*Article*

# Bicycle Traffic Model for Sustainable Urban Mobility Planning

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**Abstract:** Modelling tools and transport models are required to assess the impact of measures for the effective planning of cycling routes in cities. This paper presents the methodology for developing a four-stage macroscopic model of bicycle traffic for the city of Gdynia, and its use in planning new bicycle routes, considering a modal shift. The model presented in this paper allows for the evaluation of the influence of the characteristics of the cycling infrastructure, along with the development of the cycling network based on the choice of cycling as an alternative to other modes of transport, by taking into account the modal shift. The model takes into account the influence of the longitudinal gradient, link, and surface type of cycling routes on the distribution and demand for bicycle traffic. The results of our research allow us to assess the impact of planned cycling routes on the reduction in the volume of car traffic, which is crucial for reducing energy consumption and negative environmental impacts. Experiences from the application of the model in Gdynia suggest that the model provides a strong basis to support mobility planning and monitoring processes in cities worldwide. Cities should take into account the methods proposed in this paper when planning the development of their transport systems.

**Keywords:** sustainable urban mobility planning; macroscopic transport model; bicycle traffic model; modal shift; modal split

## 1. Introduction

Many cities (especially in Central and Eastern Europe) have developed their road transport networks with a focus on improving the efficiency of motor vehicle traffic and minimising congestion. Such activities usually aim to increase the capacity of elements of the road network. However, congestion—and the resulting increases in energy consumption and greenhouse gas emissions—can also be reduced more rationally by introducing measures to change the modal split and increase the share of cycling in daily trips. Therefore, effective development of the transport system requires prediction of the effectiveness of planned changes, and monitoring of the performance of implemented measures. Most often, cities do not use tools that allow for the consideration of cycling in the transport system and the possibility of changes in the modal split as a result of the implementation of infrastructural or organisational measures. Transport demand and transport network models can effectively support the process of mobility planning by taking into account active modes of transport, including cycling. This paper aims to review the state of the art in bicycle traffic modelling—taking into account both the modal shift, and measures contributing to the reduction in travel demand and the increase in the share of cycling trips—and to present the opportunities and benefits resulting from the application of such solutions in the example of the city of Gdynia.

Urban transport systems face major challenges due to the growth in private vehicle ownership and motorisation rates (number of private vehicles per number of inhabitants) [1,2]. There were more than 256 million passenger cars in EU countries in 2018 [3]. The World Bank's predictions indicate that by 2050 the number of vehicles on the road will double to 2 billion, and nearly 70% of the projected world population (approximately 5.4 billion people)

will live in urban areas, tripling the number of urban trips [4,5]. According to recent estimates, passenger transport (in kilometres) in the United States will increase by 30–50% by 2100 [6], and in the EU by 42% by 2050 [7]. These estimates show that cities face a growing motorisation rate that needs to be addressed. The share of urban trips using public transport is decreasing, and the rate of cycling trips remains low, especially in Eastern European countries. Pedestrians and cyclists make between 13 and 51% of all trips in Western European countries [8]. However, in terms of kilometres travelled in the European Union, only 1% of passenger kilometres are travelled by bicycle, while 73% are travelled by car [9].

Many cities around the world are experiencing urban sprawl, rapidly increasing motorisation, inadequate public transport systems, a high share of car trips, high pollution, and poor infrastructure for pedestrians and cyclists [10]. The unsustainable growth of transport activities puts a strain on our planet's ecosystems and resources. Greenhouse gas emissions (GHGs) from energy production are one of the main causes of climate change. The excessively slow transition to alternative fuel sources and propulsion systems has led the transport sector to be increasingly blamed for the possible failure of individual countries to meet their commitments in international climate change agreements [11]. For this reason, transport remains at the centre of any debate on energy savings, due to its dependence on fossil fuels in car transport (passenger and freight), but also in rail, air, and maritime transport. In Europe, GHGs decreased between 1990 and 2017, except for the transport sector [12]. The transport sector is responsible for 30% of total energy consumption and 20% of total GHGs in the European Union (with road transport having the largest share, at 72%) [12–14]. The total external costs of transport (including accidents, congestion, noise, $CO_2$ emissions, and air quality) in urban areas of the EU amount to EUR 230 billion [15]. There are increasing indications that electrification in transport will not be fast enough or sufficient to meet the energy efficiency and low-carbon targets of the transport system [14,16–18]. These trends in the development of transport require actions aimed at reducing motorised traffic. Evaluation of the effectiveness of such measures is possible through the use of transport models that estimate changes in travel demand and the modal split, taking into account active mobility modes (including cycling).

There are very few reliable, integrated, and comprehensive tools for modelling the transport system that take into account bicycle traffic at the macroscopic level [19–22]. Most existing urban transport modelling tools inaccurately or incompletely take into account the influence of cycling on the functioning of the transport network. The tools used for transport modelling most often focus only on the performance of road transport, either excluding cyclists or treating them as a disruptive factor for motor vehicle traffic. Therefore, it is necessary to develop tools and models that allow assessment of the impact of planned actions for the implementation of cycling measures, taking into account the influence on the modal shift. Such analyses allow us to look differently at the possibility of improving the conditions of travel in the transport network through the reduction in car traffic. The model proposed in this paper contributes to filling the indicated gap.

The bicycle traffic model was developed by the authors of this paper to support the city of Gdynia in planning and decision making with regard to changes in the transport network, as well as in the development, implementation, and monitoring of the Sustainable Urban Mobility Plan (SUMP). The SUMP is a document proposed by the European Commission to establish a framework for urban mobility planning, and is the result of the sustainable urban mobility planning process [21,23]. The application of the model to planning the development of transport systems, monitoring the SUMP, consulting citizens and, ultimately, making decisions is a strong innovation of the presented solution.

The structure of the bicycle traffic model is also innovative (especially on a national scale). The data and variables used allow for a reliable representation of the existing cycling traffic and its predictions. Another contribution to the research is the consideration in the model of the influence of the longitudinal gradient on the speed of cyclists, and the consideration of the types of sections of the cycling network, and their surface, in the choice of transport mode and route. The research methodology includes both a survey of residents

and direct measurements of bicycle and road traffic. The spatial approach to modelling mobility behaviour opens new opportunities for evidence-based planning and decision making in the broad area of cycling promotion and development, as well as for predicting and monitoring the effects of planned or implemented measures. The methodology for developing the model was tested and verified on the example of the city of Gdynia, but it can be an example of good practice for other cities.

This paper attempts to answer the following questions:

- Why is it important to consider a modal shift in urban transport modelling, and how can the experience from Gdynia help in the development of a bicycle traffic model that takes into account the modal shift?
- What data can be used to develop a bicycle traffic model, and what are the elements of the model to predict the choice of particular routes by cyclists?

Section 2 of this paper provides an overview of the solutions used in transport modelling, with a particular emphasis on cycling. Measures and factors that influence the modal split, the volume of bicycle traffic, cycling activity analysis techniques, and methods of estimating and predicting the volume of bicycle traffic are characterised. Section 3 presents the methodology for modelling bicycle traffic, with a particular emphasis on modelling the demand for cycling and the route choice. Section 4 presents the use of the modelling methodology in studies of the impact of cycling network development on transport demand and bicycle traffic assignment. A discussion and conclusions of the research and its results are included in Sections 5 and 6, respectively.

## 2. Modelling of Bicycle Traffic and Modal Shift in Cities: A Review

Transport models help to assess the effects of planned measures and decide on their introduction. Transport modelling allows the mapping of transport systems using mathematical tools that enable the simulation of transport processes that occur in reality [24–27]. The computer model is an abstract representation of the actual transport system, which allows researchers to study processes without having to experiment in the actual system environment. The transport model enables an analysis of the flow of people and goods in a network within an area with specific land use and socioeconomic characteristics [28]. The EU requires that the comprehensive implementation of transport measures be based on travel demand and transport network models in order to facilitate the calculation and comparison of economic indicators resulting from this implementation. Models help to supplement engineering knowledge with simulated results [29].

### 2.1. Measures Influencing Travel Demand and Modal Shift in Cycling

Motor vehicle congestion is considered one of the main problems in urban transport, as it contributes to longer travel times [30–33], increased energy consumption, and pollutant emissions [34,35] which, in turn, lead to a poorer quality of life in cities [36–38]. Therefore, it is necessary to promote infrastructure and technological development, regulatory instruments, and social change to reduce the impact of mobility demand on energy consumption and the environment [39]. Research on energy consumption and emissions in transport covers several areas of interest including, but not limited to, infrastructure measures, environmental impacts, analysis of transport policy, urban travel patterns, and lifestyles [30,40–42]. New alternative fuel technologies (e.g., electricity, natural gas, and hydrogen) are ways to break the dependence on fossil fuels in order to reduce energy consumption and traffic-related emissions. However, it is important to look for ways to change transport behaviour in the short term, as long-term technological solutions have not yet been fully realised [43–46]. Another way to reduce energy consumption and GHG emissions is to reduce VKT (vehicle kilometres travelled) and vehicle ownership rates. Due to the high level of energy consumption in the production phase, decreasing VKT alone is not sufficient—the number of vehicles owned must also be reduced [47,48]. Overcoming these negative trends is possible through the implementation of cycling, walking (active mobility or active travel), and smart mobility solutions that support them (e.g., intelligent

transportation systems services, the Internet of Things, or Mobility-as-a-Service (MaaS), with active travel as one of the options) [39,49–52].

Walking and cycling can make a significant contributions to addressing urban challenges such as air pollution, health, and energy consumption [34,35,37,38,53–59]. Negative consequences of energy production and consumption are observed for both car use and cycling. The negative impact of motor vehicles arises from fuel consumption, the energy used to manufacture and maintain the vehicle, and the production and distribution of fuel. The energy consumed in the production and maintenance of a bicycle, and the increase in food demand (energy consumed in the production and distribution of food) resulting from the increased activity of a cyclist compared to a car driver, should also be taken into account in the case of bicycles [59,60]. The greatest energy savings can be achieved by reducing the fuel consumption of cars (non-renewable energy sources, dominating in the automotive industry) and by reducing the number of cars produced, which can be facilitated by increasing the demand for cycling [59]. Compared to private motorised transport, bicycles are healthier, cheaper, and more environmentally friendly, and can be more efficient in terms of travel time for short and medium distances in urban areas [33]. In recent years, we have seen an increase in the availability of electric bikes (e-bikes), which can increase the number of bicycle trips [61]. The e-bike can replace the car for distances that are considered too long for a conventional bicycle and, thus, can contribute to the development of sustainable mobility, both at the local and regional levels [62]. Surveys of commuters suggest that e-bikes can replace around 50% of car trips [63,64]. Furthermore, research shows a decrease in VKT per e-bike user of 20–28% [65,66], and a decrease in the distance travelled by car as a total modal share of around 10% [67]. Current developments in urban cycling include the introduction of adaptive systems for electric bikes to increase the number of users [68,69]. Such enhancements can improve cycling comfort through the use of innovative technologies that are usually found in individual motorised transport.

The European Commission, in the Green Paper [70], identified the main challenges in the field of urban transport development. The challenges of prioritising cycling are to promote active mobility, to promote eco-driving, to reduce motorised traffic, and to change transport behaviour and the ways in which urban communities perceive transport. Various strategies to reduce congestion were analysed in the research conducted by the OECD and the European Conference of Ministers of Transport [71]. The research identified the need to strengthen public transport and non-motorised modes of transport (walking and cycling), while implementing traffic management strategies to effectively reduce congestion. Research on the effectiveness and cost of congestion reduction strategies shows which types of measures are most successful in reducing congestion at the most cost-effective level [72]. Research shows that multimodal transport options, including cycling, are the most effective group of measures due to their lower implementation costs. Congestion, and its negative impacts on the environment and energy consumption, can be reduced by the modal shift from motor vehicle to bike. Cycling is widely considered an appropriate alternative to motorised traffic. Therefore, policymakers and city authorities aim to improve sustainable mobility by developing and promoting cycling [73,74]. State-of-the-art evidence suggests a positive correlation between comprehensive cycling promotion/development and a modal shift toward active mobility modes [75–79]. Changing transport behaviour is time-consuming and particularly difficult. Mobility means, among other things, the ability to move and make choices in transport; therefore, the role of mobility management in cities is to stimulate informed choices [80]. Changing lifestyles to adapt to new services and systems should aim to use alternative modes of transport instead of the car, and to reduce demand for transport [23,81–83]. A change in transport behaviour can be achieved, for example, by implementing the compact urban development concept, which aims to reduce the use of urban space for transport and reduce the demand for transport—especially motor vehicles [84–87]. There is also research showing that even the perception of "nice architectural design of residential, civic buildings and/or street furniture" can be positively related to cycling [88]. In addition to measures related to appropriate land use and urban

road network planning, the following infrastructure and organisational measures should be recommended to cities in order to encourage modal shift and improve conditions for cycling:

- Development of bike lanes, paths, and bike highways [58,89–93];
- Development of traffic control strategies geared towards cyclists and pedestrians [94–97];
- Bike-sharing schemes [33,98–104];
- Improving cycling parking facilities [89];
- Traffic calming and introduction of lower speed areas [58,84];
- Mobility management measures that include educational campaigns, access restrictions (e.g., car-free areas), MaaS solutions, and congestion charges [84,105–109].

The most significant effects of changing the modal split can be achieved if infrastructural measures and those promoting active mobility are combined with measures that discourage car traffic, such as parking fees, congestion charges, or the removal of parking spaces.

## 2.2. Modelling of Transport in Cities

Models of transport demand and street networks can be developed at different levels of detail, i.e., macroscopic, mesoscopic, or microscopic [110]. Macroscopic models [19–21,111] are generally developed to analyse the flow of people and goods or vehicles over a larger area and at a lower level of detail (mainly due to limitations in research tools and data availability). Mesoscopic models allow us to simulate and study the movement of vehicle groups in road sections and intersections [112]. The third group is microscopic models, which are developed to take into account the behaviour of individual vehicle drivers [113]. Modelling of transport and traffic in heavily urbanised areas requires consideration of several factors [114]. These factors include a high density of buildings and dynamic changes in spatial development, a high density of the transport network, a high level of traffic volume, and a significant number of transport modes. The high risk of the occurrence of incidents that affect the level of reliability of the transport system should also be taken into account.

A typical model consists of several basic layers. The first element is a network model. The point (e.g., junctions, public transport stops) and linear (e.g., sections of streets, public transport routes, bicycle routes, walking routes) elements of the transport network are modelled using graph theory. The second element is the transport demand model. The demand model characterises the transport needs of particular groups of travellers in terms of the size of the needs, the origins and destinations of trips, and the motivation of traffic users. The issues of modelling demand using the classic four-step transport model are widely discussed in the literature, e.g., [115,116]. Further elements, such as transport interaction models, make it possible to take into account the relationship between the model parameters—for example, in the processes of traffic assignment or estimation of modal split and modal shift. Much research has led to the development of software packages that help to model transport demand and transport networks (supply) or their elements, and to forecast traffic or passenger trips (e.g., EMME, INTEGTARION, PTV VISUM, SATURN, TRIPS, AIMSUN, SUMO, etc.) [117,118].

Many cities in Europe, including some in Poland, have developed their models of transport networks and travel demand [119,120], but do not make full use of them. One reason for this is insufficient cooperation between the actors who use the models [29]. Many cities use models mainly at the macroscopic level, and even if they use models at the mesoscopic and microscopic levels, they do not integrate them in terms of data exchange between different models and transport authorities [121].

## 2.3. Modelling of Bicycle Traffic

Bicycle traffic models allow the resolution of problems related, among other things, to demand and supply [116,122], route choice [123], lane change, and queueing behaviour [124–126]. The demand for cycling, the choice of bicycle routes, and the choice of cycling modes were

found to be influenced by many factors, including the built environment [127–130]; socioeconomic [131–134], psychological (habits, attitudes, norms, stress), and physical characteristics [135–139]; policies that promote cycling [46,59,84,138,140–142]; infrastructure for cyclists [39,143–145]; cost; effort; distance travelled; travel time; road safety; climate and weather; and travel motivation [146–150]. The frequency of commute to work, the time to cycle, and the length of the journey are important features of active commute behaviour. For example, these variables can be used to estimate the degree of physical activity that comes from commuting. The degree of physical activity was found to vary according to sex, age, and type of activity [151,152].

Several techniques for analysing cycling activity have been developed. Overlay mapping techniques or sketch-plan methods are useful for planning and prioritising [153,154], but are usually not calibrated based on actual bicycle counts. In the direct demand model, regression analysis is used to predict cycling traffic in the network [155–157]. Other methods use graph theory centrality estimates to distribute cycling volumes collected throughout the network [158,159]. In a study conducted in Southern California, prediction models of the number of bicycles were developed using linear regression, with the number of trips as a dependent variable, and measures of demographic and spatial development as independent variables. Four explanatory variables on land-use planning and transport systems (bus frequency, land-use mix, population density of inhabitants under 18 years of age, and proximity to the cycling network) were used to predict the number of bicycle trips at the junctions in Santa Monica [160]. The San Diego model was limited to two explanatory variables (employment density and length of nearby multifunctional paths) to predict the number of bicycle trips [161]. The study of bike modelling was used to explore the possibility of using space syntax in cycling modelling. A measure of space syntax representing direct paths in the street network was combined with land-use variables to predict the volume of cycling in the Cambridge network [132].

In [22,162], the results of agent-based modelling are presented to simulate cycling in the city of Salzburg. The model mainly aimed to test the role of the surrounding Salzburg area for inner-city cycle traffic. The results indicate that commuters from the surroundings have a significant impact on the spatial distribution of traffic in the city. Agent-based modelling proved to be a useful alternative to conventional transport modelling, as intuitive parameterisation allows for exploratory system analysis. MATSim agent modelling has been extended to include infrastructure attributes that influence cyclist route choice [163]. In the case of conventional (usually four-stage) models, most of the previous works on modelling cycling activity use transport zones as an analytical unit.

Due to the growing popularity of cycling in obligatory trips, some cities have decided to develop a model of cycling trips, which is a tool to support decisions at the stage of planning the development of a cycling system, similarly to other macroscopic conventional four-stage transport models. Some regional trip demand models have been adapted to estimate the share of cycling in a defined area [164,165]. Models can include different modes of transport with or without taking into account freight-related traffic. In both cases, cycling is one of the modes of transport. Research on modelling guides the planning of the development of cycling measures [166–168], and presents methods of bicycle traffic modelling [121,142,169–171].

As the analysis of approaches in the literature shows, the bicycle traffic model can be developed in two ways: by separating cycling at the stage of a modal split procedure, or by beginning travel demand modelling based on the results of surveys (not included in the modal split procedure). The second approach is used most frequently in Poland. Bicycle traffic models are usually independent of traffic and public transport models. Such a solution limits the possibility of analysing the impact of—for example—the development of the public transport system on the transport behaviour of the inhabitants in terms of changing the probability of choosing a bicycle to travel. The characteristics of the infrastructure of the cycling system, which may determine the choice of this travel mode as an alternative, are not taken into account.

The transport system models are usually estimated at the level of the traffic analysis zone (TAZ), and are not precise enough to capture the level of cycling activity at intersections. Models that study behaviour at an individual level are useful in identifying the factors that determine the choice of mode and route, but it is difficult to estimate the volume of bicycles. Most of these models are based on detailed data from household surveys, the collection of which can be expensive. Walking and cycling measures cannot be assessed under the conventional modelling procedure because transport demand and network forecasting models usually do not include walking and cycling trips. Furthermore, variables of pedestrian and bicycle links are rarely developed, or the attention necessary to accurately reflect walking and cycling routes is not given to them. Most demand models are not detailed enough to reliably take short trips into account. Models of transport networks usually do not include many local streets. Cycling routes are often located on local streets and alongside other public areas (seashores, rivers, etc.) that are not important from the traditional travel demand point of view.

It is very difficult to model infrastructure improvements that affect walking and cycling when these routes and connections are not part of the modelling network. Therefore, it is necessary to introduce local connections into the cycling network model, and to parameterise the connections available to cyclists. One of the most developed cycling models in Poland so far is the Warsaw Bicycle Traffic Model [172]. This model includes dedicated generation and distribution travel models as elements of the four-stage model, in which the modal shift is omitted due to the limitation of the model to one mode of transport. The network model includes routes dedicated to cycling (e.g., cycle paths and bicycle contraflow lanes), as well as road sections on which bicycle traffic is present according to general principles and shared walking and cycling routes.

## 3. Methodology of the Model of Bicycle Traffic Development

The model was developed based on the Multilevel Transport System Model (referred to by its Polish acronym, MST) for the city of Gdynia. The bicycle traffic model allows the application of the MST in the planning of new bicycle connections, taking into account modal shifts. The structure of the MST (including the macroscopic model that is the basis for the development of the bicycle traffic model) is discussed in more detail in the article describing its previous applications [23], and in the report by Oskarbski et al. [173]. The bicycle traffic model was developed within the FLOW project (Furthering Less Congestion by Creating Opportunities for More Walking and Cycling) [174] to extend the four-stage macroscopic model of the MST with a cycling layer. Therefore, the condition for the development of a bicycle traffic model, in this case, is the prior development of a four-stage macroscopic model of motorised traffic and public transport. Cities that do not have a macroscopic model should take into account the development of a comprehensive model for public transport and private motorised traffic, including the cycling part of the model in the planning stage. Figure 1 shows the main elements of the model, indicating which elements come from the MST and which elements were developed within the scope of the bicycle traffic model (elements within the scope of the cycling model are marked in blue). In terms of input data, only the data for the modelling of bicycle traffic are presented in Figure 1. Sociodemographic data and data used in the model calibration process (traffic volumes) were also updated as part of the model's development. The elements of the introduced bicycle traffic model are characterised in detail in Sections 3.1–3.4 and 4, using the example of the city of Gdynia. Speed models and stochastic impedance function parameters have been developed based on data measured in the Gdynia road network. Therefore, references to the example of Gdynia are presented in the description of the methodology to better illustrate the individual elements of the model. If the model is developed for another city, it will be necessary to verify the elements of the Gdynia model in terms of speed and stochastic assignment parameters. The transport network, including bicycles, was modelled with the use of PTV VISUM software [175], which is an additional constraint for cities that do not have access to dedicated software.
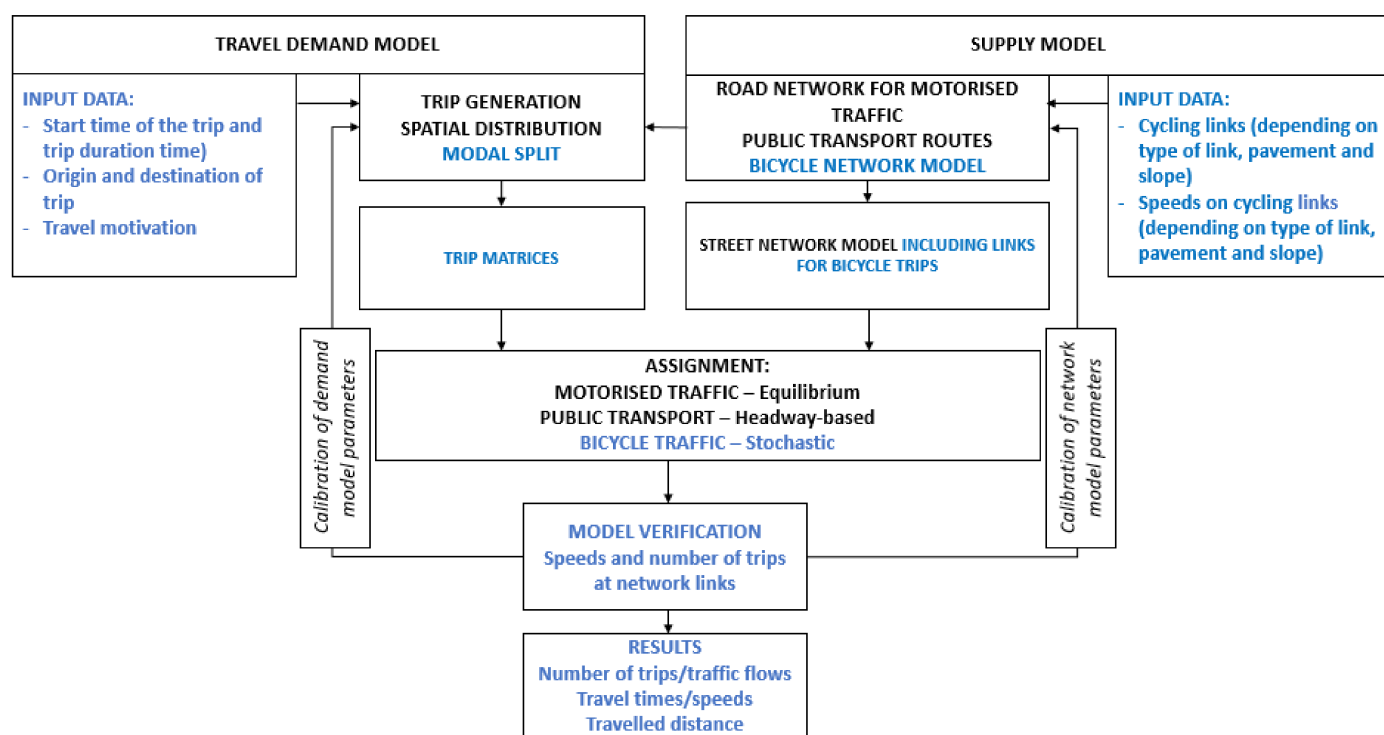
**Figure 1.** Integration of the bicycle traffic model into the MST.

### 3.1. Bicycle Network Model

The road network model in the macroscopic transport model was extended to include the modelling of important cycling links. Different types of links were developed to represent particular types of route in the bicycle network regarding the typical speed of cyclists and their separation from other traffic users, including vehicles or pedestrians. The types of links are also related to the technical class of the road along which they are located. The model also includes parameters that characterise the surface and slope of the bicycle routes. The following new attributes were developed for selected sections of the transport network, and different values of the following parameters were assigned to them (discussed in more detail later in this section):

- Longitudinal gradient;
- Available cycling infrastructure with a specification of link types: bicycle path, walking and cycling route (pavement), asphalt road on which bicycle traffic is present, together with motorised vehicles, according to general principles;
- The surface of the bicycle route, which is divided into the following types: asphalt, concrete blocks, and flagstones.

Longitudinal gradients were calculated based on the data from a numeric map provided by the Geodesy Department of the Gdynia City Hall. Each link between two nodes for which the altitude is known was assigned to one of the longitudinal slope classes. The longitudinal gradients of the cycling routes in Gdynia are shown in Figure 2. The longitudinal gradient is an important variable on which cycling speeds depend. Speeds and associated travel times were used as input parameters both in the modal split model and in the assignment of bicycle traffic presented later in this paper.
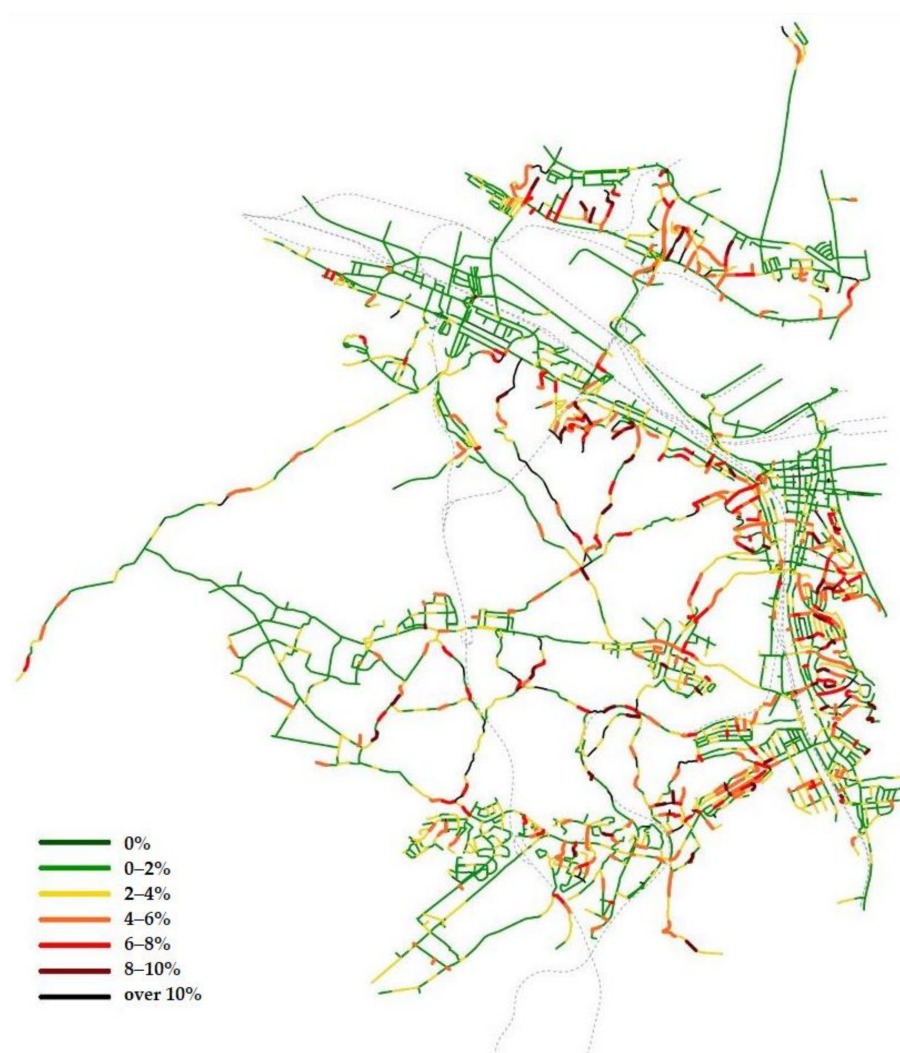
**Figure 2.** Slopes of bicycle routes in Gdynia.

The longitudinal gradient data were correlated with the average speed of sections with a given slope to determine the relationship between these variables. In addition, variables that describe the type of bicycle route and the type of road surface were also included (Section 4.2 shows the results of the survey). Based on the calculated speeds $Vel_i$ for each bicycle route section $i$ of length $L_i$ (Equation (1)), the travel times TT0r along the bicycle routes between the transport regions (Equation (2)) were calculated to be used to determine the usefulness of bicycle transport. The estimated average speeds were mainly related to cyclists who regularly participate in the European Cycling Challenge (ECC), who represent a group of frequent cyclists. Similarly, bicycle speeds were studied using the Global Positioning System (GPS) and ECC data in Bologna [176]. Additional studies should be carried out shortly to make the results more reliable due to the possible influence of occasional cyclists but, currently, the majority of bicycle users are regular cyclists who influence the modal split on typical days of the week (these cyclists were taken into account in the development of the models).

$$Vel_i = 31 - \frac{25.5}{1 + e^{0.22 - 0.4 \cdot Slope_i - 0.07 \cdot Type_i - 0.077 \cdot Surf_i}} \tag{1}$$

$Vel_i$—average speed of link $i$;
$Slope_i$—slope of link $i$;
$Type_i$—type of road of link $i$;
$Surf_i$—type of surface of link $i$.

$$TT0r = \sum_{i=1}^{n} \frac{L_i}{Vel_i} \tag{2}$$

*TT0r*—travel time on bicycle routes between transport zones;
$L_i$—length of bicycle route link *i*;
$Vel_i$—average speed at link *i*.

The function $Vel_i$ (Equation (1)) was developed by the authors of this paper, and allows the presentation of the dependence of the average speed of cycling on the longitudinal slope and the selected types of cycling link (Figure 3). Before applying the $Vel_i$ function to the bicycle traffic model, the speed distribution functions were determined for the bicycle sections at 5 km/h intervals (in the range of up to 40 km/h). In the validation process, the sampling rate distributions in each speed interval were compared for the model dataset and the control observation dataset. The mean absolute percentage error (MAPE) for the mean speed calculated from the observation data from the control group and the model results did not exceed 12% (values in the upper error range were observed for steeper gradients for downhill cycling). The longitudinal gradient was the most decisive factor in the value of the average speed. The results were found to be satisfactory for planning purposes, as confirmed by a subsequent verification of the model presented in Section 4.5.
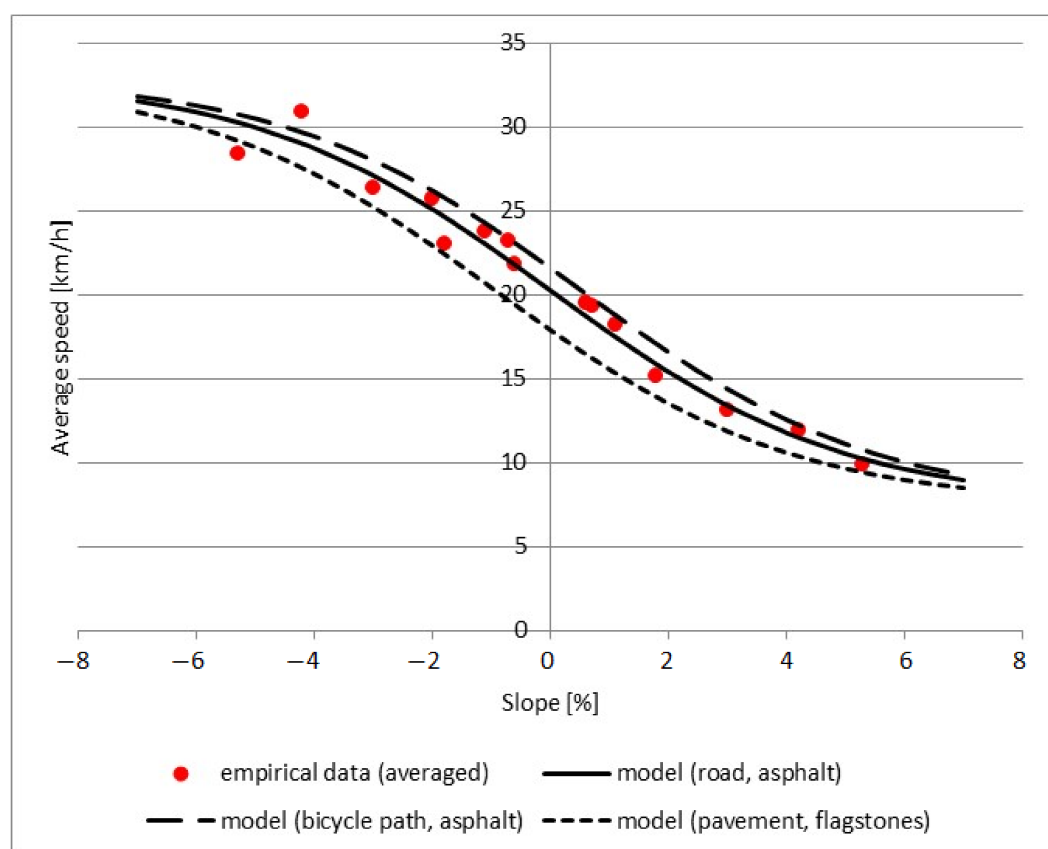


**Figure 3.** The relation between the average speed $Vel_i$ of cycling on the longitudinal slope and the characteristics of the route.

In future studies, the presented model should be further developed by taking into account different user groups, e.g., by age or cycling experience.

### 3.2. Modelling of Demand for Bicycle Trips

The data collected (in the surveys listed in Section 4.1) were processed to develop an origin–destination matrix for bicycle traffic. All bicycle trips in the database are connected with attributes that describe:

- The start time of the trip and trip duration time;
- Origin and destination transport zones (TAZs), connected to the network through centroid connectors;
- Travel motivation;
- Modes of transport chosen by the respondents (who are also divided into groups, e.g., by age).

Based on the above data, cycling matrices were developed for the day, and separately for the peak hours of 7:00–8:00 (morning peak) and 15:00–16:00 (afternoon peak), in 2016 and 2017 (according to the biannual transport survey and traffic measurements, the hours with the most trips and the highest traffic volumes in Gdynia). The matrices were used to calibrate the MST model [173], which was developed with the use of PTV VISUM software.

The stages of generation and spatial distribution of trips in the MST presented in the report by Oskarbski et al. [173] were left unchanged when the model was extended to include cycling. Models of trip generation include explanatory variables (e.g., number of inhabitants, total number of jobs, number of people over 6 years of age, number of places of education in primary schools, junior high schools and secondary schools, area of service and commercial buildings, number of jobs in the service sector) in particular transport zones. The spatial distribution (trip matrices, including cycling mode) was developed using a gravity model. The share of morning and afternoon peaks in cycling traffic was determined based on traffic analyses for individual motivations. O–D (origin–destination) matrices were calculated for all zones in the MST based on sociodemographic data, compared and calibrated with O–D matrices estimated based on survey results. The bicycle modal split was calculated based on the survey results in each zone. Then, the modal split procedure was applied based on the travel times for each mode, as described in Section 3.3.

### 3.3. Modelling of Modal Split

Development of the MST to include cycling was carried out in the field of changing the modal split and shift models, changing the parameters, and extending the transport network model by sections important in the assignment of cycling traffic to the network.

The basic model based on which dependencies were built is a logit model. A utility function was defined for each of the transport modes. The utility of a given transport mode should be understood as the degree of its attractiveness, defined by any number of variables. This utility is determined for each alternative as a function whose variables are factors that significantly affect the attractiveness of travel by a given mode of transport (e.g., travel time). Due to the later assumptions of the logit model, utility is expressed as a component of two elements: the measurable utility $V_{ij}$, and the random part $\varepsilon_{ij}$, according to the formula given in Equation (4) [116]. This approach first allows us to grasp the different preferences of users and their subjective, perceptible attraction to the alternative (e.g., not every change from one mode of transport to another is as burdensome). Second, it allows users to take into account user errors in utility assessment (underestimation, overestimation). Third, it allows for the capture of all directly unmeasurable random factors influencing the choice of modes of transport (e.g., comfort, habits). The utility functions described by the selected variables were used in models with discrete selection. Discrete logit selection models allow a utility to be determined for each alternative separately, and the probability of selecting a particular mode of transport is determined by the difference between them. Thus, according to the above, each of the transport modes $m$ has been described by a utility function $V^m_{ij}$ for the travel relationship between the origin of the trip $i$ and the destination of the trip $j$. The logit model assumes that the user chooses the option with the highest utility from the available alternatives. The utility functions characterised in this way were

used in the discrete choice model, whose parameters were adjusted using the generalised extreme value (GEV) model, which is consistent with the principle of maximisation of the stochastically defined utility function. The logit model was used to estimate the probability of choosing individual modes of transport (Equation (3)). The following available variables were used in the model: travel distance between *i* and *j*, travel time by bicycle, travel time by private transport, and perceived travel time by public transport [116,177,178]:

$$P_{gn} = \frac{e^{\mu_n U_{gn}}}{\sum_{g \in n} e^{\mu_n U_{gn}}} \cdot \frac{e^{\mu_g [\frac{1}{\mu_n} log(\sum_{g \in n} e^{\mu_n U_{gn}})]}}{\sum_{n=1}^{m} e^{\mu_g [\frac{1}{\mu_n} log(\sum_{g \in n} e^{\mu_n U_{gn}})]}} \tag{3}$$

$P_{gn}$—the probability of choosing the *n*th mode of transport belonging to the *g*th group of transport modes;
$U_{gn}$—utility of the *n*th mode of transport belonging to the *g*th group of transport modes;
$\mu_n, \mu_g$—model scaling coefficients.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{4}$$

$V^m_{ij}$—measurable utility of transport modes *m*;
$\varepsilon^m_{ij}$—random variable with a logistical distribution reflecting values not included in the utility $V^m_{ij}$.

For each mode of transport (*p*—walk trip; *R*—bicycle trip; *TI*—private transport trip; *TZ*—public transport trip), the authors of this paper developed a nested logit model with the following utility functions:

$$\begin{aligned} V_P &= \beta_{10} + \beta_{11} \cdot DIS \\ V_R &= \beta_{20} + \beta_{21} \cdot TT0r \\ V_{TI} &= \beta_{30} + \beta_{32} \cdot \frac{TTC}{PJT} \\ V_{TZ} &= 0 \end{aligned} \tag{5}$$

*DIS*—travel distance (km);
*TT0r*—calculated time of cycling trip (min);
*TTC*—calculated travel time by private transport (min);
*PJT*—perceived travel time by public transport (min);
$\beta_i$—equation coefficients.

### 3.4. Bicycle Traffic Assignment

The calculation of the traffic flow was performed using stochastic assignment. Each link was characterised by attributes that describe the type of surface and the slope class, leading to a better representation of cyclist behaviour in the modal split and the route choice in the Gdynia bicycle traffic model. Important elements determining the assignment of bicycle traffic were to take into account factors that are random or not random. Random factors were taken into account in the stochastic assignment to calibrate the model. Factors that influence the choice of the route include the following characteristics and behaviours of cyclists:

- Traffic participants do not have complete knowledge of the transport network, which means that they do not always choose the route rationally according to their preferences [179,180];
- Different routes are sometimes chosen according to the need for variety [181,182];
- Cycling times on different routes can vary from day to day due to the influence of other traffic participants, slope, traffic signals, congestion, weather conditions, etc. [127,182–187];
- Different cycling habits make certain routes more attractive to certain groups of cyclists [135–139,186];
- Cyclists may have different preferences on the choice of more attractive routes, for example, due to the quality of the surface or the surrounding landscape, and different risk awareness [181,182,188,189];

- Cyclists have different levels of tolerance to weather conditions [89,149,150].

Stochastic assignment is by far more appropriate for bicycle trips, since it reflects the process of individual discrete choice. The variety of individual choices is more important for cyclists than volume-dependent travel times. Stochastic assignment assumes that the selection of the route is caused by changes in the subjective perception of the inconvenience of cycling in a given sequence of sections of the transport network. Stochastic assignment procedures assume that traffic participants, in principle, select the best route, but evaluate individual routes differently due to incomplete and different information. It is assumed that the resistance (impedance) of the route sections consists of two parts: deterministic, and random. Each link in the transport network model is characterised by information on the type of surface and the longitudinal slope (included in the $Vel_i$ function, which characterises the individual sections of the cycling network), which affect the comfort of travel. Slopes directly influence the average cycling speed, which means greater resistance to uphill sections with high slopes. These factors greatly determine the choice of the route, and their application in the model aims to better represent the behaviour of cyclists in the transport network.

The stochastic assignment was performed using PTV VISUM software. To define the impedance of each section in the bicycle network, the authors of this paper calculated the travel time for each section of the bicycle network based on the $Vel_i$ function (i.e., taking into account the type of section of the bicycle network, the longitudinal gradient, and the type of surface). The impedance of the routes is due to the impedance of individual sections of the cycling network. The results of the research, presented in Section 4.2, were used to develop the $Vel_i$ function (Section 3.1) and parameterise the impedance of the section in the bicycle traffic model with travel time value.

According to the assignment procedure, not only is the shortest route found, but many alternative (but similar) routes are also found using a multiple best path search and a variation in the impedances of individual sections of the cycling network. The stochastic assignment procedure involves 5 steps: (1) route search considering the entire cycling network for the current impedance; (2) calculation of route independence (or commonality) based on the overlap of all routes for an origin–destination pair; (3) distribution of demand over the routes of each origin–destination pair, considering route independence (or commonality); (4) repeating the distribution of demand until demand for all origin–destination pairs is in equilibrium; (5) repeating steps 1–4 until no new routes are found, or the change in the number of connections between the two iteration steps is very small. The procedure is divided into external and internal iterations. The external (global) iteration is used to find routes. The internal iteration is used to assign the traffic volume to routes. This loop is repeated until the impedance deviations on the network elements and the bicycle traffic volume deviations on the routes between the two iteration steps are very small. The enhanced stochastic assignment procedure used in PTV VISUM is described in more detail by Szabo et al. [190].

The model was calibrated to achieve better goodness of fit between the model output data and the observed data by adding time penalties at major intersections that cause delays for cyclists (extensive intersections with traffic signals). The results of model verification are presented in Section 4.5.

## 4. Testing the Model on the Gdynia Case Study

Gdynia is a young and dynamically developing city, founded in 1926 and located on the Baltic Sea coast in the northern part of Poland; it has a population of almost 250,000, and is mainly made up of people of working age (151,000). The increasing number of motor vehicles is a potential threat to the attractiveness of the city centre, which is why the city is currently taking measures to promote sustainable transport development. Public spaces need to be designed efficiently and well. The number of inhabitants in Gdynia is decreasing; many of them move to neighbouring communes, where the population is rapidly increasing. At the same time, most people in these communities work or study

in Gdynia. The average distance between home and work or study is steadily increasing which, together with the higher affordability of private cars, results in a systematic increase in the share of private car trips. The factors mentioned above (related to land use planning and the growth of motorization) can cause increased traffic congestion, travel time, accident costs, noise pollution, and exhaust emissions, as well as increasing the number of areas designated for cars (roads and parking spaces).

Regular monitoring of the transport preferences and behaviour of the inhabitants of Gdynia has been carried out for more than 20 years by the Gdynia Management of Public Transport (ZKM). Research is conducted every 2–3 years through an individualised interview survey, standardised on a representative sample of 1% of the population. The survey conducted in 2018 allowed us to estimate the following modal split for urban trips: 11.4% of respondents declared a pedestrian trip, 48.9% by car, 37.1% by public transport, 2.1% by bicycle, and 0.6 % others, including motorcycles (surveys were not conducted in 2020 due to COVID-19). The share of public transport in travel does not increase significantly: in 2013, for non-pedestrian trips, it amounted to 45.7%; in 2015 this figure decreased to 39.8%, and in 2018 it increased to 41.8%. We can also observe an increase in the share of cycling in non-pedestrian trips (2013: 0.8%; 2015: 1.8%; 2018: 2.4%) [191,192]. The development of cycling and walking could be a solution to the increase in trips made via private motorised transport. Therefore, it is crucial to increase the attractiveness of public transport and non-motorised modes of transport. The city has taken a series of actions to meet this challenge. First, these actions are related to the improvement of pedestrian and bicycle infrastructure (aiming at achieving continuity of bicycle routes, improving accessibility). Second, traffic organisation aims to prioritise pedestrians and cyclists over private motorised traffic within the city centre (traffic restrictions, traffic signal settings). The city has also implemented measures aimed at creating attractive spaces for pedestrians and cyclists, with facilities for them (including pilot shared-space projects).

The basis for informed and effective actions is the analysis of planned and implemented measures in the transport system using tools such as integrated transport demand and network models. The aim of Gdynia's participation in the FLOW project (Furthering Less Congestion by Creating Opportunities for More Walking and Cycling) (HORIZON 2020) was, among other things, to develop tools used in the analysis of bicycle traffic. Gdynia uses a three-level transport model (MST) to model motorised private and public transport. The MST was developed as part of the CIVITAS DYN@MO project—"DYNamic citizens @ctive for sustainable mObility" (Seventh Framework Programme of the European Commission). Participation in the FLOW project allowed the extension of the transport model to include cycling, so that it could be used as a tool for planning, making decisions, and analysing the impact of cycling on traffic conditions. The results of the analyses carried out with the use of the MST updated with the bicycle traffic model help the municipal services in public consultations and the selection of effective measures to increase the share of cycling in daily trips. The transport network, including bicycles, was modelled with the use of PTV VISUM software [175]. The cycling model has been integrated into the existing macroscopic model, which is part of the MST. The model includes the same transport zones, but the network has been extended with important cycling parameters. The model includes the transport network of the city of Gdynia, with 173 TAZs. Each TAZ is characterised by variables that determine the generation of trips. The transport network model includes more than 5500 links (characterised by technical class, cross-section, capacity, and free-flow speed) and around 2100 nodes. The functions developed based on comprehensive traffic surveys conducted in Gdańsk in 2009 and the Gdynia study of the preferences and transport behaviour of the inhabitants in 2013 [191] were used to calculate the demand for trips and determine the transport behaviour of the inhabitants in a four-stage model [116,173].

### 4.1. Data Sources

Due to the different availability of data and significant costs of their acquisition in various cities, suggested data that may be used in the development of a bicycle traffic model are presented in the example of the city of Gdynia. When planning the development of a cycling model, it is advisable, in the first step, to diagnose the availability of data and to plan additional field research or the acquisition of data from other sources (e.g., mobile phone data, data from navigation systems, data from ITS services), taking into account the costs of data acquisition. The macroscopic model of Gdynia's bicycle traffic was developed using the following data (cycling data were collected in May, June, and September):

- The biannual transport survey (conducted by the local public transport authority) was used to calibrate and verify the sum of all trips and the modal split [191];
- Data collected during the European Cycling Challenge 2016 and 2017 (Global Positioning System track of 20,136 trips made within the competition, with speed estimation) were used to verify the spatial distribution of bicycle trips and bicycle traffic assignment, calibration, and speed verification;
- Data collected during the local cycling competition for companies in 2016 and 2017 (general information about all trips made within the competition)—necessary for the selection of transport system improvement scenarios;
- Surveys conducted amongst participants in a local cycling competition for companies in 2016 (1146 bicycle trips) were used to parameterise sections and select improvement scenarios;
- Cyclist traffic research (bicycle traffic volumes) in key city locations (at bicycle route sections and street intersections), along with surveys dedicated to FLOW in 2016 (1208 bicycle trips), were used for calibration and travel matrix verification, travel motivation, bicycle traffic volumes, and parameterisation of sections;
- Public and private transport and MST traffic parameters (VISUM, VISSIM, SATURN) [173], supported by data from intelligent transportation system services that form the TRISTAR system in Gdynia) [193];
- Statistics for individual transport areas in 2016 (e.g., number of inhabitants in particular transport areas, total number of workplaces, number of people aged 6 and over, number of study places in schools, area of service and commercial buildings, number of workplaces in the service sector) were used to update the transport demand model.

### 4.2. Survey Results

Based on the surveys (conducted amongst participants of a local cycling competition for companies in 2016—1146 bicycle trips and surveys dedicated to FLOW in 2016—1208 bicycle trips), it can be concluded that frequent cyclists travel not only for daily activities, but also for recreational purposes (obligatory trips with home–work or work–home motivation—40%; with motivation to educational places—5%; recreation—38%; other trips can be connected with shopping, for example). Modal split models do not take into account recreational trips, which are likely to have little impact on the modal share of daily trips during typical weekday peak hours.

Cycling surveys in key locations in the city showed that the largest group of cyclists was between the ages of 35 and 50 (32%); the second-largest group was 25–34 years old (25%). The joint share of the above age groups in cycling was more than half of the share of all users combined. The group over 50 years of age amounted to 25%. The least numerous group was children under 12 years of age, whose share in cycling did not reach 1%. In the breakdown by gender, the cyclists were mostly men; women constituted a much smaller group. The gender distribution in cycling can be expressed in a numerical ratio of 3:2.

The results of the research were used to develop the $Vel_i$ function (Section 3.1), and to parametrise the impedance of the section in the bicycle traffic model with travel time value (according to the stochastic assignment procedure described in Section 3.4) in terms of the section type (Figure 4) and surface type (Figure 5), in a possible range of evaluation from 1 to 5.
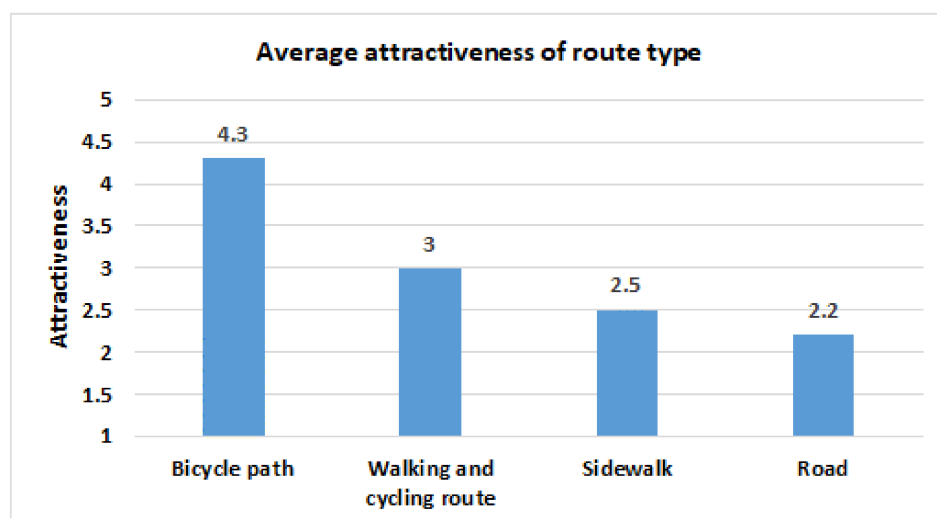
**Figure 4.** Attractiveness of the bicycle route to the user in terms of the route section type.
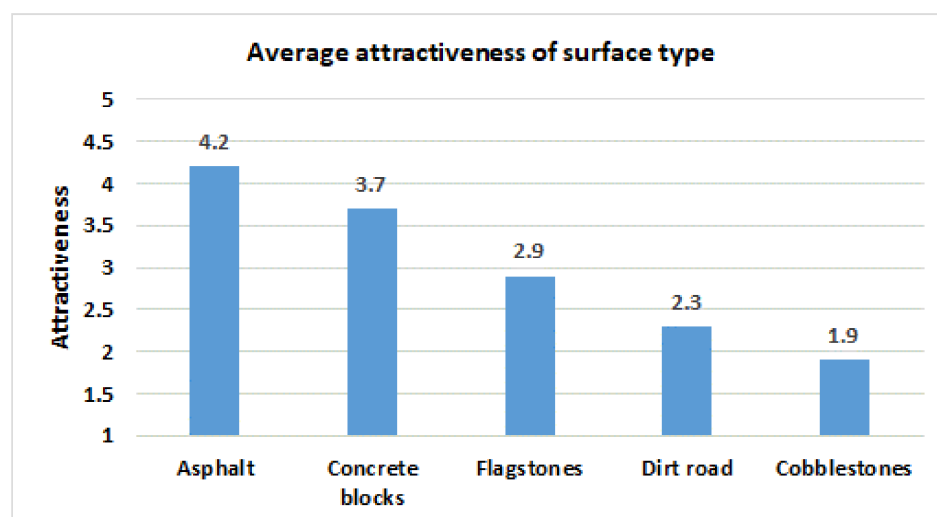


**Figure 5.** Attractiveness of the bicycle route to the user in terms of the route surface type.

The presented results of the surveys confirm previous findings that cyclists prefer separated on-street infrastructure or off-street paths [127,182–185]. To a lesser extent, cyclists indicated the attractiveness of mixed-traffic sections (marked walking and cycling routes, and sidewalks mostly made of flagstones that cyclists share with pedestrians, as well as road sections shared with motorised vehicles). According to the answers of the respondents, the pavement that cyclists indicated as the most attractive is a smooth surface without irregularities; these are made from asphalt and, to a lesser extent, smooth concrete blocks. Cobblestones (regular stone pavement) and dirt roads (most often forest roads) were indicated as the least attractive and most discouraging to cyclists.

*4.3. Scenarios of the Development of the Bicycle Network in Gdynia*

The bicycle traffic model was used to analyse various scenarios of the development of the bicycle network in Gdynia. The macroscopic model was used to estimate the effectiveness of the following six planning scenarios for the development of the urban cycling network compared to the baseline scenario (Scenario 0—without implementation of measures) (Figure 6):

- Scenario 1—bicycle overpass between Hutnicza and Wisniewskiego streets;
- Scenario 2—bicycle connection between the city centre and Oksywie across the harbour channel;

- Scenario 3—bicycle path along Wielkopolska and Zwyciestwa streets;
- Scenario 4—seaside bicycle path in Orlowo district;
- Scenario 5—17 December Avenue, a new path in the city centre;
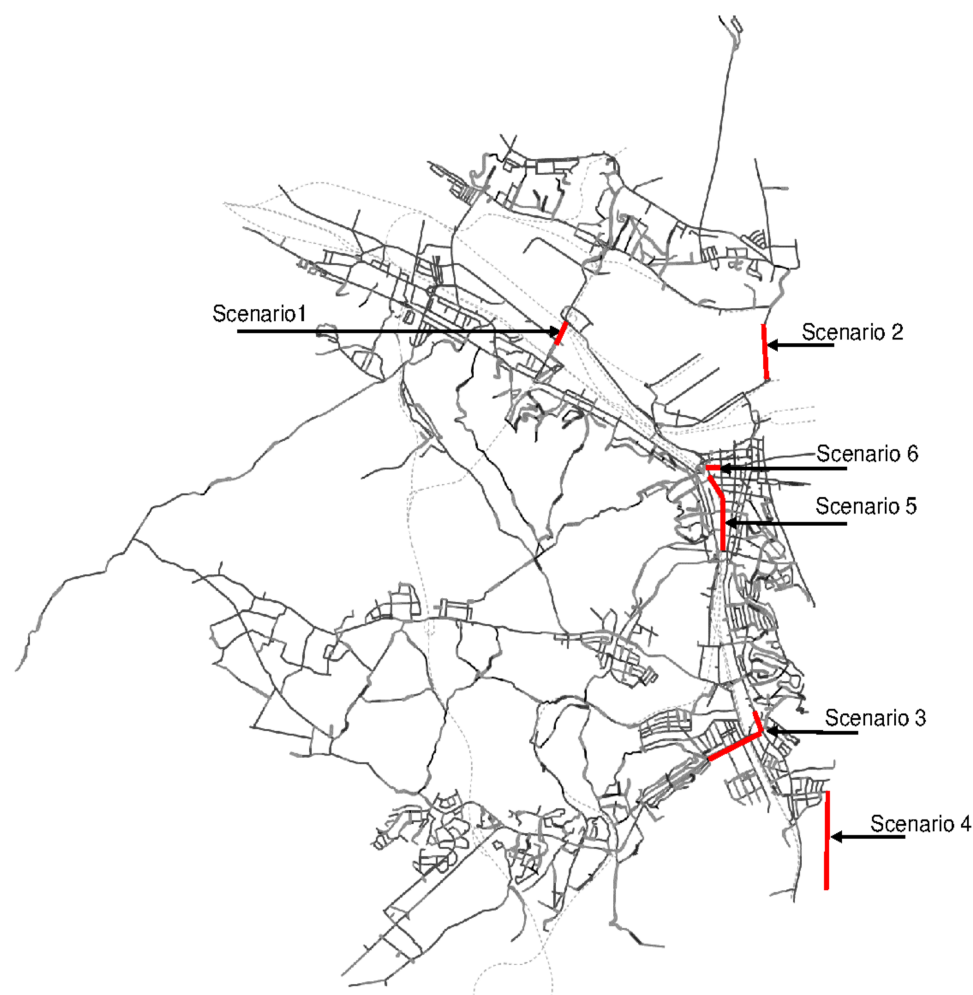- Scenario 6—completion of bicycle paths in the city centre.



**Figure 6.** Scenarios for the development of the Gdynia urban cycling network.

### 4.4. Results of Research Carried Out Using the Bicycle Traffic Model

The results of the simulation include data on bicycle traffic flow, travel time, speed, and the share of bicycle traffic on particular streets. The selected results of the simulation research are presented in Table 1. The results are also useful for assessing the travel conditions for each mode of transport in the network.

The implementation of each of these scenarios leads to a reduction in the average distance travelled, as well as the average and total travel time for cyclists, while at the same time the demand for cycling increases (Table 1). Figures 7 and 8 show example results for Scenario 2. The implementation of Scenarios 1, 2, and 5 has the greatest impact on the increase in cycling utility, although the increase in the number of cycling trips is quite small due to minor changes in the utility of other means of transport. These scenarios assume the development of new cycling routes, which significantly shortens the distance between important destinations in the city. In addition, they provide reliable and fast bicycle connections that are competitive with congested traffic routes during peak hours. These new cycling routes will reduce the average cycling time in the entire network by only ~3%, but will save time between origins and destinations that will be connected by the planned routes by up to 30%.

| Scenario | Traffic Demand (Cyclists/ Hour) | Bicycle Traffic Demand Increase (%) | Bicycle Network Performance | |
| --- | --- | --- | --- | --- |
| | | | Total Travel Time (Pers-h) | Total Travelled Distance (Pers-km) |
| 0—base | 1689 | – | 556.0 | 12,381.1 |
| 1 | 1710 | 1.24 | 549.6 | 12,370.6 |
| 2 | 1704 | 0.89 | 543.4 | 12,115.0 |
| 3 | 1700 | 0.65 | 554.6 | 12,395.3 |
| 4 | 1693 | 0.24 | 553.0 | 11,490.7 |
| 5 | 1703 | 0.83 | 543.6 | 11,910.2 |
| 6 | 1702 | 0.77 | 552.6 | 12,375.8 |
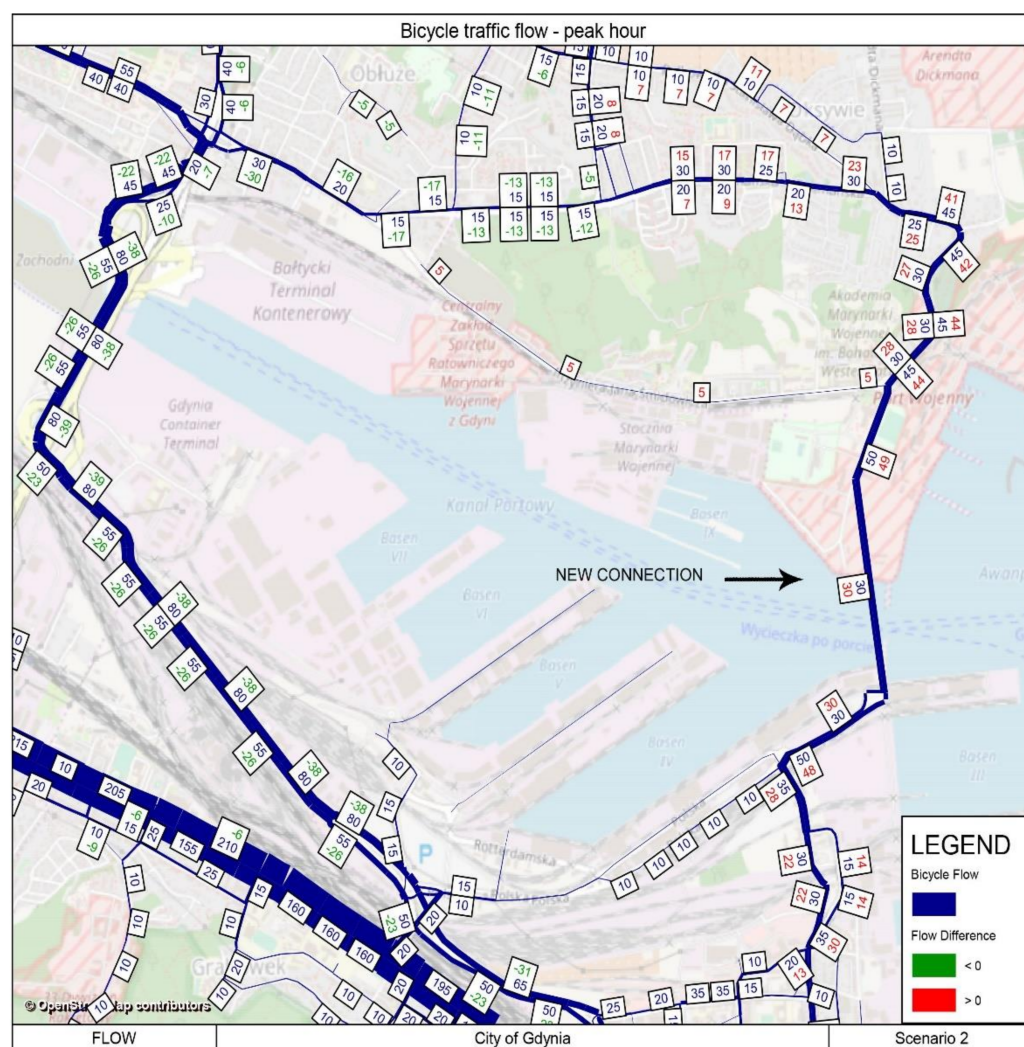


**Figure 7.** Bicycle traffic volumes in Scenario 2, and comparison of values with the baseline scenario.
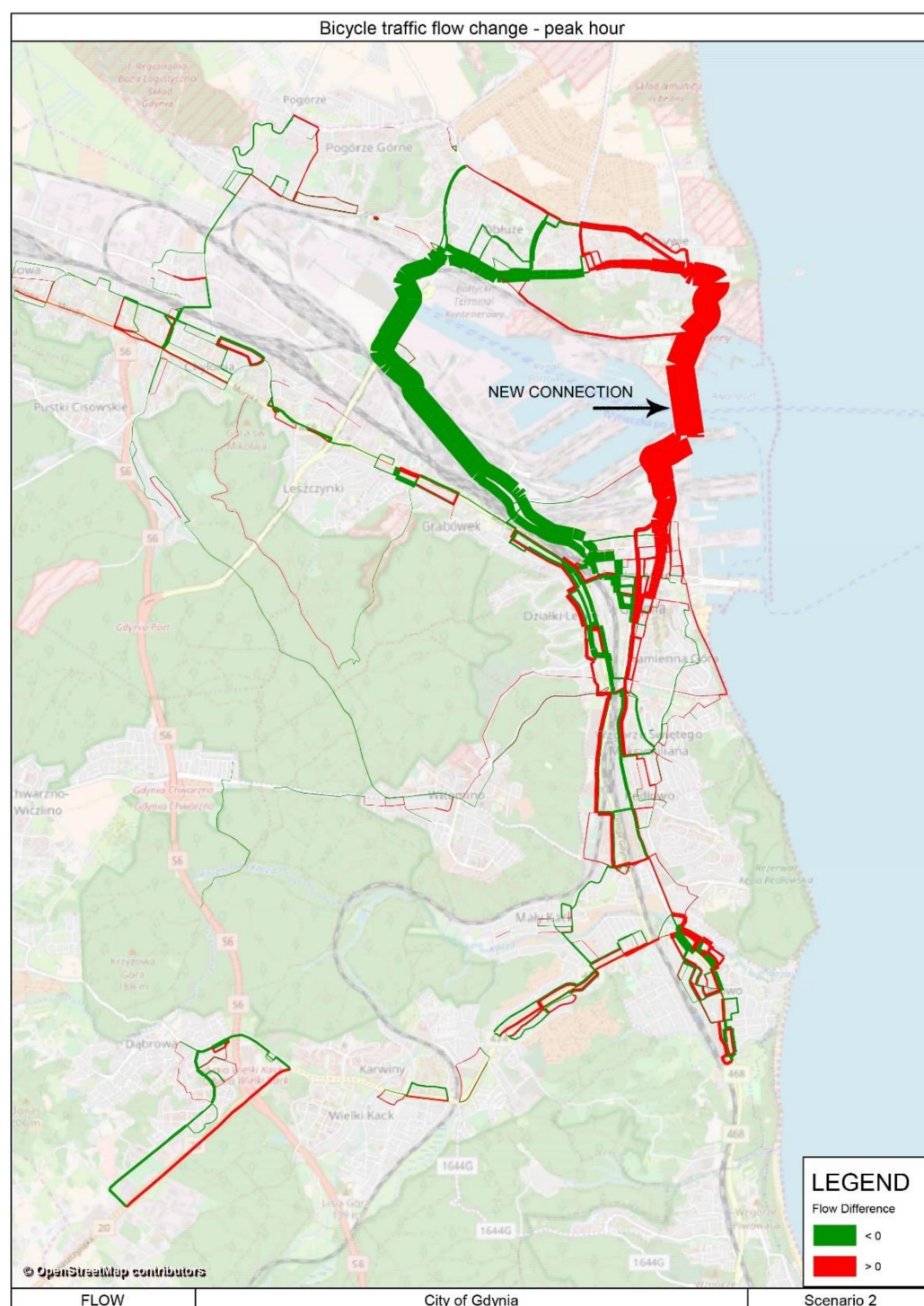
**Figure 8.** Change in bicycle traffic volumes in Scenario 2 compared to the baseline scenario.

The development of a section of a new bicycle path along the main arteries of the city was planned in Scenario 3. There is a noticeable gap in the network of bicycle paths along the main arteries in the south of the city today, which encourages cyclists to use the surrounding secondary roads. The evaluation carried out using the model showed that the completion of the main bicycle path network will attract cycling, and ~30% more cyclists will use a slightly longer but more comfortable route despite the longer distance.

Although the implementation of Scenario 4 has less impact on the change in cycling demand, the results show that cyclists would be more likely to use a comfortable bicycle path near the sea coast. It is noticeable that when choosing a route, the cyclist prefers to be

separated from the car traffic, and not to have to cross the road within the intersections. A similar conclusion can be drawn from the results of Scenario 5, which includes the transformation of a park path in the city centre into a bicycle path. The development of a new high-speed bicycle connection through the city contributes to a significant reduction in travel time, and improves the efficiency of the transport network by reducing the distance travelled by bicycle.

The implementation of Scenario 6, including filling in gaps in the bicycle network in the city centre, has little impact on the change in travel time. On the other hand, a coherent and comfortable cycling network in the city centre encourages cycling.

### 4.5. Model Verification

The baseline scenario of the bicycle traffic model was verified, taking into account the average speed (Equation (1)), characterised by the described variables, such as the occurrence and type of separation of bicycle routes, slopes, and the type of road surface (Figure 9). For a separate control sample of data from GPS traces not used earlier to develop the model, a coefficient of determination of R2 = 0.94 was obtained.
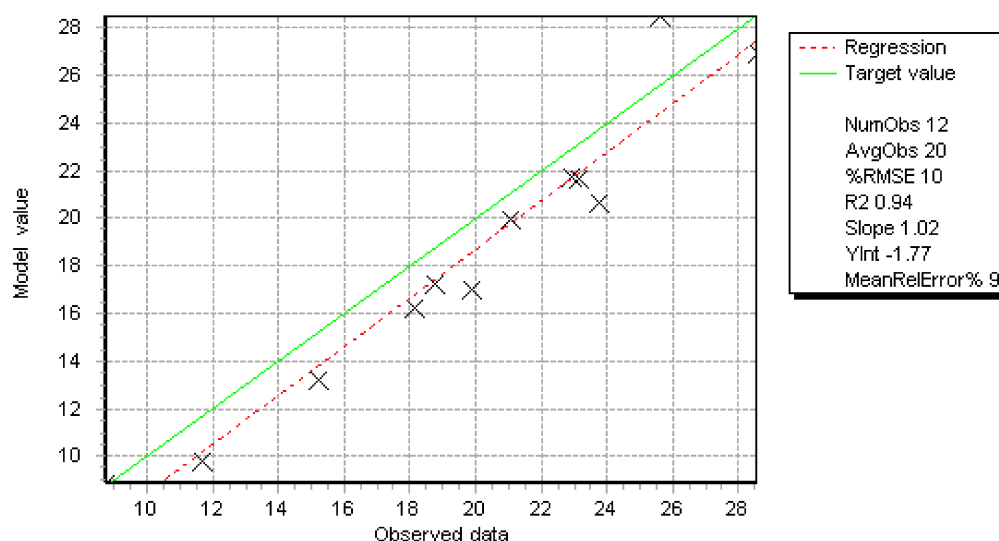


**Figure 9.** Goodness of fit of the model output data to the observed data from another measurement period for average bicycle speeds.

The model was also verified for the volume of bicycle traffic in particular sections of the transport network. A good fit ($R^2$ = 0.77) of the volume of bicycle traffic was obtained (Figure 10).

The application of the described approach makes it possible to consider the cycling mode of transport. The attractiveness of cycling is compared to the attractiveness of other modes. This approach makes it possible to determine the impact of road, cycling, or public transport investments or measures on the modal split.

The results show the need to improve the cycling network. The development and completion of the cycling network give the potential to improve the competitiveness of cycling with other modes of transport. The key factor that determines the modal split is the travel time of the different modes of transport. The impact of educational and promotional activities has not been directly analysed, but it may also affect the choice of mode of transport. At present, there is little interest in cycling as a mode of transport in Gdynia. As a result, the increase in the demand for cycling calculated based on the model is also insignificant. Educational and promotional activities that encourage cycling, as well as the introduction of the city bicycle system, can increase the number of cycling trips. These issues will be the subject of separate research. However, the proposed analytical

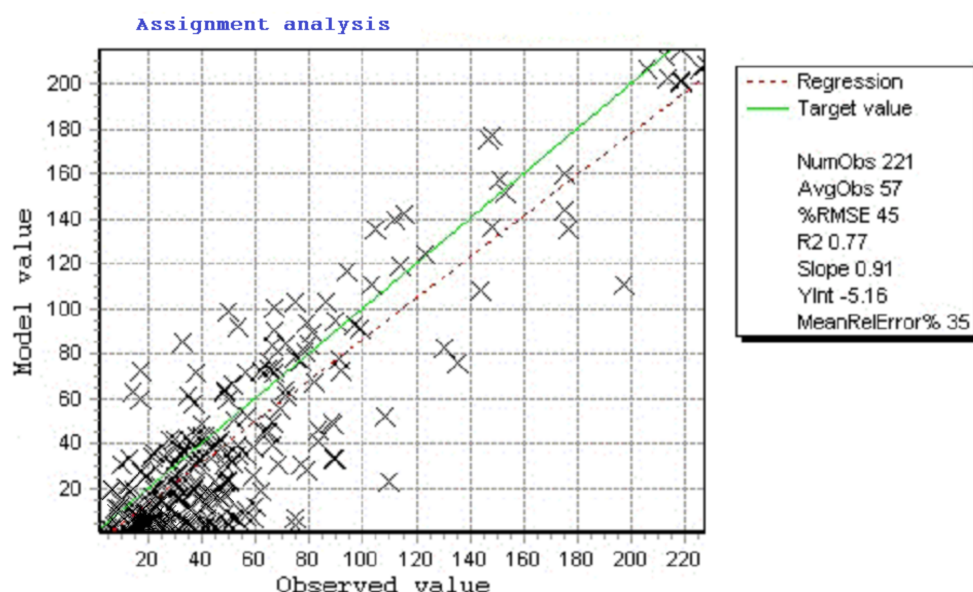methodology is useful in the planning and decision-making process to select the most effective solutions.



**Figure 10.** Goodness of fit of the bicycle traffic assignment to the Gdynia transport network.

## 5. Discussion

Many European cities implement their mobility planning processes following the EC guidelines [21], with the participation of decision-makers, stakeholders, and residents. Demand and transport network models can effectively support the mobility planning and decision-making process, taking into account active travel modes. Demand and transport network models can effectively support mobility planning and decision making. However, the inclusion of active modes of travel (such as cycling) in mobility planning requires knowledge about the impact of such measures on the performance of the transport system, taking into account the modal shift.

*5.1. Considering the Modal Shift towards Cycling in Mobility Planning in the Example of Gdynia*

It is essential to answer the question of why the consideration of a modal shift in urban transport modelling is important, and how the experience from Gdynia can help in the development of a bicycle traffic model, taking into account modal shift. Transport demand and transport network models have been key tools in shaping transport policy [29], but cities do not use them to their full potential, especially with regard to cycling and its impact on other modes of transport. The reasons for this may include insufficient cooperation between urban planning and transport management authorities, or different stakeholder perceptions of the importance of the models [29]. The perception of cycling in reducing the demand for other modes of transport and reducing congestion in the transport network is rather low. Thus far, cities use transport models to a very limited extent, and very rarely—especially when modelling active travel and its influence on motor vehicle trips and trips made via public transport. One of the reasons for this is the scarcity of reliable, integrated, and comprehensive tools to model the transport system while taking into account cycling traffic at the macroscopic level [19–22]. The tools used for transport modelling most often include the functioning of motor vehicle road transport and public transport, excluding cyclists or treating them as a factor disrupting traffic conditions.

Transport planning strategies consider the promotion and development of cycling as an appropriate way to address the problems associated with increased car traffic, such as energy reduction, pollution, congestion, and limited space. The modal shift towards cycling contributes to reducing the above problems. Cycling influences the demand for motor vehicles and public transport, as presented in the paper, and should be taken into

account in feasibility studies of investments regarding the development of infrastructure and organisational measures dedicated to all modes of transport, as well as in the decision-making process. For this reason, it is necessary to develop and use tools and models that allow the evaluation of the impact of planned actions concerning the modal shift.

The model used in the planning and decision-making process provides quantitative results. As a result, an ex ante assessment of the effects of the decision-making process can be made. Effectiveness evaluations of planned measures are based to a greater extent on assumptions or subjective assessments if demand and transport network models are not applied. If an evaluation can be justified by modelled results, the conclusions are easier for residents to understand, and can significantly improve public participation as a complement to other decision support tools and methods [194–196]. The use of integrated models should be recommended for cities that are starting or participating in mobility planning. Such tools must first be developed or adapted to take into account multiple modes of transport, which requires planning and spending, but brings significant benefits in the process of transport planning and management.

The model presented in this paper was developed to support the city of Gdynia in developing and monitoring the Sustainable Urban Mobility Plan (SUMP), as well as in planning and decision making regarding changes in the transport network. Lockdown policies around the world—including travel bans, border closures, restrictions on public activities, and the closure or restriction of businesses, offices, and schools [197]—have changed transport behaviour and travel growth, with the fear of infection in public transport also playing a role. The COVID-19 pandemic allowed the authorities to take several measures to improve the sustainability and resilience of the transport system [198]. In Polish cities (including Gdynia), particular attention has been paid to investments in physical infrastructure, including the expansion of the cycling network, along with traffic calming and the introduction of lower speed areas to stimulate active travel. The application of the model to planning for the development of transport systems, SUMP monitoring, citizen consultation, and decision making is a strong innovation of the presented solution.

In the decision-making process of choosing the most effective solutions, it is justified to take into account the impact of types of cycling sections on road traffic safety, energy consumption, and the environment. The model presented in the paper can be used as a basis for estimating energy consumption and exhaust emissions. This approach has been used, for example, in research in which the transport model was applied to estimate exhaust emissions in the Polish city of Bielsko-Biała [199]. The main barrier to the application of such an approach is the difficulty of obtaining data on vehicle traffic at the local level (in Polish cities). However, in future studies, these aspects will be developed using the model, so an analysis of cycling network development scenarios resulting in a change in the modal split will allow assessment of the impact of such measures on the reduction in emissions and energy consumption.

An important element of the citizen consultation process, but also of improving the work of municipal departments, is to enable the acquisition, geographical visualisation, and analysis of data. In the case of the Gdynia model, the simulation results are presented to the citizens during meetings or through a dedicated website [23]. However, the data calculated using the model may in the future feed advanced solutions such as cyber–physical platforms for real-time management of smart cities. Such platforms could use artificial intelligence methods to manage data and replicate transport model databases [200,201].

*5.2. Aspects of Bicycle Traffic Modelling*

The method of analysis and the results give a different perspective on the possibility of improving travel conditions in the transport network, taking into account the reduction in car traffic and the change in demand for travel via public transport. The model and the methodology of its development, as well as the manner of using the available data, contribute to the filling of the indicated gap. However, in most cases, the evidence base for

optimal cycling development, planning, and promotion are weak, and there is not enough information about cycling patterns with sufficient resolution.

Therefore, the next part of the discussion concerns the questions of which data can be used to develop a bicycle traffic model, and which elements of the model allow the prediction of the choice of particular routes by cyclists.

### 5.2.1. Data

Data on where and when people cycle within the urban transport network are still scarce [202]. Despite advances in measurement methods and sensor technology, cycling mobility data are still difficult to obtain and process. This is often the reason for deficiencies in data representativeness and integrability [203,204], which leads to the planning and implementation of cycling infrastructure in the absence of reliable data while, at the same time, the effects of infrastructural, organisational, and promotional measures of cycling cannot be properly monitored. Due to the considerable costs of data collection, different cities collect data useful in transport modelling at different scales. When planning the development of a bicycle traffic model, it is advisable in the first step to diagnose the availability of data and to plan additional field research or to collect data from other sources (e.g., mobile phone data, data from navigation systems, data from ITS services, MaaS solutions, or the Internet of Things), taking into account the costs of their collection. This paper presents the use of data available in the city of Gdynia, which may be used for the development of a bicycle traffic model. The methodology presented in this paper includes the use of the survey of inhabitants, as well as direct measurements of cycling (also using GPS tracking). This paper presents how to make full use of the data held by a city, or data that can be obtained at no or low cost, to build a transport model, showing that it is possible to use data from different sources to achieve the modelling objective. The methodology and structure of the model are also innovative (especially on a national scale). The data and variables used allow for a reliable representation of existing and predicted bicycle traffic. Multimodal modelling of transport, including cycling, requires the use of a very wide range of different data.

It is also very important to note that the surveys presented in this paper were conducted before the COVID-19 pandemic. Due to changes in transport behaviour and travel patterns, a study of bicycle use will be necessary in the post-COVID-19-pandemic period. In times of social distance, people travel less, try to avoid crowded public transport, and aim for more physical activity [205,206], which can be achieved through active modes of transport.

In addition, a more complex analysis using econometric techniques would be required in order to statistically identify the key variables that determine bicycle use. Finally, future research is needed in order to quantify the carbon footprint and impact of electric bicycles for certain components, such as batteries.

### 5.2.2. Method of Model Development

A four-stage macroscopic model was used to develop the bicycle traffic model [115,116]. The presented methodology of development of the model allows the analysis of the influence of the development of the public transport system, or individual motorised transport, on the transport behaviour of inhabitants in terms of a change in the probability of choosing bicycles for travel; it also takes into account the characteristics of the infrastructure of the transport system, which can determine the choice of cycling as an alternative to other modes of transport. An alternative approach to comprehensive modelling of travel demand and transport networks could be agent-based modelling [22,162]; however, the range of data available for modelling led the authors of this paper to use a four-stage approach. The availability of data can determine the choice of the modelling method. An additional constraint for cities is the availability of analytical tools and previously developed models. In the case of the model presented in this paper, a prerequisite for its development was the prior development of a four-stage macroscopic model of motorised

traffic and public transport. Cities that do not have a four-stage macroscopic model should, in the planning stage, take into account the development of a comprehensive model of public transport and individual motorised traffic, including the cycling part of the model. A better representation of cycling can be achieved by taking into account factors in trip generation models related to facilities for pedestrians and cyclists, or land-use functions that encourage cycling. The Urban Transport Modelling System (UTMS) uses additional models to overcome the disadvantages described above [164]. In the case of the model presented in this paper, additional models (described in Section 3) were also developed to enable a more reliable representation of bicycle traffic.

The use of artificial intelligence (AI) methods, including machine learning, is worth considering [207]. The use of machine learning models can be considered for estimating O–D matrices (especially using data from satellite navigation, mobile phones, or the Internet of Things). However, such data are not widely available, or are expensive to acquire. The use of such methods may also raise problems in identifying users or groups of users travelling on the transport network. Identifying users is essential to predict changes in demand and travel routes, taking into account future changes in land use, especially over long time horizons. However, with the development of technology, mobile applications, and algorithms based on artificial intelligence, and the increasing availability of open data, AI methods—especially in the field of machine learning—are worth considering for use in transport demand modelling and route choice modelling, especially for short-term prediction.

The choice of a four-stage approach modelling method has met the expectations in terms of modelling cycling traffic for planning purposes.

### 5.2.3. Bicycle Network

A model with an accurate representation of the cycling network (including the type of pavement, the type of cycle path, the slope of the road, and the perceived attractiveness of each section of the cycle route) can be useful to predict the modal split and route choice. Relatively large transport zones limit the reliable replication of shorter routes for non-motorised modes (e.g., walking, cycling). Moreover, the length of links in networks is sometimes estimated manually by the modeller. Such methods often lead to imprecise calculations. Geographic information system (GIS) mapping systems provide a more accurate calculation of the length of links. These networks should also be improved with digital height models to ensure that topographic effects are included in distance and speed estimates (slope effects are essential in estimating link resistance for cycling travel mode). Other network inaccuracies may also cause problems in the reliable replication of the transport system. If links or intersection attributes (e.g., cycling speed) are inaccurate or misrepresented, this affects the estimation of speed and travel time. These inaccuracies can reduce the sensitivity to choosing a bike as a mode of transport to avoid congested road sections.

Networks of regional or urban models usually do not describe in detail the layout of local streets and the land-use mix. Such models cannot take into account street sections, local travel speeds, and the facilities available to pedestrians and cyclists due to the generalisation of local conditions. Large TAZs present a challenge to modelling local conditions, including facilities available to pedestrians and cyclists.

The model presented in this paper reliably represents the cycling network, taking into account longitudinal gradients, type of pavement, and type of cycling link by defining speeds $Vel_i$ on particular sections of the cycling network based on these variables. In future studies, the presented model should be further developed by taking into account different user groups, e.g., by age or cycling experience.

A further contribution of this research is the inclusion in the model of the influence of longitudinal gradient on the speed of cyclists, using the GIS environment. The adopted number of transport regions and the level of network mapping are sufficient to reliably

represent trips in the primary transport network, as confirmed by the model verification results presented in Section 4.5.

5.2.4. Modal Split

The basic model on which the relationships are based is the logit model. The choice of the model was dictated primarily by a four-stage approach, but also by the possibility of including the modal shift in the model results. The model takes into account the utility of individual modes of transport, expressed as a component of two elements: the measurable utility, and the random part. This approach allows us (1) to capture the different preferences of the users and their subjective perceived attraction to the alternatives, (2) to take into account user error in the evaluation of utility, and (3) to capture all directly non-measurable random factors influencing the choice of means of transport (e.g., convenience, habits). The logit model assumes that the user chooses the option with the highest utility among the available alternatives. The model uses cycling journey times calculated based on cycling speeds in particular sections of the cycle network.

The key factor that determines the modal split is the travel time of the different modes of transport. However, it should be noted that delays (affecting travel times) affect not only car drivers, but also other travellers, i.e., pedestrians, cyclists, and public transport passengers. Most road users perceive delays as the most important effect of congestion. Delay plays an important role in determining travel behaviour, but is only one factor of interest to travellers [208]. Delay occurs when the actual travel time exceeds a threshold acceptable to the traffic participant. Travellers who choose different modes of transport perceive delays differently. The perception of delay also depends, for example, on the motivation for the trip and the relationship between delay and total travel time, and is not linear [209,210]. In future research, issues related to travel time perception and the reliability of transport network performance should be developed.

More research and improvement of modal split (and traffic assignment) models are required, which should take into account, for example, the impact of weather conditions or the seasonality of cycling. Other factors to be considered in further research are the impact of educational and promotional activities, and the impact of cycling's accessibility (e.g., implementation of a city bike-sharing scheme) as a mode of transport, on bicycle traffic.

The Tri-City agglomeration (of which Gdynia is a part) is currently in the process of implementing a bike-sharing scheme. This system will mainly include electric bikes. This change will undoubtedly influence the modal split, as demonstrated by the research conducted so far on both bicycle-sharing systems [33,98–103] and the use of electric bikes [62–67]. Choosing an e-bike instead of a car for travel can reduce energy consumption, but the positive impact on the health of users may be less than if a conventional bicycle were used. Furthermore, a tool such as a bicycle traffic model can also be a data source for the study of the feasibility of this type of project, and the analysis of the effects of its development direction.

Another element that should be taken into account in further research is the integration of MaaS solutions into the cycling model, together with shared mobility services (including bicycle sharing, which is currently being implemented in the Tri-City agglomeration), and the possibility of changing the mode during the journey, to encourage modal shift and improve conditions for cycling. Shared mobility services, such as bike sharing, car sharing, ride sourcing, etc., influence travel behaviour by changing mobility patterns and modes and, thus, compete with more traditional modes of transport [4,33,46,51,101,105,106,108,211]. Shared mobility services have a positive impact on urban transport, as they can reduce the use of private vehicles and, thus, alleviate the current problems of public space scarcity, congestion, and negative environmental impacts. However, it is important to note that bicycles (including bike-sharing schemes) can also capture the demand for public transport [212]. Therefore, shared mobility services, in their current form, have an unclear impact on urban sustainability [213]. This fact underscores the importance of integrating cycling with

public transport to promote its complementary use (including through multimodal trips, e.g., cycling to feed the public transport system in less accessible areas as a last-mile mode of transport).

### 5.2.5. Traffic Assignment

The calculation of the cycling flow was carried out using a stochastic assignment. Compared to deterministic distributions, the element that influences cycling assignment is the inclusion of random factors. In the case of cycling, the randomness of the assignment is influenced by incomplete knowledge of the transport network, which means that cyclists do not always choose a route rationally according to their preferences [179,180], that the choice of routes may be due to the need for a variety [181,182], and that cyclists may have different preferences to choose more attractive routes due to the quality of the road surface, sharing the route with other road users (cars or pedestrians), or different awareness of the risk of being involved in a road accident [181,182,188,189].

With the stochastic assignment, compared to equilibrium deterministic assignment, even in a less loaded network (such as the bicycle network), more routes are loaded, because some demand is also assigned to alternative but similar routes. This property is closer to reality than a strict application of Wardrop's first principle (as found by Daganzo [179]).

Stochastic assignment is more appropriate for bicycle travel, as it reflects the process of individual discrete choice. The variety of individual choices is more important to cyclists than volume-dependent travel times. Factors that influence the choice of a route to a large extent (information about the type of surface, type of section of the cycling network, and longitudinal gradient is included in the function characterising individual sections of the cycling network) influence the comfort of travel, and are particularly important for cyclists. According to the stochastic procedure, not only the shortest route is found, but also many alternative (but similar) routes, using multiple searches for the best path and the impedance variability of the different sections of the cycle network, which allows a more reliable distribution of cycling traffic, and the selection of routes to which cycling traffic would not be allocated if strictly deterministic distribution methods were used.

It can be observed in the evidence from Gdynia that, when choosing a route, cyclists preferred to be separated from motorised traffic, and to not need to cross the road at junctions (using separated on-street infrastructure or off-street paths), confirming previous research [127,182–185]. The model was calibrated by adding time penalties at major intersections that cause cyclist delays, but more detailed research in this area will be required.

Cyclists also prefer flat longitudinal gradients on bicycle routes, as confirmed by previous research [181,188,214]. From the opinions of the respondents presented in Section 4.2, it also appears that the pavement indicated by cyclists as the most attractive is a smooth, even surface (asphalt and, to a lesser extent, smooth concrete blocks). Many previous studies indicate that the type of surface is a factor that determines the choice of route by a cyclist [22,129,130,163,215,216]; however, it is difficult to find direct research results on cyclist preferences with regard to this issue [217,218]. One of the few works that unambiguously states that the quality of the surface is an important decision factor for cyclists when choosing a cycling route is the study by Landis et al. [219]. The results presented in this paper are an additional contribution to the knowledge in this field.

The factor concerning traffic safety was indirectly taken into account when assessing the attractiveness of particular types of bicycle routes. However, a more detailed approach will be required in future research. To update and improve the quality of the bicycle traffic model, it is necessary to conduct regular travel surveys with appropriate sample selection in smaller transport areas. This would allow for increasing the accuracy of the estimation of the origin–destination trip matrices. Cycling speed measurements must be carried out more comprehensively, taking into account, among other things, the type of journey, the experience of cyclists, and other personal characteristics, which will help to represent the behaviour of travellers with greater precision. As the volume of cycling increases, it will

also be necessary to consider the capacity of the elements of the cycling network to address cycling bottlenecks.

### 5.2.6. Results of the Gdynia Case Study

The results of the calculations presented in Section 4 show that each planned element of the development of the cycling network will improve the efficiency of the entire Gdynia transport system. The development of the bicycle network leads to a reduction in the average travelled distance and the average and total travel time for cyclists, while the demand for cycling increases. Cycling has the potential to reduce car traffic, leading in turn to reductions in congestion, energy consumption, and emissions. The model, with a precise representation of the cycling route network that includes the type of pavement, the separation from other types of traffic, and the slope of the sections of the route, can be useful in predicting route selection and modal split due to the utility of each mode of transport based on travel times.

The results show that the greatest benefits for cycling in Gdynia can be achieved by filling in the gaps in the bicycle network—in particular, by connecting the city centre with the northern parts of the city. The most efficient connections compete with congested traffic routes during peak hours, and significantly shorten the distance and travel time between important points in the city. The implementation of bicycle routes separated from motorised traffic (bicycle paths), with flat longitudinal gradients and an asphalt surface, also contributes to the attractiveness of these routes.

## 6. Conclusions

Transport demand and network models that take into account active modes of travel can effectively support the mobility planning process, as demonstrated in this paper. Models should be used to evaluate measures implemented in the transport system to determine the impact of such measures on reducing traffic and congestion on the road network, and the resulting reductions in energy consumption and pollutant emissions. The models provide a better understanding of the changes in the functioning of the transport system and the behaviour of travellers in different scenarios for the development of this system. However, to allow for a reliable evaluation, it is necessary to use models that allow for the estimation of a modal shift towards cycling.

The model presented in this paper allows the analysis of the influence of the development of the public transport system or road infrastructure on the transport behaviour of inhabitants in terms of the change in the probability of choosing bicycles for travel. The model also allows us to assess the influence of the characteristics of the cycling infrastructure and the development of the cycling network on the choice of cycling as an alternative to other modes of transport. The application of the presented methodology and tools for transport planning provides a solid basis for the selection of the most effective solutions in the planning process.

As data on cycling times and routes within the urban transport network are still scarce, in addition to a survey of residents, direct measurements of cycling—including GPS tracking and data from ITS services—were used in the modelling. It is important to use data fusion from multiple available sources to reduce research costs.

A further contribution of this research is the inclusion in the model of the influence of longitudinal gradient on the speed of cyclists, using the GIS environment, and taking into account the types of cycling network sections and their surface in the choice of the mode of transport and the route of travel.

The model presented in this paper reliably represents the cycling network, taking into account longitudinal gradients, the type of pavement, and the type of cycling link by defining speeds on particular sections of the cycling network, based on these variables.

The key factor that determines the modal split is the travel time of the different transport modes. The logit model was applied to model modal split. The model takes into account the utility of individual modes of transport, expressed as a component of two

elements: the measurable utility, and the random part. The model uses cycling journey times calculated based on cycling speeds in particular sections of the cycling network. The proposed approach makes it possible to model and estimate modal shifts between different modes of transport, taking into account random factors. This feature of the model is important for analyses that aim to determine the degree of reduction in congestion, emissions, and energy consumption.

The calculation of the cycling traffic flow was carried out using stochastic assignment, taking into account random factors. Stochastic assignment is more appropriate for bicycle trip assignment because it reflects the process of individual discrete choice. The variety of individual choices is more important to cyclists than volume-dependent travel times. When choosing a route, cyclists prefer separation from motorised traffic, flat longitudinal gradients, and smooth surfaces without bumps (asphalt and, to a lesser extent, smooth concrete blocks) in the cycle routes. The longitudinal gradient of a cycling route is the most important factor in determining the choice of route.

The simulation analysis carried out using the macroscopic model showed that well-thought-out and appropriate investments in the development of a network of bicycle transport are the most favourable in terms of potential changes in the transportation behaviour of the inhabitants. The results show that the greatest benefits for cycling in Gdynia can be achieved by filling in the gaps in the bicycle network.

The verification of the model confirmed its usefulness in planning the bicycle network, but some issues should be taken into account in future research related to modal split and route choice: future development of transport systems (bicycle-sharing systems and other MaaS solutions); travel time perception; and the reliability of transport network performance, including cyclist behaviour at intersections, different user groups—e.g., by age—cycling experience, and modelling of other personal characteristics, post-pandemic transportation behaviour of travellers, the impact of weather conditions or the seasonality of cycling, and the impact of educational and promotional activities on cycling travel preferences and behaviour.

The spatial approach presented to modelling cycling behaviour opens new opportunities for planning and evidence-based decision making in the broad area of cycling promotion and development, as well as for predicting and monitoring the effects of planned or implemented measures.

The methods proposed in this paper are worthwhile, and cities that plan the development of a bicycle traffic model should apply them in the mobility planning process. The example of Gdynia shows that the development of the MST with a bicycle traffic model can also be offered as a good practice for other cities. This may be important for cities with emerging economies and dynamic motorisation development, which will soon face the challenge of sustainable transport behaviour and transport needs.

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