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Enhancing Smart Cities through Third-Party Logistics: Predicting Delivery Intensity

Mariusz Kmiecik * and Aleksandra Wierzbicka

Department of Logistics, Silesian University of Technology, 44-100 Gliwice, Poland; aleksandra.wierzbicka@polsl.pl
* Correspondence: mariusz.kmiecik@polsl.pl

Abstract: This article addresses the key and current issues of smart cities in the context of last-mile supply management. Specifically, it explores how third-party logistics (3PL) activities impact last-mile delivery management in smart cities. It examines how 3PL affects delivery volumes, expanding the predictive capabilities of logistics operators. A research question included in the Introduction of this paper is also posed to explore the problem in depth. The research conducted focuses mainly on a case study conducted on the operations of an international 3PL logistics operator. In addition, predictive methods are used to analyse the shipment volume data for individual barcodes in the two analysed cities in Poland. Currently, the concept of a smart city assumes the limited participation of logistics operators in creating improvements for cities. The case study analysis shows that in the cities studied, 3PL companies, through predictive actions, can regulate the flow of vehicles out of the logistics centre and into the city, thus influencing the traffic volume in the city. The research is limited to two cities in Poland implementing smart city solutions and one logistics operator. The research also does not include e-commerce. The authors acknowledge that the results obtained cannot be generalised to a larger scale. This paper bridges the research gap on 3PL activities for last-mile logistics improvements. In addition, the paper proposes the first concept related to the implementation of a 3PL company's predictive activities associated with the operator's ability to control the impact on urban traffic.

Keywords: smart city; 3PL companies; last-mile delivery; traffic studies

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1. Introduction

A key challenge for 21st-century logistics is increasing urbanisation. The growing urban and suburban population is one of the drivers of urban freight flows. Increased traffic on streets in city centres causes constant congestion, with undesirable effects such as delays and air pollution. All these elements mean that urban logistics is seeking new solutions to eliminate the negative impact of transport on the quality of life of residents. Distribution centres are increasingly being built on the outskirts of cities to facilitate last-mile management. Another solution is the creation of new sending and receiving points, where it is possible to store many shipments at the same time to reduce the dispersion of deliveries. It is estimated that the freight intensity in urban areas will increase by 40% by 2030 and by more than 80% by 2050 compared to 2005 [1]. As the aforementioned urbanisation increases on a global scale, the development of smart cities has become an inevitable step towards efficiency, sustainability and improved quality of life for residents. In the context of dynamic socioeconomic change, last-mile delivery in smart cities is a key infrastructure component [2], affecting not only city logistics but also the overall service quality and customer satisfaction [3].

A response to the needs of citizens resulting, among other factors, from the increase in urban freight flows is the smart city concept. More and more Polish cities are implementing this strategy in their operations. Examples of cities implementing the smart city concept in Poland are Warsaw and Wroclaw, which ranked 69th and 95th, respectively, on the international IESE Cities in Motion Index in 2019 [4]. However, despite advances in the smart city field, there is a significant research gap regarding third-party logistics (3PL) activities for last-mile logistics improvements. This paper aims to address this gap by discussing the ability of 3PL to influence the volume of urban deliveries in extending the predictive activities of logistics operators. For this reason, the authors attempt to answer the following research question in this paper:

RQ.1. Can 3PL influence the volume of urban deliveries as part of their predictive activity?

The paper therefore focuses on the role of 3PL companies in improving the performance of last-mile delivery in the smart city, with a particular emphasis on predictive capabilities. The analysis is mainly focused on a review of the literature on smart cities and the activities of 3PL precisely in the areas of modern cities, as well as on empirical research that concerns the pilot implementation and testing of the results of the use of predictive capabilities in the framework of last-mile delivery, based on the example of two selected cities in Poland. The paper also describes the first concept related to the implementation of this solution on a larger scale, supporting the activities of logistics operators with an algorithm for the prioritisation of deliveries and, as a result, the possibility of reducing the volume of deliveries in the smart city area by 3PL.

2. Theoretical Background

2.1. Last-Mile Delivery in the Context of the Smart City Concept

The smart city is a very broad concept and there is no universal definition of it. There are many approaches to the definition of a 'smart city', in which the word 'smart' has been replaced by a number of other adjectives that reflect similar, but not the same, meaning. In some interpretations, a 'smart city' is a 'digital city' using many telematics solutions, while, in others, one can find terms such as sustainable city, eco city, future city, ubiquitous city and aerotropolis [5]. The definitions of a smart city can also be divided into those defining a 'smart city of smart people', for which the criteria include free internet access or the availability of many online services, and smart solutions where, in turn, management using advanced systems and the ability to create 'intelligent mobility' play an important role [6]. According to G. Kinelski [7], the smart city concept refers to cities that are able to use the available information and communication technologies to improve the interactivity and efficiency of their infrastructure, as well as to increase the awareness of their inhabitants in various aspects and areas of life. A similar view of the smart city concept is held by A. Korenik [8], who, in her paper, emphasises that it is a city of a creatively thinking society, able to use the available and innovative technological solutions and, additionally, to use communication and information technologies. Thus, it is important that projects in the construction of a 'smart city' result from the cooperation of residents, local authorities, entrepreneurs and other stakeholders, using the diversity of roles that they play. Some researchers, in their papers, similarly identify three areas of the smart city: technology, people and institutions [9,10]. The people and institutions category considers infrastructure design, transport, education and communication. The technology-related categories, on the other hand, should be understood as a variety of techniques and tools that can transform health, life, education, transport and other diverse aspects of modern society [11]. The smart city as a complex construct was presented by Gupta et al. [12]. According to the authors, it consists of smart people, smart governance, a smart economy, smart mobility, a smart environment and smart living. Undoubtedly, transport is an important part of a smart city. Both passenger and freight transport affect the functioning of the society and institutions in a city. According to studies, the transport of goods in a city affects, to a very large extent [13],

- catering supplies;
- the speed of delivery of individual courier consignments;
- accessibility to goods and services.

Smart city technologies in relation to transport are applied to, among other aspects, selecting an appropriate route [14], controlling the current location of the means of transport and optimising the costs and minimising the impact of transport on the environment and residents. Implemented solutions are expected to improve the freedom of movement, promote environmentally friendly modes of transport and smooth traffic by temporarily limiting accessibility zones for deliveries. The idea of the smart city implies appropriate changes in urban transport. Thus, in the context of the smart city, one can also speak of intelligent transport. Many definitions of smart transport can be found in the literature. Most of them point to similar aspects, i.e., the use of information technology, appropriate communication and data flows and increasingly new systems. Mazur [15], on the other hand, writes that smart transport in combination with smart traffic management in the city, using sensors, automation and messaging technologies, will revolutionise the concept of urban mobility and reduce congestion, especially in city centres.

Nowadays, according to experts in the field of smart cities, it is smart transport that is crucial to improving the quality of life of residents in urban areas. Thus, the determinant of management also in the area of smart transport should be to ensure the efficiency of the flows of goods and passengers in the city [1].

A major challenge for the smart city, and especially for smart transport, is last-mile delivery, which typically involves the transport of goods from a warehouse or distribution centre to the end customer [16]. The point of last-mile delivery depends on the customer's preferences and the opportunities that the shipper provides [17]. The important role of last-mile delivery in the entire supply chain implies the need for high-level logistics management, including a flexible response to the ever-increasing needs of customers. This creates a number of challenges in organising the delivery to end customers, in each of the three dimensions of sustainability [17]:

- From an economic point of view—efficient management of the delivery procedure by planning the most optimal route while focusing on ensuring cost efficiency and on-time delivery;
- From an environmental point of view—minimising emissions to the lowest possible level, including CO_2, noise and congestion;
- From a societal point of view—ensuring the highest quality of supply to customers with commensurate consideration of its impact on human health and safety.

The topic of last-mile transport may be considered to refer only to the final phase of the delivery process, being merely a formality for the entire supply chain. However, this assumption is incorrect. This last phase is found to be the most crucial, costly and complicated aspect of the entire logistics procedure. An additional complication is the ever-increasing expectations of customers regarding not only delivery times but also their environmental performance, as an increasingly conscious society places an increasing emphasis on this [18]. It should be noted that last-mile logistics is part of city logistics. This is due to two closely related facts. Firstly, the impediments to last-mile logistics are related, among other factors, to the increase in population in urban areas and nearby green spaces, which consequently leads to an increase in the number of pick-up points and a more complex system of urban delivery planning. Secondly, the traffic intensity is increased in urban areas, which often slows down delivery and complicates the planning process [13]. The primary goal of city logistics, but also of smart city management, is to improve the quality of life and living conditions of residents by optimising operations. Last-mile deliveries generate a disproportionate amount of pollution. With the current model, it is estimated that, by 2030, the number of delivery vehicles will increase by 36% in the world's 100 largest cities, and the emissions that they generate will increase by 32%. Fiscally, road congestion could increase by more than 20%. This is why it is important to identify smart solutions not only for passenger transport but also for the last-mile delivery of goods.

2.2. Smart City Technologies for Last-Mile Delivery Management

Deliveries of last-mile goods are one of the causes of increased van traffic throughout the city. They significantly reduce the functioning of the entire transport system in the city, due to the large number of loading points and the often unused loading areas [19]. Due to the significant increase in the importance of urban freight transport caused, among other factors, by the COVID-19 pandemic, more and more solutions associated with the smart city and specifically aimed at transport are emerging in cities. Smart transport measures can be divided into two groups of solutions: information–organisational and technological.

One of the information and organisational solutions is the intelligent transportation system (ITS). In his publication, Mazur [15] highlights that, according to the US Department of Transportation, transport systems can be considered intelligent transportation systems (ITS) when they use various technologies to monitor, evaluate and increase the efficiency and safety of transport in a city. The task of intelligent transport systems is to increase the efficiency and safety of all traffic participants. The use of ITS methods and tools contributes to [20]:

- a reduction in investment in transport infrastructure with similar effects of improved system efficiency;
- reduced carbon emissions by making the traffic flow smoother;
- reduced travel times, both for passengers and goods;
- a reduced number of traffic accidents, which is one of the causes of congestion in the city;
- the increased capacity of existing sections of the transport network.

Within the framework of smart city technology for urban transport, we can distinguish the following systems, among others:

- Advanced Traveller Information System;
- Intelligent Traffic Signal System (I-SIG);
- Signal Priority (transit, freight);
- Mobile Accessible Pedestrian Signal System (PED-SIG);
- Emergency Vehicle Preemption (PREEMPT);
- Dynamic Speed Harmonisation (SPD-HARM);
- Incident Scene Work Zone Alerts for Drivers and Workers (INC-ZONE);
- Dynamic Transit Operations (T-DISP);
- Dynamic Ridesharing (D-RIDE);
- Freight-Specific Dynamic Travel Planning and Performance—Drayage Optimisation.

The smart city systems currently available and in use are targeted towards the collection of data and information gathered by the city in the form of a survey of traffic volumes at a specific time on a specific stretch of road, and a study of the behaviour of relevant traffic participants. The literature states that the participants in the operation of ITS are three groups. The first are those who manage the roads in order to achieve local objectives, e.g., maintaining the traffic flow. The second group comprises the drivers of vehicles who wish to reach their destinations without accidents, in the shortest possible time. The last group comprises travellers or pedestrians who use ITS to obtain traffic information or request emergency assistance [21]. It should therefore be noted that businesses, despite being one of the most important stakeholders of the city [22], are not included in the development of ITS concepts. According to the authors, the failure to include the analysis and data management capabilities of 3PL companies in the planning of smart city deliveries is related to the lack of consideration of one of the main drivers of urban freight flows. However, smart-city-oriented IT and organisational solutions are innovative means of delivering goods in the city. Examples include the advent of parcel vending machines and many new pick-up points to streamline the delivery of multiple parcels to many different recipients [23].

The second group of solutions is technological solutions. In the literature, numerous improvements are based on the modernisation of delivery vehicles, aiming at zero-emission last-mile deliveries to improve the quality of life of residents [24]. One example of such a solution is the cargocap. This system is a type of underground transport that carries goods placed on pallets below ground level by means of special transport pipelines characterised by a diameter of 2.8 m and a capacity of up to three europallets. The underground pipelines, known as caps, represent autonomous, automated and electrically powered vehicles for seamless transport regardless of the above-ground conditions. This idea fits perfectly with the smart city concept, with the main idea being to make deliveries using underground transport technology over relatively short distances, at a speed that allows for transhipment and loading functions, and the integration of hub points with above-ground infrastructure elements (pick-up points). Unfortunately, to date, the project has not been implemented [25]. Another example of an urban delivery method that aligns with smart city concepts is undoubtedly the use of alternative fuels or electric-powered cars. A noticeable trend in many cities is to move away from internal combustion vehicles to electric or hybrid vehicles. There are environmental and economic arguments in favour of the use of such vehicles. Nowadays, the operating cost of an electric vehicle is lower than that of a petrol or diesel car, and they are much more environmentally friendly than traditional vehicles [26]. An example of the use of electric vehicles (BEV) is the case of Deutsche Post DHL. The DP DHL Group's interim goal is to eliminate liquid and gas emissions in all logistics operations by 2050. At the end of 2017, this company had a fleet of 5000 electrically powered delivery vehicles, each of which could travel up to 80 km on a single charge. Using the StreerScooter WORK and WORK L vehicles, the annual reduction in CO_2 emissions per means of transport, according to the technical data, was expected to be between 3 and 4 tonnes, and diesel consumption would be reduced by 1100–1500 L. The smart city concept assumes that vehicles delivering goods along the last mile should be environmentally friendly and that the transhipment itself from larger trucks to smaller ones should take place on the outskirts of the city [24].

In addition to the solutions presented in this paper, many other transport-oriented smart city projects can be found in the literature, including, e.g., bicycles [27], drones [28], aircraft [29] and autonomous vehicles [30]. Both IT–organisational and technological solutions in the context of the smart city involve many actors, so it is necessary to consider whether a 3PL company is able to influence the improvement of freight flows in the city, thus fitting with the smart city concept.

2.3. 3PL in the Context of Smart City

Often, 3PL companies are not associated with the smart city in academic works. In the authors' opinion, this is an interesting area for exploitation, because the smart city also contains flows of goods and information that are managed by companies that adapt their entire business models to achieve even better results regarding logistics services for customers and other companies. Other connections between 3PL operators and the smart city concept introduced by various authors are presented in Table 1.

Table 1. Other connections between 3PL operators and the smart city concept by various authors.

Author of the Publication	Combination of 3PL Operators with the Smart City Concept
Golinska-Dawson and Sethanan, 2023 [31]	3PL as an entity having to adapt modern technologies like drones, autonomous delivery robots, autonomous vehicles, cargo bikes, electric vehicles and combined passenger-and-cargo transportation rapid-transit systems for the smart city
Asthana and Dwivedi, 2020 [32]	3PL as an entity having to adapt modern technologies or Internet of Things (loT) technologies
Gerrits and Schuur, 2021 [33]; Sebe and Muller, 2021 [34]	In these publications, the improvement of delivery technologies by 3PL operators is indicated as the direction for the application of modern technologies
Wang et al., 2022 [35]	The use of modern technologies in the supply of special products, such as fresh agricultural products
I-Ching et al., 2018 [36]; Liu et al., 2023 [37]	Implementation of last-mile delivery services, whether from the perspective of e-commerce or freight parking management in last-mile delivery

Source: own elaboration.

It is noteworthy that the solutions presented place 3PL as a service contractor with no real influence on freight flows but only on means of implementing processes aiming to meet the needs arising from smart city activities. According to the authors, this is not a beneficial approach, mainly because 3PL is generally successful in creating value-added services [38] and designing logistics services [39,40]. However, an interesting concept is presented by Rosenberg et al. [41], where the authors suggest the creation of a consolidation centre managed by 3PL for small shipments to be delivered to a city operating under the smart city concept. The concept is of interest to the authors of the present paper as it assumes more power for 3PL to build flows to cities. In other publications that are not indexed in the SCOPUS database, the problem of including 3PL as low-competence entities also arises. Typically, 3PL is considered as an outsourcing link for last-mile delivery, even when the concept is to extend the distribution to include integrated distribution and transportation [42], or as an outsourcing link for innovative on-demand warehousing e-marketplaces [43]. Authors have also evaluated the sustainability benefits of 3PL that arise at the interface between logistics and the smart city [44]. Given the above, the present authors believe that the greater integration of 3PL into smart city flows should be the subject of extended research. The first study aims to verify the possibility of translating the predictive capabilities of 3PL into tangible benefits for the smart city.

2.4. Predictive and Coordinating Capacities of 3PL

One of the key aspects of integrating 3PL into the realisation of logistics flows is that such a company meets the relevant evaluation criteria. There are many studies on this topic, including those by researchers such as Singh et al. [45]. However, a purely criteria-based approach can lead to difficulties in collaboration, especially if logistics companies are treated merely as suppliers limited to specific contracts. Huo et al. [46] note this risk, emphasising that relationships with logistics suppliers should be based more on partnership. Darko and Vlachos [47] also emphasise the importance of valuable supplier relationships, as their case studies show. On the other hand, supply management academics, as shown by the research of Merminod et al. [48], show strong interest in the relationship between suppliers and buyers of logistics services. This interest can be explained by the developing outsourcing strategies of manufacturers and large retailers, leading to the emergence of powerful logistics service providers. Moreover, 3PL plays a key role in integration and coordination in supply chains. As Mortensen and Lemoine [49] point out, 3PL is essential for successful integration with manufacturers. Other researchers emphasise its role in the coordination of transport and warehousing activities [50,51]. Additionally, 3PL not only positively influences the customer experience [52,53] but also plays an important role in environmental and sustainability issues [54]. It includes not only integrators but also supply chain organisers [55,56]. They are capable of managing and coordinating and sometimes even act as sub-coordinators [57]. They are indispensable in managing information and information flows in the supply chain [58]. Although the concept of fully utilising 3PL as coordinators is rarely discussed (e.g., in the work of Kramarz and Kmiecik [59]), there is a need to fully exploit its potential in line with management and business concepts. Demand and supply management issues are much less often addressed by researchers, and, when they are, it is usually not holistically. Authors mainly focus on either demand management or supply management. For example, some studies highlight the need for 3PL managers to focus on developing and combining demand management skills and knowledge resources to achieve cost advantages [60]. In addition, it is recommended that advanced technology be introduced into such a mix of resources and capabilities to achieve customer service innovation. Demand management by 3PL is also discussed as one of the factors in the benchmarking assessment model [55]. Krasnov et al. [61] address the process of supply management, i.e., the purchasing side, by 3PL when different modes of transport and an intermediate distribution centre are used. On the other hand, supply management from a 3PL perspective in the supply chain is extensively discussed in work based on research conducted in Scandinavian countries [62]. As a result, effective supply and demand management contributes to a company's competitiveness, a better understanding of the market and stronger relationships with business partners. In some publications, the authors point to the great importance of coordinating supply and demand management activities [63–65]. From the city's perspective, the fact that 3PL can manage demand management relationships at the contract logistics level can bring a number of tangible benefits that can contribute to building a smart city.

3. Methods

3.1. Description of Case Study

This article focuses primarily on a case study of the activities of an international 3PL logistics operator. The 3PL company studied is an international logistics service provider that offers a wide range of supply chain solutions. Among the company's main areas of specialisation are mainly warehousing, transportation, co-packing, dedicated solutions and sustainability. The company offers advanced warehousing solutions for both food and industrial products. The warehouses are equipped with state-of-the-art management systems to optimise the processes and effectively manage the inventory. The company provides transport services over various distances, both within one country and internationally. They operate on a door-to-door basis, meaning that they undertake the collection, transport and delivery of goods to the end customer. The 3PL company surveyed also offers co-operative packaging services, which allow customers to customise the product packaging to meet individual market needs. The company also provides specialised customised services, such as returns management or e-commerce solutions. One of the company's priorities is ecology and social responsibility. This means investing in green technologies, minimising its carbon footprint and promoting sustainable practices throughout the supply chain. A hallmark of the 3PL company surveyed is a commitment to continuous improvement and innovation. The company uses cutting-edge technologies such as automation, warehouse management systems and artificial-intelligence-based solutions to provide customers with the highest quality of service while increasing the operational efficiency. The operator activity studied within this paper is restricted to the results concerning its activity in Poland. Poland is a country that is in continuous development in terms of fitting cities to the smart city ideology [66–68], so, according to the present authors, this offers a broad space to seek new solutions that propel Polish cities further towards smart cities. In the territory of Poland, the described operator has nine logistics platforms that serve both Poland and partly the Czech Republic, Hungary, Austria and Slovakia. The authors choose the two Polish cities that show the greatest likelihood of becoming smart cities in Poland, i.e., the city of Warsaw and the city of Wroclaw. The choice of these two cities is related to their strong positions in terms of smart city implementation. In Poland, according to the report "IESE Cities in Motion 2020" and the Polish report "Polskie Miasta Przyszłości 2020" (Polish Cities of the Feature 2020), these two cities are the most developed in this respect. Warsaw is the capital of Poland, with an area of 517.2 square kilometres and a population of 1,765,000 (2017 data). Wroclaw is a city with an area of 295.8 square kilometres and a population of 638,659 (2019 data). Both of these cities are among the most infrastructurally developed areas in Poland. A simple diagram related to the logistics operator's involvement in city deliveries is presented in Figure 1.

The activity of the logistics operator in the city, in the case described, relates to the management of material flows for orders placed by Points of Sale (POS)—as orders that are fulfilled in pallet releases. In terms of transport planning, a pallet is equivalent to the pallet space that needs to be allocated for transport and refers to a standard EUR pallet (1200 $\times$ 800 $\times$ 144 [mm]), where smaller pallets are proportionally reduced in size. The second type of order handled comprises parcels, which relate to online orders generated by end customers. The research presented in this paper is based on selected data provided from the operations of a selected 3PL. The authors of the article propose supplementing the activities of logistics operators with the establishment of cooperation with the city management centre. In the authors' opinion, such a solution would bring mutual benefits.

Based on forecast data, a potential delivery schedule could be created, which could be systematically supplemented with data on the traffic intensity in the city. The city, however, would gain greater control over the flow of goods. The initial outline of this concept is presented in Figure 2.

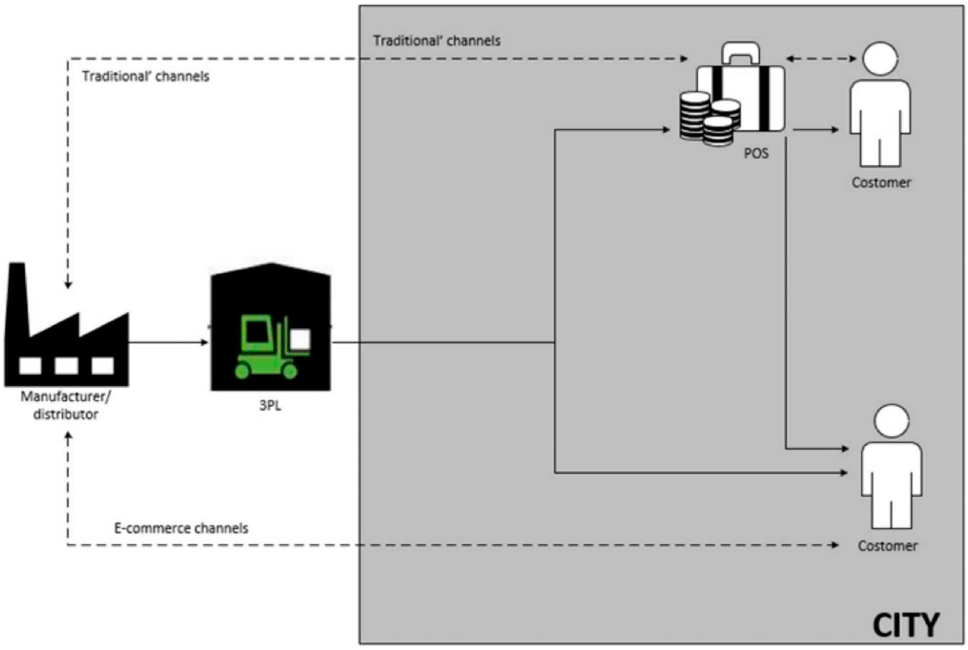

Figure 1. The 3PL activities for cities. Source: own elaboration.

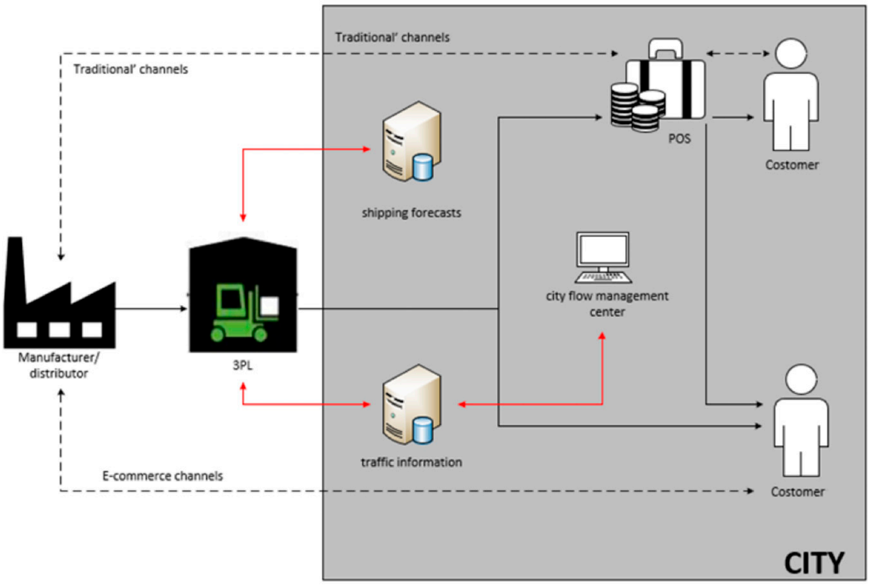

Figure 2. The 3PL activities for cities—authors' concept. Source: own elaboration.

3.2. Description of the Data

The data were collected based on the operational activities of a selected 3PL company. The data were obtained from the WMS and TMS systems by the authors, and they were related to the distribution activities of the 3PL company for two selected Polish cities (Wrocław and Warsaw). Sample data exported from the 3PL database are presented in Table 2.

Table 2. Sample of data taken as input for analysis.

Shipping Date	Pallet Quantity	Parcel Quantity	Delivery Address Postal Code	Delivery Address City	Delivery Address Code (Country)
25 December 2023	1	0	50304	WROCLAW	616
8 August 2023	11	0	50422	WROCLAW	616
1 August 2023	3	0	03977	WARSAW	616
7 July 2023	1	2	34122	WARSAW	616
...	...	...	...	...	...

Source: own elaboration.

The range of data taken for analysis was 4 months for data collected daily, and the exported data contained about 200,000 records. A limitation on the history of the data was related to the limitations associated with the computing power needed to calculate the prediction. As part of the pilot testing, an arbitrary judgement was made that this length of data would be appropriate to conduct the first calculations and would be increased when appropriate results were produced. This would also translate into increased processing costs for the calculations.

The data collected were related to two cities, and Table 3 shows a summary as to the number of postcodes to which the 3PL company delivered during the set period in the specified cities.

Table 3. Number of postal codes in the particular cities in the ranges of days with deliveries per work week.

Percentage of Delivery Days in the Total Work Days	Number of Reception Points (Postal Codes)	
	City Warsaw	City Wroclaw
0.00–25.00%	2513	771
25.00–50.00%	69	69
50.00–75.00%	21	21
75.00–100.00%	8	1

Source: own elaboration.

Postcodes can be considered equivalent to the number of points that the logistics operator carrying out the delivery service had to visit and the percentage of working days on which, on average, goods were delivered to the points in question. As can be seen from the analysis, the largest percentage comprised points that were supplied very irregularly during the week. In total, goods were delivered to individual cities during the period under study as follows:

- To Warsaw: 27,691 pallets (in terms of full pallet spaces) and 174,600 parcels;
- To Wroclaw: 11,328 pallets (in terms of full pallet spaces) and 84,898 parcels.

The operator works 5 days a week, which, for Warsaw, on a daily basis, results in the need to provide transport for about 346 pallet places, and, for Wroclaw, for about 141 pallet places. Looking at the capacity of a standard semi-trailer truck (33 EUR pallets), it can therefore be concluded that, on average, this generates the need to send about 10 shipments to Warsaw and 4 shipments to Wroclaw per day. It is worth bearing in mind, however, that smaller-capacity means are often dispatched due to constraints in the cities and that these rough calculations do not, of course, include e-commerce; however, even without this, the scale of the problem of overloaded deliveries in the cities can be seen.

3.3. Description of the Predictive Algorithm

The prediction of the volumes delivered to individual points in the cities was made using three selected functions from the library ('forecast') reflecting the forecasting algorithms used. The selected functions in the R programming environment are shown in Table 4.

Table 4. Description of R function as a calculation engine for prediction algorithm.

Prediction Function in R Environment	Short Description
auto.arima()	Returns best ARIMA model according to information criteria (either AIC, AICc or BIC value). The function conducts a search over possible models within the order constraints provided.
nnetar()	Feed-forward neural networks with a single hidden layer and lagged inputs for forecasting of univariate time series.
ets()	Estimates the model parameters (error, trend, seasonality) and returns information about the fitted model.

Source: elaborated based on www.RDocumentation.org (accessed on 3 February 2024).

Three algorithms were chosen to calculate the prediction: auto.arima(), nnetar() and ets(). auto.arima() uses the ARIMA (Autoregressive Integrated Moving Average) algorithm, which combines autoregressive (AR), integrating (I) and moving average (MA) models. ARIMA models are used very frequently when making predictions [69–71]. The 'auto' function in the name refers to the automatic selection of model parameters, including the degree of autoregression (p), degree of integration (d) and degree of moving average (q) [72]. The function automatically tests for stationarity and seasonality and can also differentiate the data to achieve stationarity. It uses information criteria, such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), to select the best model [73]. Pallet and parcel count forecasting is suitable if the data have a complex structure that can be described by a combination of AR and MA patterns.

The nnetar() algorithm uses artificial neural networks with time delays, known as neural autoregression (NAR) or artificial neural networks (ANN), for time series prediction. The topic of using artificial neural networks for prediction is one shows a major trend among researchers [74–76]. The algorithm used in this paper creates a neural network with a single hidden layer to which delayed time series values are given as inputs. It typically uses a backward error propagation method to train the network [77]. The use of this algorithm can be useful in forecasting pallet and parcel quantities if the data do not follow traditional linear patterns and may have non-linear relationships.

The ets() algorithm refers to a family of exponential smoothing models that are flexible in modelling different time patterns, including trends and seasonality [78,79]. Despite the fact that the exponential smoothing of time series is one of the traditional methods, it is further used for forecasting in business contexts due to the fact that the created forecasts can further produce adequate results [80,81]. The exponential smoothing model automatically adjusts the level, trend and seasonality in the time series data. ets() automatically selects the best model based on the data. This is suitable for forecasting pallet and parcel volumes, especially if the data show clearly expressed, regular seasonal patterns and/or a trend. The algorithms cited were implemented within the created workflow for the prediction tool (Figure 3).

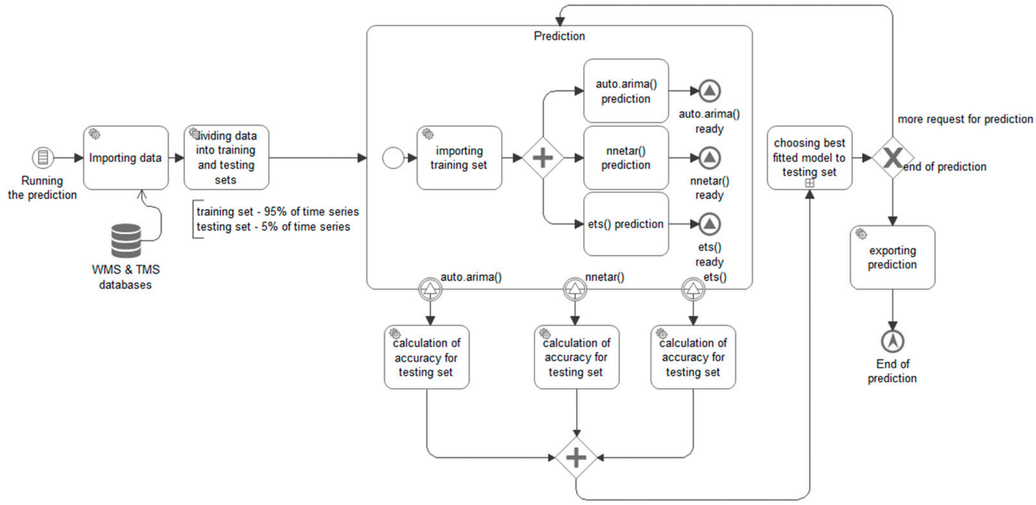

Figure 3. General overview of prediction algorithm workflow. Source: own elaboration.

The first step is the selection of appropriate algorithms: auto.arima(), nnetar() and ets(). Each processes data in a different way, which directly affects the accuracy of the forecasts. auto.arima effectively deals with data that have both linear and non-linear patterns, while nnetar is more suitable for data with complex, non-linear relationships. In turn, ets excels with data showing clear seasonal patterns. The parameterisation of each of these algorithms, such as the degree of autoregression in auto.arima, hidden layers in nnetar or smoothing parameters in ets, directly impacts the results of the forecasts. The data for prediction are drawn from the warehouse management system (WMS) and transport management system (TMS), systems that are generally already implemented in logistics companies [82–84], which, to some extent, demonstrates the adaptability of the proposed tool to a wider group of companies. Data gathered from WMS and TMS systems are crucial for forecasting. The quality of these data directly affects the results of the forecasts. Inaccurate or incomplete data can lead to erroneous forecasts, while well-prepared and accurate datasets increase the likelihood of more precise predictions. The data extracted from the aforementioned systems are automatically split into a training dataset (which is used to determine the relevant parameters for the algorithms) and a test dataset (which is used to compare the results of the three algorithms used and select one to make a forecast for subsequent periods beyond the historical data). The approach of splitting the main dataset into a subset of training and learning data is a well-known approach [85]. In the case of this paper, the authors decided that the length of the training set would be 95% of the time series and the test set would be the remaining data. This choice was guided by the need to obtain a forecast as close as possible to the recent data. Dividing the data into training (95%) and testing (5%) sets is key in evaluating the effectiveness of the models. This stage decides how many data are used to train the models and how many are used for their verification. A small test set may not include all patterns in the data, while a large training set may lead to overfitting in the model. Once the forecasts have been calculated, they are compared on the test set in terms of the accuracy of the forecasts made, where the authors choose three popular indicators to assess the accuracy of the forecast, i.e., the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These are standard indicators used to assess forecasts, which are further considered even in current scientific publications [86–88].

Each result in terms of forecast accuracy is assigned a weight (MAE—0.33; RMSE—0.33; MAPE—0.33) and, based on these, a decision is automatically made as to which algorithm to use to make a forecast for subsequent periods. The weighting criterion for different accuracy indicators in choosing the appropriate forecasting algorithm is addressed in some research papers [59,89]. The forecast for subsequent periods is a prediction of the delivery volume of individual cities and postal codes. A thorough analysis of these indicators allows for an understanding of how each algorithm copes with different aspects of the data, such as errors, trends or deviations. In summary, each stage presented in Figure 4 is crucial for the overall performance of the forecasting tool. From the selection of algorithms, through data processing, to the analysis of results, each step affects the final accuracy and usefulness of the forecasts. Our study emphasises the importance of the careful and thoughtful implementation of each stage in the forecasting process.

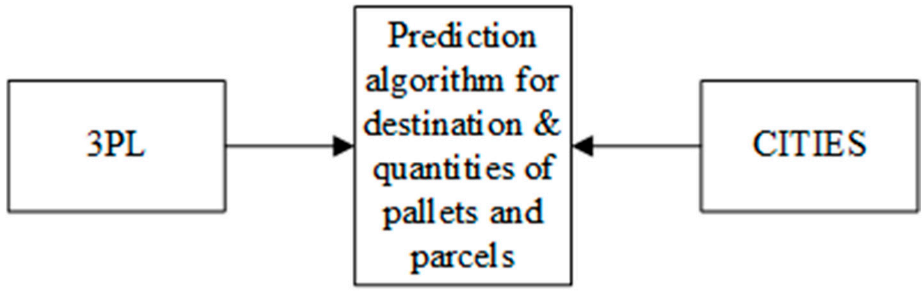

Figure 4. Pilot implementation concept. Source: own elaboration.

3.4. Conceptualisation

The research presented in this paper consists of two parts. The first part deals with the pilot implementation (Figure 4), where the results of the created algorithm for the prediction of the destination and quantities of pallets and parcels are shown together with its verifiability. The second part deals with the development of the research towards implementation in a smart city and the potential to use solutions that are already in place in cities while involving more 3PL operators (Figure 5). In the second case, the authors additionally show the performance of the algorithm to prioritise deliveries when handling more 3PL, and data from other 3PL companies are simulated. Both steps are described in detail in the Results.

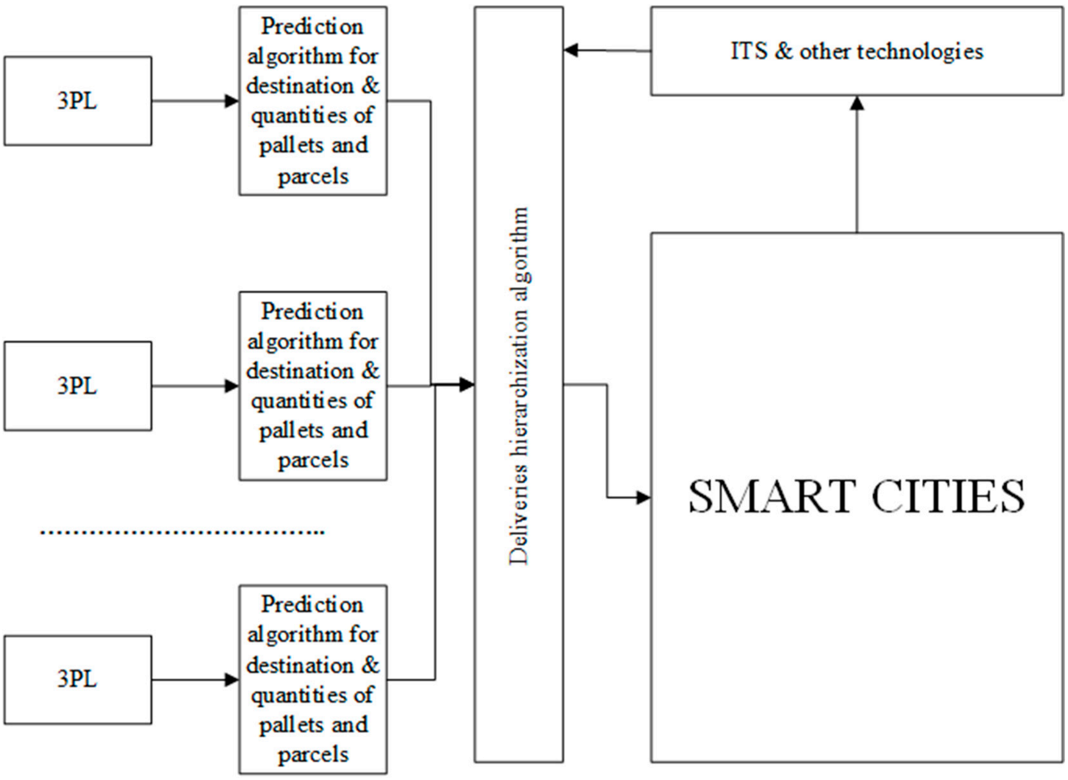

Figure 5. Concept for smart city. Source: own elaboration.

4. Results

In the first step, the accuracy was calculated for the collective prediction of values related to pallet deliveries and shipments in general to the selected cities (Table 5). The prediction was created based on the previously presented workflow. Forecasts were created with a 2-week horizon, where the input data were updated after two weeks. The accuracy of the forecasts made was calculated using the MAPE index, and the period associated with inferring the performance of the prediction system for city deliveries took place over a 24-day period (two forecast updates).

Table 5. Total average MAPE value per city and prediction type.

City	Prediction Type	Prediction Parameter		
		MAPE	Algorithm (Chosen Based on Testing Part for Particular Time Series)	
			First Update	Second Update
Warsaw	pallets	0.36%	nnetar()	nnetar()
	parcels	17.47%	nnetar()	nnetar()
Wroclaw	pallets	3.78%	auto.arima()	nnetar()
	parcels	4.03%	nnetar()	auto.arima()

Source: own elaboration.

The table shows the MAPE values for city delivery forecasts in two different categories—pallets and shipments. For Warsaw, the forecast accuracy for pallet deliveries was 0.36%, while, for shipments, it was 17.47%. For Wroclaw, the accuracy of the forecasts for pallet deliveries was 4.78% and, for shipments, it was 4.03%. The algorithm selected on the basis of tests for specific time series differed according to the type of forecast and the city, as it was selected dynamically according to the procedure outlined earlier in this paper. At this stage, it can be seen that parcel shipments are characterised by less accuracy, and the most frequently selected algorithm that performed best in the testing part of the time series is the nnetar() algorithm. However, from the perspective of last-mile deliveries, according to the authors, forecasts for specific locations (in the case analysed, specific postcodes) are more meaningful.

Forecasts for specific postcodes were made in the same way as the earlier forecasts for cities. Table 6 provides a summary related to the indicators that determine the discrepancies between the real volumes delivered to individual locations and the forecast volumes.

Table 6. Chosen parameters for differences between real values and forecasts.

City	Prediction Type	Average Difference	Av + SD	Av − SD
Warsaw	pallets	−0.09	2.52	−2.69
	parcels	−0.30	16.25	−16.86
Wroclaw	pallets	0.15	1.85	−1.56
	parcels	0.02	14.80	−14.77

Source: own elaboration.

The average difference (AV) is calculated as the average of the differences in the delivered volumes to the forecast volumes calculated for all postal codes in the towns analysed. The standard deviation (SD) is calculated according to accepted statistical rules also for the aforementioned differences. The forecasts for palletised shipments in Warsaw tend to slightly underestimate the average value, and the forecasts themselves tend to deviate from the average by about 2.52 pallets. For parcel shipments in Warsaw, the forecasts have an average difference of −0.30, with a large standard deviation of 16.25. This may indicate greater volatility in the forecasts for this type of shipment. For palletised shipments in Wroclaw, the forecasts have an average difference of 0.15, with a standard deviation of 1.85. This may indicate more stable forecasts compared to Warsaw. For parcel shipments in Wroclaw, the forecasts have an average difference of 0.02, with a standard deviation of 14.80. As for pallets, these forecasts appear to be relatively stable. Figures 6–9 show the details of the Mean Errors (ME) for individual postal codes, with the values associated with the mean, and the mean plus and minus the standard deviation, plotted.

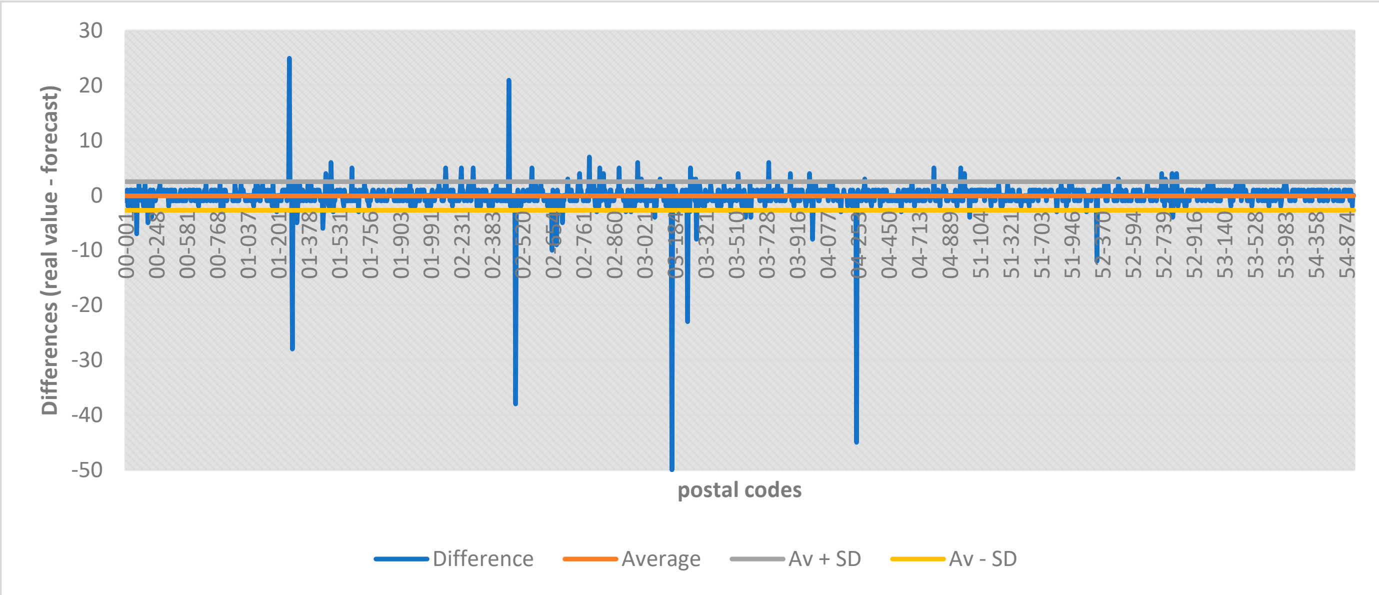

Figure 6. Differences between delivered pallets and forecasts per postal code for Warsaw. Source: own elaboration.

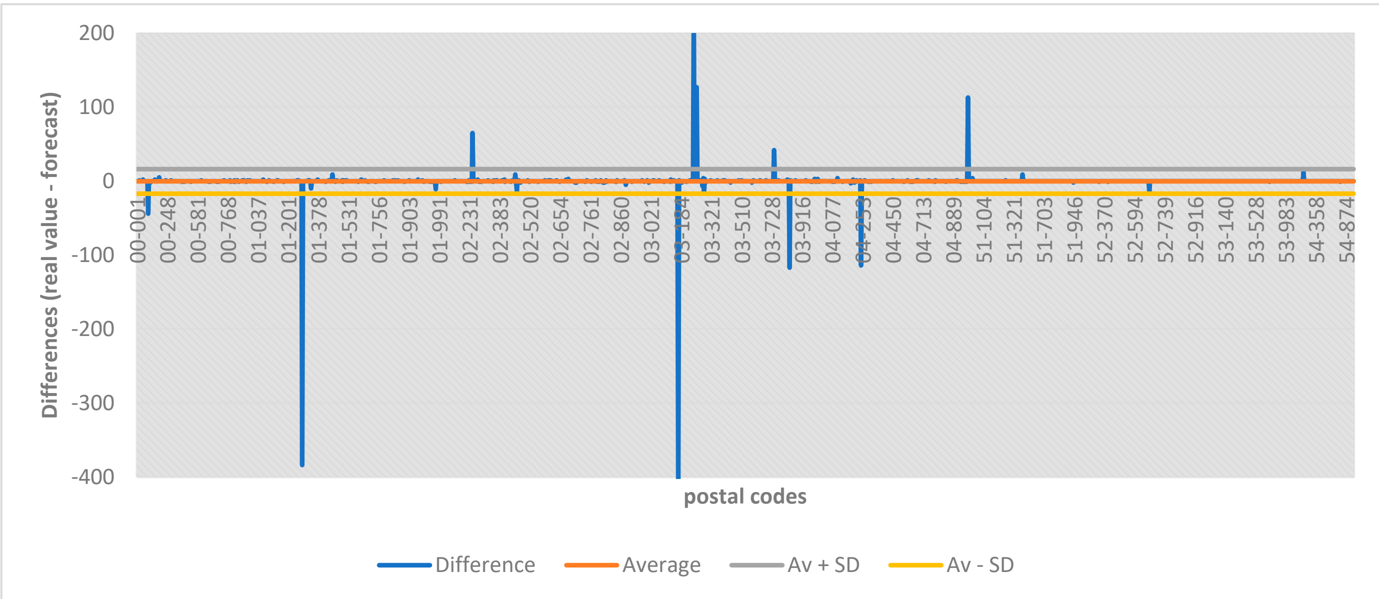

Figure 7. Differences between delivered parcels and forecasts per postal code for Warsaw. Source: own elaboration.

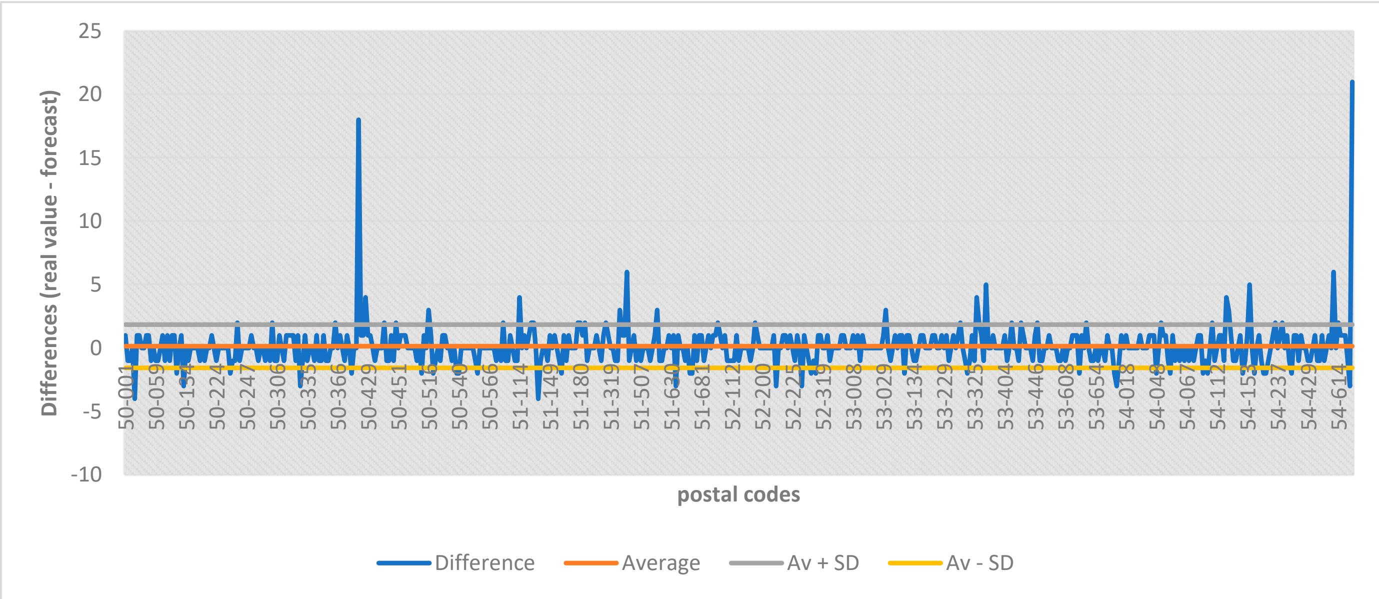

Figure 8. Differences between delivered pallets and forecasts per postal code for Wroclaw. Source: own elaboration.

Figure 9. Differences between delivered parcels and forecasts per postal code for Wroclaw. Source: own elaboration.

In the case of palletised shipments within Warsaw, it can be concluded that the 3PL logistics operator made relatively accurate forecasts, where the problem of the large overestimation of the forecast covered six locations within the city, while the problem of the underestimation of the forecast covered two locations.

In the case of parcel shipments, the significant overestimation of the forecasts occurred in four locations and underestimation in five. In this case, however, the overestimations and underestimations were much larger, according to the authors, which may have been due to insufficient flexibility in providing new data to the forecasting tool, which did not quite, in the problematic locations, provide an effective response to the dynamically changing trends and market needs.

In the case of Wroclaw, the pallet shipment forecasts were much more often underestimated than overestimated, but these overestimations and underestimations were much smaller in volume than in the identical case of pallet shipment forecasts for Warsaw.

The forecasts for parcel shipments, on the other hand, were very similar to those for Warsaw, i.e., a small number of under- and overestimates, but, when they did occur, they were very significant. Figure 10 shows the MAPE volumes generated by day for different types of shipments for each city.

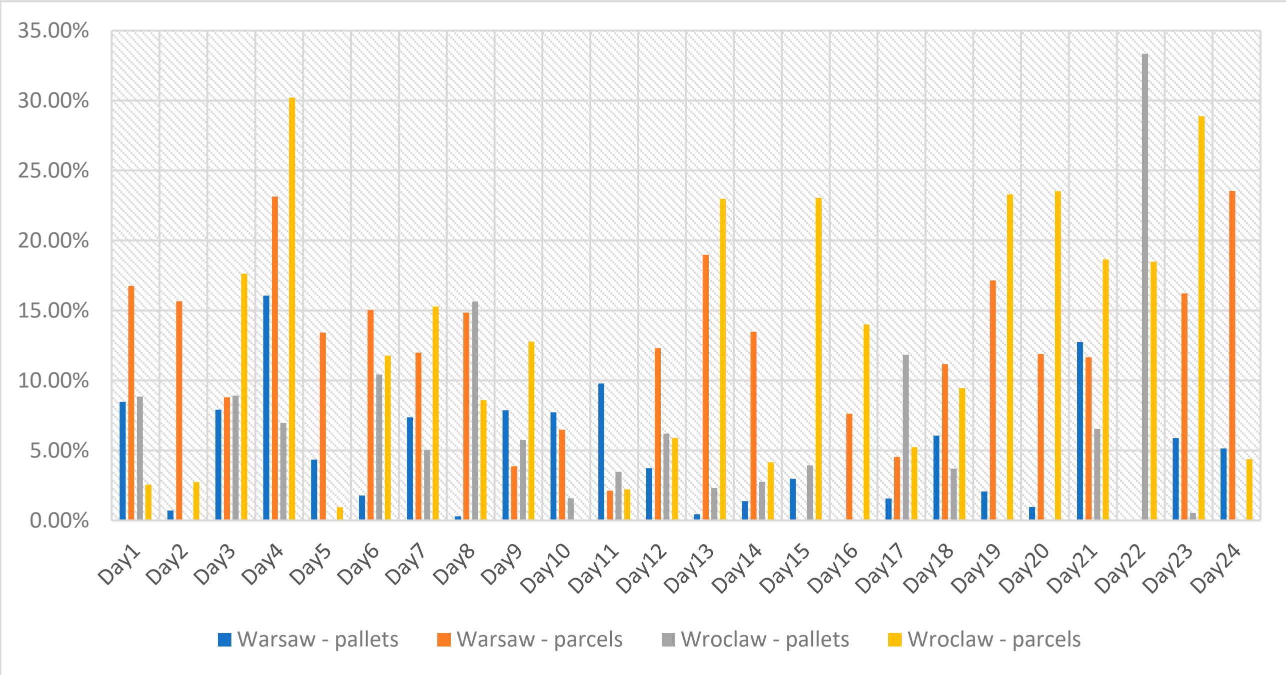

Figure 10. MAPE values per day. Source: own elaboration.

For pallet shipments to Warsaw, the largest error occurred on day 4 (16.06%), suggesting difficulty in forecasting pallet volumes. Day 8 had a low error (0.30%), indicating good forecast accuracy on this day. The average MAPE error for Warsaw regarding pallets is around 6.09%. For parcel shipments in this city, days 1 and 3 show a higher error (16.75% and 15.66%), which may indicate difficulties in forecasting parcel volumes. The lowest error occurred on day 15 (0.04%), suggesting good forecast accuracy on this day. The average MAPE error is approximately 10.20%. For pallet shipments for Wroclaw, the largest error occurred on day 22 (33.33%), which may indicate great difficulty in forecasting pallet volumes at this location. Day 20 has a low error (0.96%), indicating good forecast accuracy on this day. The average MAPE error is around 7.54%. For parcel shipments, the largest error occurred on day 13 (22.98%), suggesting difficulty in forecasting parcel volumes. Day 16, on the other hand, is characterised by zero error, indicating ideal forecast accuracy on this day. The average MAPE error is approximately 10.69%. At both locations, the forecasting errors vary, which may be due to the different factors affecting deliveries. There are days where the errors are particularly high, which may require more sophisticated forecasting methods. However, the forecasts generated by the 3PL even at this level of error can, according to the authors, already provide a basis for their smart city efforts. A concept proposal to support the smart city through the possibility of using the forecasting function of logistics operators will be presented later in the paper.

5. Discussion

5.1. Predictive Actions of 3PL in the Pilot Studies

The research carried out demonstrated the logistics operator's relatively strong ability to make predictions on the volumes associated with pallet and parcel shipments. The choice of the nnetar(), auto.arima() and ets() algorithms for prediction ensured that predictions were produced with relatively high accuracy, even for complex data. The supply time series can be complex and contain linear and non-linear patterns, seasonality and trends, all of which can be modelled effectively by the aforementioned functions. Each of these methods additionally has mechanisms for the automatic selection of appropriate parameters, which is useful in practical applications where the manual adjustment of models would be time-consuming. These methods allow a wide range of time series behaviour to be modelled, which is crucial in forecasting as distributional data often change over time. The study also highlighted the poorer testability of the forecasts made for parcel shipments. The poorer verifiability of forecasts for e-commerce and parcel shipments is the subject of much academic dispute. This also applies to the algorithms used in this paper. Researchers point to this problem in ARIMA-based algorithms [90,91] and algorithms based on artificial neural networks [92,93].

In the course of the research, the developed predictive algorithm was applied to only two cities. Implementing this solution on a wider scale will primarily require greater computing power. Nowadays, however, there are many methods and tools available to perform even such large calculations in a very short time. Such solutions include the use of distributed computing power [94] or cloud computing [95].

In the context of the analysis of the results, it is important to note that the relatively high forecast performance for palletised shipments is a positive result of the study. However, the phenomenon of poorer forecast performance for parcel shipments poses challenges that require further research and analysis. The academic literature highlights that the e-commerce sector, which is one of the main customers of logistics services, is characterised by high demand variability and complex consumer behaviour patterns [96,97]. Therefore, there is a need to explore the specifics of these irregularities and apply more advanced modelling techniques that can better deal with the dynamic nature of the data. It should also be mentioned that the differences in the verifiability of forecasts between pallet and parcel shipments may be due to a number of factors, such as the heterogeneity of goods, differences in the treatment of shipments by logistics systems or the complex structure of the delivery network. Therefore, further research should take these factors into account in order to understand more precisely the specifics of forecasting in the context of parcel shipments.

A deeper interpretation of the MAPE values can provide valuable insights into the practical implications of forecast accuracies, particularly in the context of last-mile deliveries. The variations in accuracy between pallet and parcel shipments hold significant implications for the overall efficiency and effectiveness of logistics operations in urban environments. The higher accuracy in forecasting pallet shipments suggests the more reliable and predictable flow of these goods, leading to better resource allocation and scheduling in the logistics chain. This can result in more efficient loading, routing and delivery processes, ultimately reducing operational costs and improving service quality. For logistics operators, this means the ability to optimise their vehicle fleets, minimise idle time and potentially increase the number of deliveries per route, enhancing the overall operational efficiency. On the other hand, the lower accuracy in forecasting parcel shipments, which are often characterised by their smaller size but higher frequency and variability, presents a challenge for last-mile delivery operations. Inaccurate predictions in this segment can lead to inefficiencies such as underutilised delivery capacities, increased delivery times and higher operational costs. Furthermore, the unpredictability in parcel deliveries can lead to challenges in managing customer expectations and maintaining high service levels. This is particularly critical in e-commerce, where timely and reliable delivery is a key factor in customer satisfaction and retention.

The contrast in forecast accuracy also has implications for the strategic planning and long-term investments of logistics companies. For instance, companies might need to allocate more resources and advanced technological solutions towards improving the accuracy of parcel shipment predictions. This could involve investing in more sophisticated data analytics tools, real-time tracking systems and dynamic routing software that can adapt to the high variability and rapid changes typical of parcel deliveries. The study's findings regarding the forecast accuracy have far-reaching implications beyond the theoretical aspects of logistics management. They touch upon the operational, strategic and policy dimensions of urban logistics, especially in the context of the burgeoning e-commerce sector. Future research should, therefore, not only focus on enhancing the accuracy of predictions but also on understanding and mitigating the practical challenges arising from forecast inaccuracies in last-mile deliveries. This holistic approach will be essential in shaping the future of efficient and sustainable urban logistics systems.

5.2. Concept for the Smart City

The concept for the use of the presented research on a larger scale involves creating a delivery prioritisation tool that will automatically, based on the forecasts provided from the various 3PL companies, queue the loads to the various destination points tagged as postcodes. Such an algorithm should primarily include

- An objective function minimising congestion in the city;
- A parameter related to the current traffic volume data extracted from ITS systems;
- A parameter related to the volumes of forecasts generated by 3PL companies;
- Individual point weight information in the form of postcodes for each 3PL.

The objective function associated with minimising congestion in a smart city corresponds to general trends shown by many researchers [98–101]. The approaches used in this context are typically associated with responding to current traffic volumes through the use of advanced systems for traffic control. The proposed approach could use predictive data and, mainly on this basis, plan the time intervals of provision to different parts of the city. The algorithm associated with the prioritisation of deliveries should also include data collected on an ongoing basis from ITS systems. ITS systems themselves are considered to be one of the basic elements of smart city operation in terms of transport management and congestion control [102]. The forecasts generated by 3PL are of the utmost importance in this context, as they will form the basis for the planning of warehouse operations (related to planning the loading of deliveries to different points in the city) and transport operations related to planning delivery schedules for different 3PL. In this case, 3PL companies should aim to achieve the highest possible verifiability of the forecasts. In determining the weights for the different points (postcodes), it is important to consider the location of the starting point (warehouse or other 3PL distribution point) and the end points, taking into account the path that the delivery has to take (including how many and which intermediate points have to occur) in order to make the last-mile delivery in the smart city. In the literature, there are many developed algorithms related to last-mile delivery planning [103], algorithms that take into account the hierarchy of deliveries and algorithms that take into account the role of logistics service providers in deliveries [34]. Taking into account the multitude of studies in terms of delivery algorithms directed towards reducing delivery costs or congestion, the authors believe that it will be possible to develop an algorithm based on today's known delivery planning techniques, which additionally takes into account 3PL and the forecasts that it generates. This concept will be developed in further research on the issue of the role of 3PL in building a smart city.

In addition, the concept presented can be extended to include the development of cargo consolidation centres in the vicinity of the city, which, operating on a cross-docking basis, would enable cargo to be transhipped beyond the city and delivered in a planned manner based on the aforementioned delivery hierarchy according to the 3PL's predictive capacity. This concept is similar to that presented by Rosenberg et al. [41], where the authors suggest the creation of a consolidation centre that would be managed by 3PL for small shipments to be delivered to a city operating under the smart city concept.

5.3. Main Limitations and Further Research Directions

The main limitation of the study was that it was carried out in only two cities; however, the study was a pilot study to test the validity of the wider exploitation of the subject matter undertaken. In addition, the accuracy of the forecasts obtained was related to the testing of forecasting errors during the normal period of operation of city deliveries, where extraordinary situations such as increased demands for deliveries during festive or promotional periods were not taken into account. Undoubtedly, the next step in the development of this study is to expand the geographical scope over which the developed predictive algorithm is applied. It is also worth considering the integration of different data sources, such as meteorological data, holidays or trade promotions, in order to obtain a more comprehensive representation of the factors influencing logistics processes. This could significantly improve the effectiveness of the predictions, especially for parcel shipments, where external factors can have a significant impact on their temporal distribution. In addition, future research will be extended to create and test an algorithm dedicated to the prioritisation of deliveries, the assumptions of which were described in an earlier section. It would also seem to be an interesting extension of the research to investigate the impact of the exploited concept on the support of omnichannel building by 3PL, as 3PL is actively involved in and highly influenced by omnichannel building [104–108]. According to the authors, the concept presented here could be an interesting addition to the role of 3PL in building omnichannel in urban delivery. The aforementioned issues are areas for further discussion and research in the context of improving forecasting processes in contract logistics for the smart city. Ultimately, the development of modern technologies, such as artificial intelligence or cloud computing, opens up new perspectives for the improvement of the effectiveness of logistics forecasting in a complex and dynamic market environment.

To further enhance the concept presented in the paper, the following concepts connected with contemporary technologies can be considered:

- Blockchain-Based Systems and Applications [109];
- Data-Secure Storage Mechanisms of Sensor Networks Based on Blockchain [110];
- A Search System for Internet of Things Based on a Hierarchical Context Model [111];
- Algorithms for Superposed Data Uploading Problems in Networks with Smart Devices [112].

The integration of blockchain technology can revolutionise the transparency and traceability aspects of third-party logistics in smart cities. By creating a decentralised and immutable ledger, blockchain can provide a tamper-proof record of all transactions and movements of goods. This would not only enhance the accuracy of the predictive algorithms by providing reliable data but also improve the trust among all stakeholders. For instance, blockchain can ensure the integrity of data used to predict the delivery intensity, thereby making the forecasts more reliable and efficient. The use of blockchain in securing data from sensor networks in a smart city environment can significantly enhance the security of data collection and storage. With the exponential growth in IoT devices and sensors in smart cities, securing these data becomes paramount. Blockchain can provide a secure and scalable solution to protect data from tampering and unauthorised access, ensuring that the input data for predictive models in logistics remain uncompromised. Implementing a hierarchical context-model-based search system for IoT can greatly improve the efficiency of data collection and analysis in smart cities. This system can prioritise data based on the context, relevance and urgency, enabling logistics providers to quickly access and process the most pertinent data to make accurate predictions. This approach can be particularly useful in handling the dynamic and complex nature of urban logistics, where real-time data processing is crucial. Addressing the challenge of superposed data uploading in networks with smart devices is critical in ensuring the timeliness and accuracy of the data used in predictive models. Developing algorithms that can effectively manage and prioritise data uploading from a multitude of smart devices in a city will enhance the data quality and reduce the latency. This is particularly important for real-time traffic management and dynamic routing in urban logistics.

6. Conclusions

The development of smart cities has become an inevitable step towards efficiency, sustainability and improved quality of life for residents. The increasing number of goods coming into the city makes it necessary for city authorities to prepare a modern cargo delivery system. This, in turn, according to the authors, requires cooperation between the city's various stakeholders, including, in particular, 3PL companies, which, by creating the appropriate forecasts, are able to regulate the volume of freight traffic in the city. The automation and digitisation of the city logistics management process, the implementation and improvement of solutions of the smart city concept or the use of artificial intelligence, which has recently been gaining popularity, can also provide solutions to this challenge. By combining the predictive capabilities of logistics operators and smart city solutions, it is not only cities that will benefit, by reducing the number of shipments, but also companies, where this raises the prospect of reducing costs, especially those of the last mile, improving logistics processes but also making their operations more environmentally friendly. The research shows that 3PL companies have a relatively strong ability to forecast the number of palletised shipments, and advance knowledge of possible freight flows in the city would undoubtedly help to coordinate them. Parcel shipments prove to be more difficult to forecast, due to a number of external factors, e.g., the seasonality of products or trade promotions. In this case, the authors recommend considering the integration of different data sources to obtain a more comprehensive representation of the factors affecting logistics processes, which could significantly improve the effectiveness of forecasts, as external factors can have a significant impact on their temporal distribution. The authors will probably continue their research on the use of the predictive capabilities of 3PL companies in the context of managing flows in the city. The next step will likely be to explore advanced predictive modelling techniques specifically tailored to the dynamic nature of parcel shipments and discuss the impact of external factors on the time distribution of deliveries. The authors also plan to create a simulation algorithm that combines forecast data with the traffic intensity in the city, allowing for the determination of the most advantageous delivery times of goods to the city. The paper makes a significant contribution to management science by partially filling the research gap regarding the potential for 3PL to influence the management of urban freight flows and the creation of modern smart city solutions targeting last-mile delivery. Answering the research question posed at the beginning of this paper, the authors unanimously state that a 3PL company can influence the volume of urban deliveries as part of its predictive activity.

Building on the existing conclusions, this paper adeptly addresses the research gap concerning the role of 3PL within the smart city framework, particularly focusing on enhancements in last-mile logistics. The integration of 3PL into the smart city concept is explored as a means to increase the efficiency of urban deliveries. This integration is crucial in reducing congestion and environmental impacts, thereby contributing to the sustainability and liveability of smart cities. The paper specifically delves into how the predictive activities of 3PL companies can streamline last-mile logistics. By utilising advanced forecasting methods and data analytics, these companies can predict delivery volumes more accurately, leading to better resource allocation and route optimisation. This not only improves the delivery efficiency but also minimises traffic congestion and reduces the carbon footprint associated with urban deliveries. In tackling the research question about the influence of 3PL on the volume of urban deliveries, the paper provides substantial evidence that 3PL companies, through their predictive capabilities, can significantly shape and optimise urban freight flows. The authors present a detailed analysis of how the precise forecasting of delivery volumes by 3PL entities can lead to a more strategic and efficient approach in managing urban logistics. This includes reducing the number of unnecessary trips and optimising delivery routes, which directly impact the volume of urban deliveries. The paper significantly contributes to the field by showcasing how 3PL activities, especially their predictive capabilities, are integral to advancing last-mile logistics within the smart city context. This aligns with the broader aim of improving urban living conditions through more sustainable and efficient logistics practices.

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