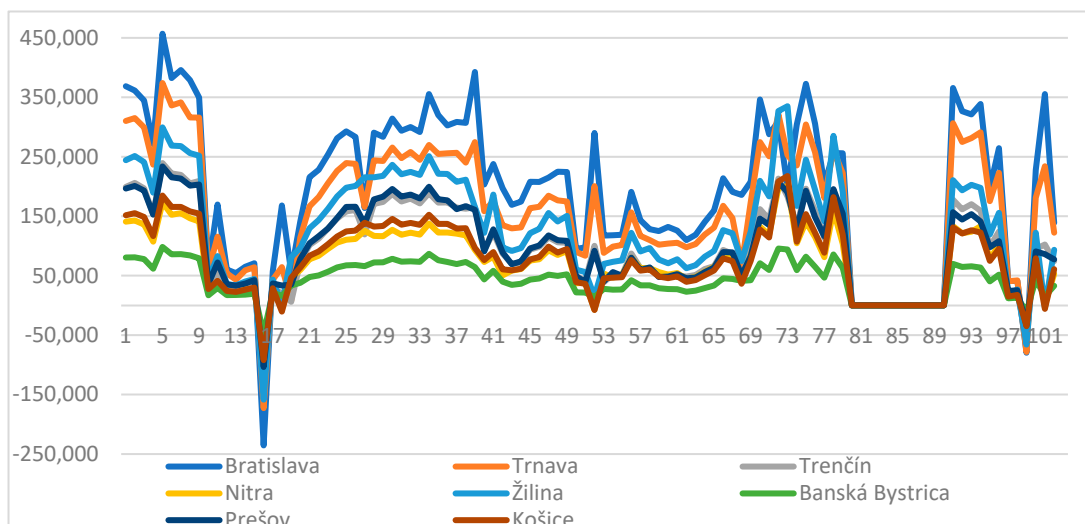


Figure 23. Model results for the measure Restriction of movement.

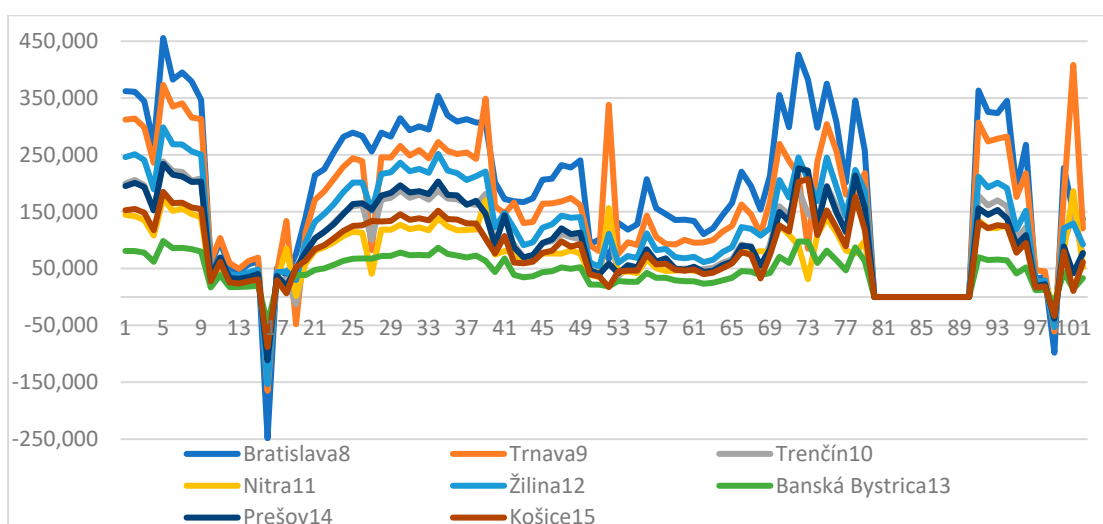


Figure 24. Model results for the measure Shops.

Due to the use of seasonally adjusted data, the forecast produced by the model covered a two-year period, using data from 2021 and 2022. By excluding the seasonal component, regularly recurring fluctuations (for example holidays, summer vacations) were eliminated, which increased the accuracy of the prediction. The modelled data across individual regions show a very similar development; the same applies to the individual measures, where deviations between the graphs are only minimal. Although the model was designed to allow region-level analysis, the empirical results confirm that regional differences in Slovakia during the pandemic were relatively minor. This can be attributed to the predominantly nationwide character of government restrictions in 2020 and the late introduction of regionally differentiated measures in 2021. Additionally, the strong centralization of the Slovak rail network along the Bratislava–Košice corridor reduces regional heterogeneity in travel patterns. Nevertheless, maintaining a regionally sensitive modelling framework is valuable, as it enables scenario testing and capacity planning for potential future events with stronger local impacts (district-level outbreaks or natural disruptions). Figure 22 illustrates the modelled time series (forecast) of changes in passenger mobility (number of passengers) in rail transport for the measure Entry into employment.

Figure 23 presents the modelled time series (forecast) of changes in passenger mobility (number of passengers) in rail transport for the measure Restriction of movement.

The modelled time series (forecast) of changes in passenger mobility (number of passengers) in rail transport for the measure Shops is shown in Figure 24.

When comparing these predicted (modelled) data with the actual development, it was confirmed that the model correctly captures the fundamental dynamics of mobility changes under the introduction of different levels of measures. This demonstrates its ability to reflect the relationships between restrictive interventions and passenger behaviour.

When comparing the predicted (modelled) data for a given region and measure using chain indices between weeks with different levels of restrictions, the correlation was also confirmed. Figure 25 shows the development of modelled data for education measures in the Bratislava region.

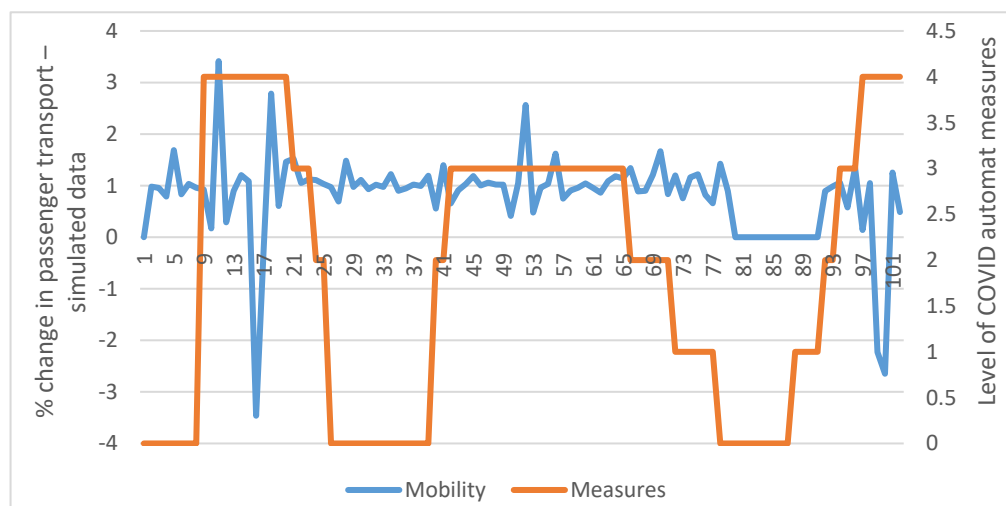


Figure 25. Model results for the measure Education sector in the Bratislava region.

Figure 26 presents the development of modelled data for the measure Workplace entry in the Bratislava region.

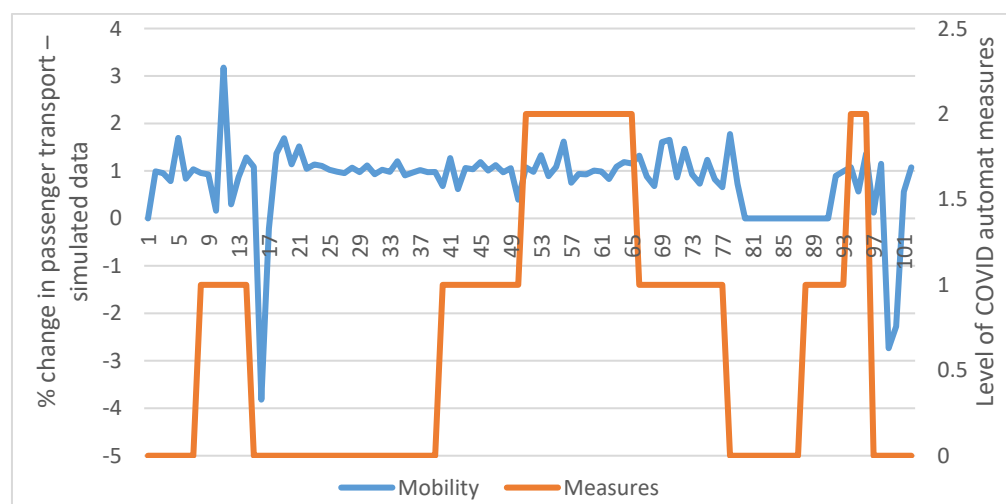
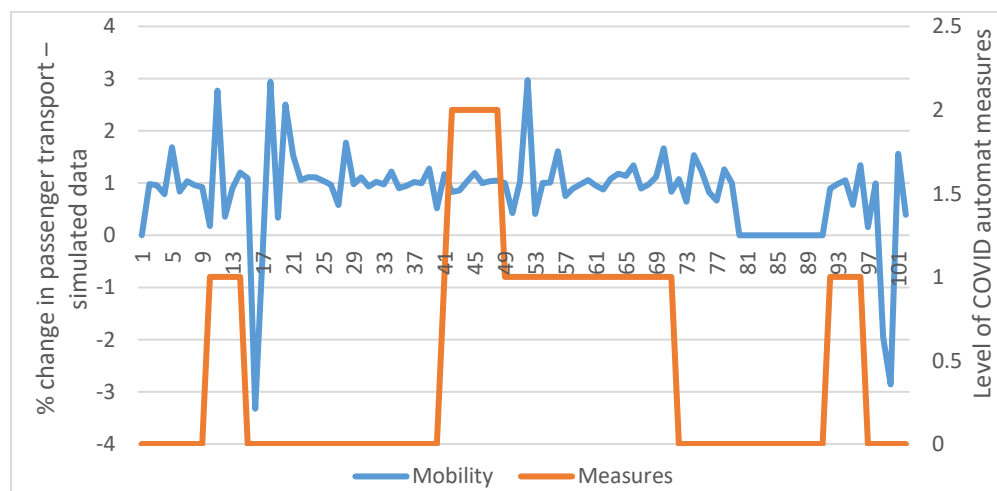


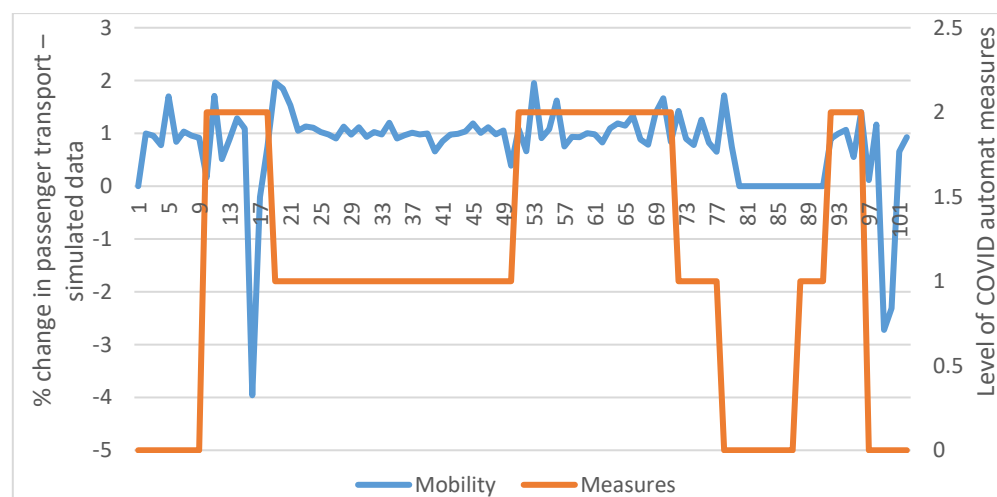
Figure 26. Model results for the measure Workplace entry in the Bratislava region.

The development of modelled data for the measure Restriction of movement in the Bratislava region is shown in Figure 27.



**Figure 27.** Model results for the measure Restriction of movement in the Bratislava region.

The last modelled measure in the Bratislava region was Shops, which is illustrated in Figure 28.



**Figure 28.** Model results for the measure Shops in the Bratislava region.

The modelled and predicted data are characterized by several extreme values resulting from the chosen method and the training of the neural network. The main cause of these extremes lies in the markedly different measures applied in individual areas at a given time. A neural network-based model cannot selectively isolate such phenomena, and at the same time none of them can be excluded during model creation (network training), since they act simultaneously on the development of rail passenger mobility. These extreme values should therefore be interpreted with caution—they do not represent an error of the model, but a natural consequence of its attempt to reconcile the conflicting effects of multiple measures implemented at the same time.

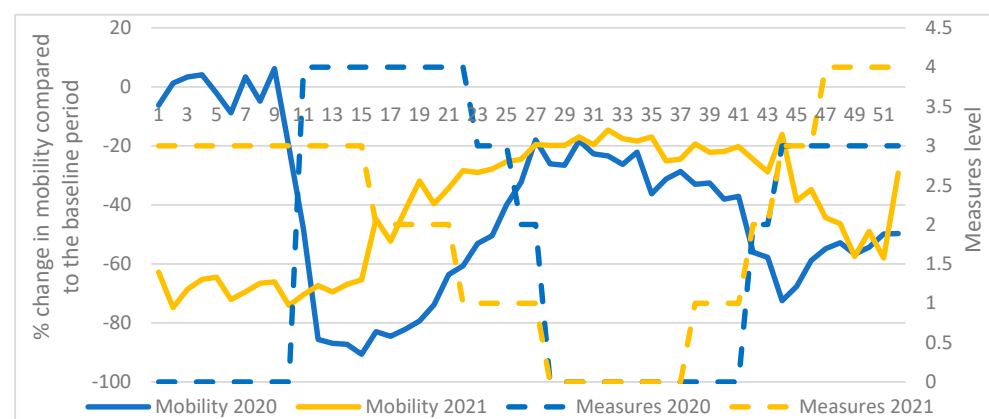
The prediction of passenger rail mobility based on the established model is possible both for Slovakia as a whole and for individual regions or specific measures. In this way, the model becomes a universal tool that can be applied during crisis situations of both national and regional scope. By entering the relevant measures, it is possible to simulate their expected impact on the demand for rail passenger transport.

### 5.2.2. Proposal for Measures for Rail Transport

Since the model was built using a binary variable, when proposing concrete measures (reduction of realized performance in train kilometres), we carried out a comparison of the number of passengers transported before and during the COVID-19 pandemic. Passenger transport in individual weeks of 2019 was taken as the baseline for comparison with 2020 and 2021. Such a comparison is justified, as the developed and validated model confirmed the existence of a correlation between the levels of restrictions in different areas and the number of passengers transported in rail transport.

#### Schools

Measures introduced to prevent the spread of coronavirus in the education sector were among the strictest and had a significant impact on changes in mobility in rail passenger transport. Figure 29 shows the comparison of the level of restrictions in education and the change in mobility in the Bratislava region.

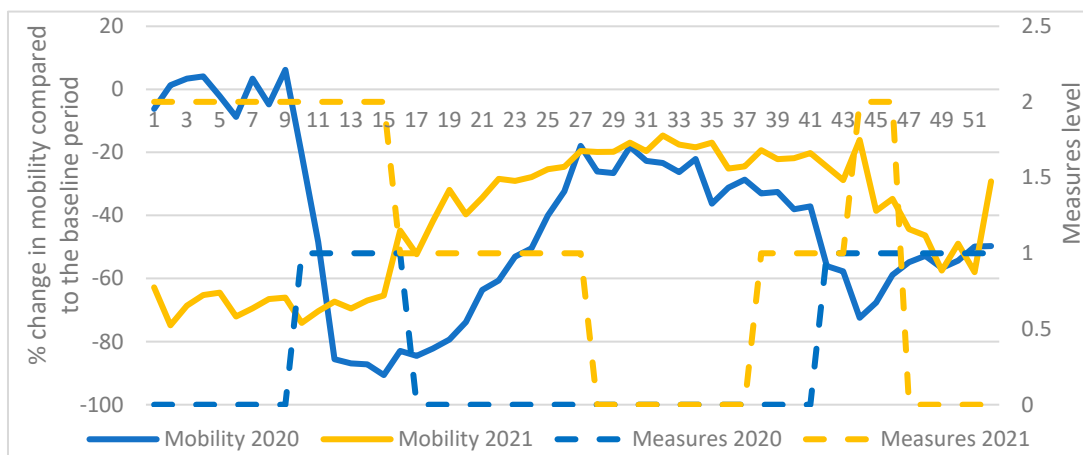


**Figure 29.** Development of measures in education sector and percentage change in rail passenger transport in the Bratislava region.

The change in the number of passengers transported in relation to the introduction of individual levels of measures in education followed a similar pattern across all eight regions. When the strictest measure, i.e., level 4, was introduced—when in-person teaching was replaced by distance learning—the average decrease in passenger transport reached 75%. At level 3 (in-person teaching with a limited number of pupils/students depending on vaccination status or compliance with the OTP regime—vaccinated, tested, recovered—or according to the “school COVID automat”), rail passenger mobility decreased on average by 65%. The second level of restrictions in education (increased in-person teaching capacity under the OTP regime) resulted in an average reduction of 40%. Under level 1 (at universities: 400 people for OTP, 1000 for fully vaccinated, while other schools operated in-person according to the school COVID automat), transport performance decreased on average by approximately 20%. These results confirm that education is among the key areas with the strongest impact on rail mobility, primarily due to the daily commuting of pupils and students.

#### Entry into Employment

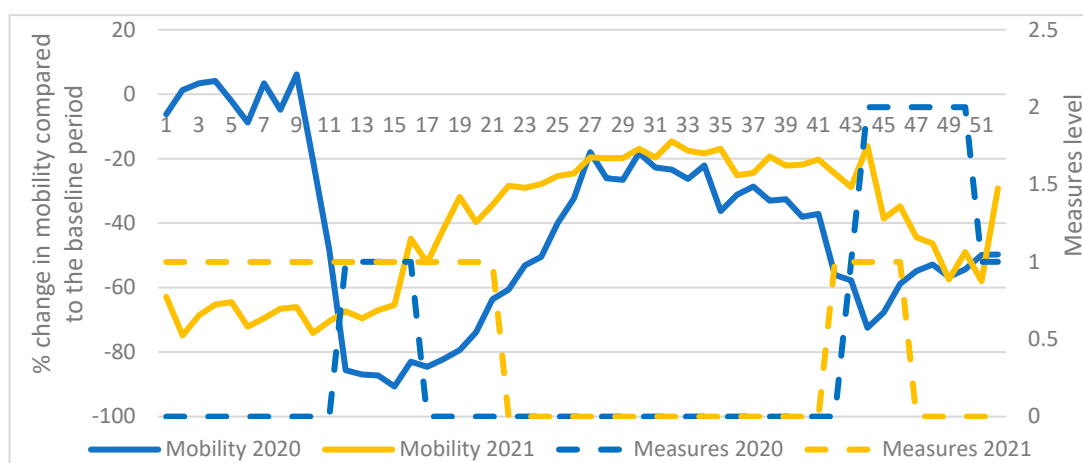
Measures in all other examined areas had a roughly comparable impact on changes in rail passenger transport. Figure 30 illustrates the comparison of passenger transport changes in relation to the level of restrictions introduced for entry into employment in the Bratislava region.



**Figure 30.** Development of measures related to entry into employment and the percentage change in rail passenger transport in the Bratislava region.

**Restriction of Movement**

Figure 31 presents a comparison of passenger transport changes in relation to the level of restrictions introduced for the limitation of movement in the Bratislava region.

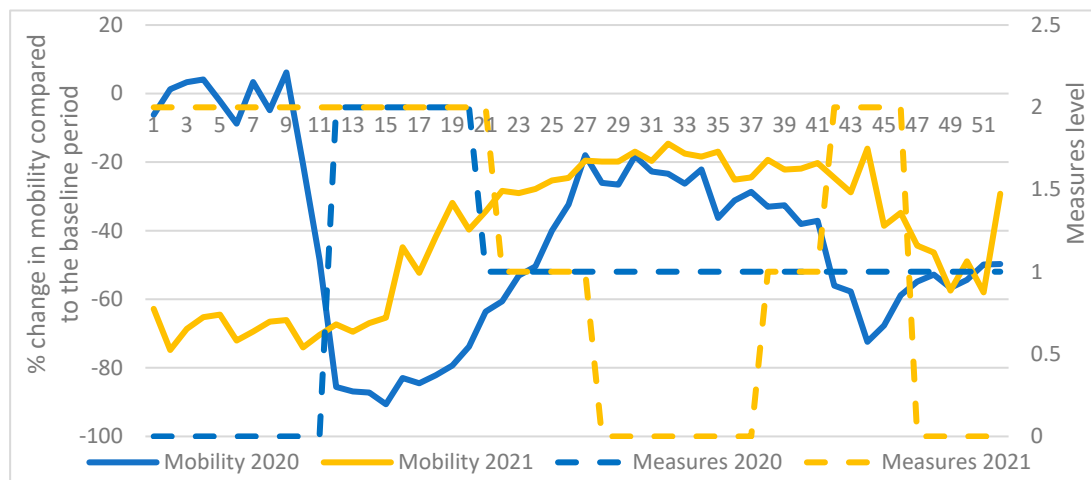


**Figure 31.** Development of measures related to the restriction of movement and the percentage change in rail passenger transport in the Bratislava region.

Measures associated with the restriction of movement were among those that had an immediate and direct impact on population mobility. Under the strictest levels of restrictions (curfew with exceptions, limitations on inter-district travel), the average decrease in the number of rail passengers reached approximately 60–70%. At lower levels of restrictions, when travel to work or school was still permitted under certain conditions, the decline in mobility was less pronounced—around 25–35%. It is important to emphasize that these “intermediate” measures reveal the capacity of rail transport to retain part of its ridership even during a crisis, particularly when no suitable alternative in the form of individual transport is available.

**Shops**

Figure 32 shows the comparison of changes in rail passenger transport with respect to the level of restrictions imposed on shops in the Bratislava Region. The analysis indicates that limiting the number of customers per unit area in retail establishments had a measurable impact on mobility, particularly during periods of stricter measures.



**Figure 32.** Development of measures in shops and the percentage change in rail passenger transport in the Bratislava Region.

The development of changes in rail passenger transport was influenced by the severity of individual measures, with notable differences observed between periods of nationwide restrictions in 2020 and the COVID automat system introduced in 2021. This distinction reflects the changing policy framework associated with the availability of COVID-19 vaccines and the corresponding adjustments in governmental responses. The results therefore demonstrate that identical measures could have had different effects in various periods due to the evolving social and epidemiological context. In general, strict measures (a limit of one customer per 1 m<sup>2</sup> of retail space, or restrictions on movement with only a few exceptions) led to an average decrease in rail passenger transport of approximately 70%. By contrast, less stringent measures (recommended but not mandatory home office arrangements) were associated with an average reduction of around 30%.

Based on the constructed and validated neural network model in MATLAB, the following conclusions can be drawn:

- Passenger rail transport was significantly influenced by measures implemented in the areas of education, workplace entry, restrictions on movement, and limits on the number of customers in shops. Other measures did not have a substantial impact on changes in passenger numbers.
- Although measures in 2021 were introduced at the regional level according to the evolving epidemiological situation, the same level of restrictions generally led to comparable percentage changes in the number of transported passengers across different regions.
- A comparison of transport capacity and passenger demand in rail transport revealed considerable over-dimensioning of rolling stock capacity under the strictest measures, particularly those related to education and workplace entry.

Based on these findings, we propose the following reductions in rail transport capacity (achieved either by reducing the number of coaches per train or by decreasing total train kilometres):

- Under the strictest measures—a reduction of capacity by 40%;
- Under medium-level measures—a reduction of capacity by 30%;
- Under mild measures—a reduction of capacity by 10%.

These recommendations are derived from the validated model and the analysis of passenger transport dynamics in relation to the introduction of specific measures. Importantly, stricter measures required higher capacity per train due to mandated physical distancing between passengers.

The application of demand-modelling approaches in the context of pandemics or other crisis situations can lead to significant reductions in social costs in passenger rail transport, as well as improvements in the management of technological processes and human resources. The implementation of these recommendations could therefore contribute to more efficient use of available resources, cost savings at the societal level, and more flexible management of railway operations during crisis conditions.

## 6. Discussion

The analysis and modelling results confirm that the most decisive factors influencing rail passenger mobility during the COVID-19 pandemic were measures related to schooling, access to workplaces, restrictions on movement, and retail activities. Among these, the closure of schools proved to be the strongest driver of mobility reduction, with an average decline of up to 75%. This underscores the crucial role of daily commuting of pupils and students in shaping passenger flows in the Slovak rail network.

The application of the NARX neural network model demonstrated its suitability for capturing nonlinear relationships between pandemic measures and passenger mobility. The model achieved a high overall correlation ( $R = 0.88$ ) between the imposed measures and the number of passengers and provided a robust basis for simulating alternative scenarios. This makes it a valuable tool for transport authorities, enabling them to design adaptive strategies and implement flexible capacity planning during crises.

Despite its robustness, the model also has several limitations. Extreme predicted values were observed in certain cases, which can be attributed to the simultaneous implementation of multiple measures and the neural network's limited ability to disentangle their individual effects. Moreover, the analysis relied on aggregated regional-level data, which may obscure differences in mobility behaviour across socio-economic groups or trip purposes. Finally, the study focused in detail on the Bratislava region, which was chosen due to its role as the most significant commuting hub in Slovakia, with a high concentration of both regional and long-distance flows. While this focus allows for an in-depth analysis of the area most affected by restrictions, it also limits the generalizability of the findings to other regions with different demographic or infrastructural profiles.

When compared to international findings, the results are consistent with studies from neighbouring countries. It is important to note that, although the study set out to emphasize a regional perspective, the observed differences between Slovak regions proved modest. This outcome reflects both the uniform nationwide response during most of the pandemic and the high interconnectedness of the country's rail system. However, the modelling framework remains regionally applicable and can support targeted decision-making should future crises require geographically differentiated interventions. Research in the Czech Republic [44] using regression-based approaches confirmed that school closures were the strongest determinant of passenger demand declines, with reductions exceeding 70%. Similar outcomes were reported in Italy, where passenger numbers dropped by more than 70% during lockdowns, while studies applied discrete choice models and agent-based simulations to capture behavioural shifts [30,45–47]. These findings suggest that the Slovak results are in line with broader European experiences.

While the proposed NARX model achieved a high correlation between restrictions and passenger demand, several limitations and potential sources of bias should be acknowledged. First, the binary representation of tightening or relaxing measures cannot fully capture the heterogeneity of real restrictions, for example partial school closures or mixed home/office work regimes may have different impacts than assumed. Second, the analysis is based on aggregated weekly and regional data, which may mask short-term behavioural shifts and differences among socio-economic groups. Third, long-distance

commuting patterns, especially from Eastern Slovakia to Bratislava, may distort regional comparability and partly explain the anomalies observed in Prešov and Košice. Finally, the model's predictive ability decreases when multiple extreme restrictions are imposed simultaneously, as the neural network cannot always disentangle interacting effects. These aspects should be considered when interpreting the forecasts and applying the results to operational planning.

In addition, although the model suggests capacity reductions of up to 40%, practical implementation may be constrained by the availability of rolling stock and crew, contractual obligations with service providers, and the need to maintain minimum connectivity for remote regions.

Another important limitation lies in the binary coding of government measures. The model treats any tightening of restrictions as a single-step change, regardless of whether it represents a minor intervention (for example mandatory masks) or a major disruption (for example full lockdown). This simplification can reduce the model's ability to distinguish between moderate and severe policy impacts and may partly explain extreme predicted values when multiple measures were implemented simultaneously.

Another methodological limitation is the lack of a formal benchmark comparison with simpler time-series models such as ARIMA or regression. Although these approaches were considered and dismissed due to pronounced non-stationarity and nonlinear demand shocks, their explicit inclusion as baseline models would make the argument for NARX's superiority more robust. The notable drop in predictive accuracy from the training set ( $R \approx 0.96$ ) to the validation and testing sets ( $R \approx 0.65$ – $0.74$ ) also indicates a potential risk of overfitting that should be examined more systematically.

A limitation of this study is the lack of extended validation procedures beyond R and MSE. The model has not yet been tested with cross-validation, sensitivity analysis, or compared with simpler baselines such as ARIMA or regression. Incorporating these robustness checks would help confirm the necessity and superiority of the NARX approach. A further limitation of the current validation is its reliance solely on standard goodness-of-fit statistics (R and MSE). Without scenario-based or sensitivity analyses, it remains unclear how stable the model predictions are under moderate perturbations of key input variables. For instance, it is unknown whether small changes in the stringency or timing of workplace restrictions produce proportionate effects on predicted ridership or cause abrupt, unrealistic swings. Incorporating such analyses would clarify model behaviour and strengthen its practical relevance.

Since the acute pandemic period, passenger rail transport in the Slovak Republic has shown gradual but incomplete recovery. Data from the national rail operator ZSSK indicates that ridership in 2022 and 2023 increased compared to 2021, as restrictions were lifted and students as well as employees partly returned to daily commuting. However, demand has not yet fully reached pre-2019 levels. A lasting change is the higher prevalence of hybrid and remote work, which continues to reduce peak weekday flows, while leisure and weekend travel rebounded faster. The pandemic accelerated several modernization steps in Slovak passenger rail, digital ticket sales and reservations became the dominant channel, real-time passenger counting systems are being expanded, and timetable adjustments are more dynamic than before. ZSSK also tested flexible train compositions and partial capacity reductions on low-demand routes. Nevertheless, the vulnerability of the system to sudden demand shocks remains, and there is still no fully institutionalized mechanism for rapid scaling of capacity during crises. These developments confirm the practical relevance of predictive approaches such as the NARX model, which can support more adaptive and resilient railway operations in the long term.

Taken together, the visual trends (Figures 9–18) highlight a strong policy–mobility coupling: education and workplace restrictions exert primary control over national passenger flows, while other measures contribute only secondary, short-lived effects. This implies that operators can anticipate major demand shocks by closely monitoring educational and work-related policy changes. It also underlines the resilience of leisure and shopping trips, which tend to recover quickly once restrictions ease, offering opportunities for targeted marketing and dynamic pricing.

Beyond Europe, mobility reductions were observed worldwide. The study [48] showed that a 20–40% decrease in mobility can reduce the effective reproduction rate of COVID-19 below 1, particularly when related to commuting, transport, and retail activities. In the United Kingdom, car use decreased by around 30% over 2020 compared to pre-pandemic levels, with a 50% reduction during the first lockdown. Rail passenger numbers fell by 76% between March and December 2020, and public bus ridership declined to only 15% of the previous year’s level [49]. Comparable decreases were documented in Germany [50], Sweden [51,52], Switzerland [53], the Netherlands [54], Indonesia [55], Colombia [56], China [57–59], Australia [60] and Japan [61]. Compared to these international studies, the Slovak case highlights the added value of using neural networks, which are capable of capturing nonlinearities often overlooked by traditional econometric techniques.

The findings also have several implications for railway policy and operations. Adjusting capacity according to the severity of restrictions—for example, reducing train kilometres by 40% during the strictest measures—could lead to significant cost savings and more efficient use of resources. Such adaptive planning is not only economically relevant but also environmentally beneficial, as it reduces unnecessary energy consumption and associated CO<sub>2</sub> emissions during periods of reduced demand. At the same time, capacity reductions must be carefully balanced to maintain sufficient space for safe distancing during health crises, which highlights the need for flexible train composition and dynamic crew management. The recommended capacity reduction of 10–40% is directly based on the demand drops predicted by the NARX model under different levels of restrictive measures. Specifically, the model scenarios that included the most severe nationwide restrictions (e.g., full school closures, mobility bans) showed passenger reductions approaching 40%, while moderate interventions such as partial workplace limitations or mask mandates resulted in approximately 10–20% demand loss. These forecasts provided the quantitative basis for translating predicted ridership decreases into practical capacity adjustment recommendations, rather than relying solely on descriptive historical trends.

By employing a neural network–based simulation framework, the study contributes to the field of data-driven modelling and simulation of transportation systems. This aligns with the scope of the Special Issue, demonstrating how machine learning methods can capture complex dynamics under crisis conditions and provide actionable insights for policymaking.

Finally, the applicability of the model extends beyond pandemic situations. The NARX-based framework can be adapted to forecast mobility under other crisis conditions, such as extreme weather events, energy shortages, or regional epidemics. In such contexts, the ability to quickly simulate different restriction scenarios and their impact on passenger demand can significantly support decision-making and improve the resilience of transport systems.

Future research should focus on integrating additional data sources, such as real-time ticketing systems or automated passenger counts, to refine predictive accuracy. Extending this approach to other modes of transport would provide a more comprehensive understanding of multimodal mobility dynamics. Combining neural network models with

agent-based simulations could further capture behavioural heterogeneity at the individual level, thereby enhancing the robustness and policy relevance of crisis mobility models.

## 7. Conclusions

This study analysed the demand for rail passenger transport in the Slovak Republic during the COVID-19 pandemic, with a particular focus on the Bratislava region. The results confirmed that the most decisive factors influencing mobility were measures in schooling, access to workplaces, restrictions on movement, and retail activities. Among these, school closures had the strongest impact, causing an average reduction of up to 75% in passenger numbers. The application of the NARX neural network model demonstrated a strong correlation ( $R = 0.88$ ) between the severity of restrictions and the decline in passenger demand, thereby providing a reliable framework for forecasting mobility during crisis situations. Unlike most previous studies that analysed pandemic-related impacts on rail passenger demand at a national or highly aggregated level, this work applies a nonlinear NARX neural network to the Slovak rail system and explicitly integrates government restrictions as exogenous variables. This combination provides a regionally applicable yet nationally interpretable modelling framework that, to our knowledge, has not been presented in the existing literature.

The findings highlight important implications for railway policy and operations. Adaptive capacity management, including reductions of 10–40% depending on the severity of restrictions, could improve the efficiency of resource allocation and reduce social costs, while maintaining safe travel conditions. Although the analysis focused on the Bratislava region, similar mobility patterns were observed across other Slovak regions, with differences mainly reflecting regional variations in infection intensity and the COVID automat. The proposed capacity adjustments (10–40%) reflect the model's scenario outputs: the NARX predictions under varying policy intensities were translated into actionable ranges for railway planners. This strengthens the practical link between the modelling results and operational recommendations.

Nevertheless, the study has certain limitations. First, the model was built on binomial variables representing the tightening or relaxation of measures, which cannot fully capture the heterogeneity and complexity of real-world restrictions. Second, the analysis relied on aggregated weekly data, which may conceal short-term fluctuations in mobility. Third, the regional focus on Bratislava, while justified by its role as the country's most important commuting hub, constrains the generalizability of the findings to regions with different mobility structures.

Future research should address these limitations by integrating higher-resolution data (daily or real-time passenger counts), incorporating more nuanced representations of measures, and extending the analysis to additional regions and transport modes. Such extensions would provide a more comprehensive understanding of mobility dynamics under crisis conditions and further strengthen the capacity of transport authorities to design resilient and adaptive transport policies.

Despite the robust performance of the proposed NARX model, several limitations should be acknowledged. The use of binary indicators for tightening or relaxing measures cannot fully represent the complexity and heterogeneity of real government interventions. Weekly and regionally aggregated data may conceal short-term fluctuations and differences in passenger segments, such as commuters versus occasional travellers. Moreover, the model was trained on data from 2019–2021 and primarily validated on the Bratislava region, which may limit its direct transferability to areas with different mobility structures.

Future research should focus on incorporating higher-resolution and real-time passenger data, such as automated counts and smart-ticketing systems, to refine predictive

accuracy. Extending the model to multimodal mobility (bus, metro, long-distance coach) could provide a more holistic view of crisis-induced travel changes. Combining neural networks with agent-based or discrete choice models may also better capture behavioural heterogeneity. Finally, evaluating the model's performance on new disruptions beyond pandemics (for example, energy price shocks or extreme weather events) could further strengthen its resilience and practical applicability. Future work should replace the current binary representation of policy measures with a more granular or weighted coding scheme that reflects the true intensity of interventions. This refinement could help the NARX model better differentiate between mild and severe restrictions and thus improve forecasting accuracy for various crisis scenarios. Future research should incorporate explicit benchmarking of the NARX neural network against simpler baseline models, such as ARIMA or regression with exogenous inputs, to confirm its advantage and mitigate concerns about overfitting. Such comparative analysis would provide stronger evidence for selecting neural network methods in crisis-related mobility modelling. Future work should include scenario-based testing and sensitivity analysis to complement fit statistics. By systematically altering the intensity and sequence of governmental restrictions or other exogenous variables, researchers could evaluate the robustness of the NARX predictions and provide decision-makers with a clearer understanding of confidence intervals and risk margins.

The presented model is limited to using a simplified coding of restriction severity and by reliance on historical data from a single crisis period. Benchmarking against simpler time-series approaches (for example, ARIMA) and sensitivity or scenario analysis would strengthen robustness and generalizability. Future research should refine the coding of interventions, test the model on multimodal transport systems, and explore dynamic capacity allocation strategies for different crisis scenarios.

Based on the NARX demand forecasts under different levels of restrictive measures, railway operators can prepare tiered capacity strategies for crisis situations. When education closures or severe workplace restrictions are introduced, a capacity reduction of 30–40% is justified, while moderate measures may require only a 10–20% adjustment. Essential commuter services, especially on main interregional corridors and to/from Bratislava, should be prioritized to maintain connectivity for key workers. Operators could pre-design flexible emergency timetables that reduce train frequency but preserve core routes and use demand-monitoring dashboards to dynamically add or remove services as restrictions change. Coordination with regional authorities is crucial to ensure that school and work policies inform capacity decisions in real time.

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