European Research Studies Journal
Volume XXVII, Issue 3, 2024

pp. 209-224

Price Valuation Modeling of Less-Than-Truckload (LTL) Shipments for Financial Continuity Assurance

Submitted 18/05/24, 1st revision 06/06/24, 2nd revision 27/06/24, accepted 29/07/24

Paulina Owczarek[1]

Abstract:

Purpose: *The aim of the research is to develop a mathematical model for LCVs that carry LTL loads. The model considers the intensity of vehicle usage and the number of loading and unloading points.*
Design/Methodology/Approach: *This article presents an analysis of the fulfilment of LTL orders in 7 transport companies. The dataset covers 2 years and describes the use variables of 24 different N1 category vehicles with a maximum permissible gross weight of 3.5 tones. A set of indicators was used to assess the intensity of vehicle use and a statistical analysis was performed. Based on a dataset of technical and operational parameters describing the execution of LTL orders a multivariate regression model was developed to determine the value of LTL orders. Variables with a significant impact on the value of a transport order were selected. The estimation of regression parameter values was carried out based on the least squares method.*
Findings: *Due to the specificity of LCV transport and the lack of necessity for monitoring them, research in this area is challenging and data are less frequently available. The developed model can be a practical tool for determining the value of LTL orders for LCV carriers.*
Practical Implications: *This paper presents a tool that carriers can use to assess the efficiency of their LTL orders. In practice, the tool can form part of a strategy that will support companies in securing financial continuity, creating healthy competition and industry standards.*
Originality/Value: *Transport modeling primarily focuses on minimizing costs or maximizing profits. Available studies primarily present optimization models for Heavy Goods Vehicles (HGV). The literature does not offer a financial continuity model for Less Than Truckload (LTL) transport aimed at Light Commercial Vehicle (LCV) carriers. This paper addresses a gap in the literature by proposing a specialized reference a multivariate regression model specifically to the transport sector.*

Keywords: *LTL, efficiency, modeling, transport process, financial security.*

JEL classification: *C15, R40.*

Paper type: *Research article.*

[1]*Ph.D., Military University of Technology, Poland, ORCID: 0000-0001-6442-9576,*
e-mail: paulina.owczarek@wat.edu.pl;

1. Introduction

At the turn of the last few years, the Freight Forwarding industry has been facing difficulties caused by the dynamics of change in the global economy. Following the crisis caused by the Covid-19 pandemic, the industry has adapted to the new conditions and has begun to evolve in a direction dictated by the thriving e-commerce market.

Growth in e-commerce-generated shipments from 2019 to 2021 was around 20%, while EU retail sales in the second half of 2021 increased by 22% year-on-year (TSL Ranking, 2022). Online trading has a very strong impact on the freight forwarding industry. Behind increasing production and sales, the demand for transport is steadily increasing (Głodowska and Owczarek, 2020).

The TSL 2022 ranking showed that the revenue of the 150 ranked freight forwarding companies achieved revenue growth of 28.8% in 2022 compared to the previous year. In comparison, Amazon Fulfillment Poland recorded a 97.5% revenue growth.

Supply chain management forces haulers to adopt strategies and tactics that meet the objective of both maintaining financial continuity and the level of service quality specified by the customer.

According to the CSO (Central Statistics Office) report, considering cargo transport in domestic transport by distance zones: up to 49 km, 50 - 149 km, 150 - 299 km, 300 - 499 km, 500 km and more, it can be noted that at a distance up to 49 km by car transport was transported in: 2021 r. - 45.4%, in 2022. - 46.3% of all freight.

Statistics confirm the ever-increasing demand for LTL (*Less-Than-Truckload*) transport, which is more complex and demanding to manage than FTL (*Full-Than-Truckload*). LTL transport is characterized by the handling of a variety of goods with small dimensions, usually many shippers and receivers and often the need for additional transshipments and consolidation of goods.

Determining the optimal rate for fulfilling a transport order becomes problematic in this area. The rate offered by the hauler should consider the rational use of cargo space, short delivery times and the highest service quality and efficiency. As a result, the revenue should cover the costs of order fulfilment and bring a satisfactory profit. The challenge for LTL haulers, therefore, is to plan and calculate the price of multi-stage process of general cargo transportation, which is often defined by incomplete information.

This year represents another challenge for the transport industry, the crisis caused by the war in Europe, progressive inflation, a significant increase in fuel prices, a shortage of qualified drivers. Supply chains are being disrupted by shortages of raw materials, production stoppages, payment bottlenecks or customs problems.

This significantly affects the availability of products in both stationary trade and e-commerce platforms. The result is an increasingly frequent interruption of financial continuity for companies.

Transport companies are trying to adapt to the rapid changes and are looking for alternative solutions, e.g. by shifting their operations from international to domestic or from FTL to LTL groupage. In practice, effective methods and simple tools are being sought to enable haulers to quickly analyze and calculate the price of transport order.

The research presented here was carried out for 7 companies providing LTL groupage transport services over a 2-year period. The dataset includes variables relating to the use of 24 different N1 category vehicles with a maximum permissible gross weight of 3.5 tons. A set of indicators was used to assess the intensity of vehicle use and statistical analysis was carried out. The aim of the research conducted was to develop a model for assessing the value of LTL freight order fulfilment in relation to securing financial continuity.

2. Status of the Issue Under Examination

In operations research, the problem faced by general cargo transport is mainly categorized as a class of marshalling (route planning) or *vehicle* routing *problem* (VRP). In the classic approach, also referred to in the literature as CVRP (*Capaticised VRP*), customers are visited exactly once by a haulers and each vehicle delivers the entire demand to a specific customer.

The Vehicle Routing Problem is defined as a graph G = (V, E), where V = {0, . . . , n} is the set of vertices. In the undirected case where E = {(i, j): i, j ∈ V, i < j} represents the set of edges, vertex 0 is the loading point (depo) and the other vertices are the customers. Each vertex of V {0} is assigned a non-negative demand value qi and each edge (i, j) a non-negative cost or distance cij (Laporte *et al.*, 1999).

Supply planning problems constitute a broad family of issues arising primarily from the dynamic nature of transport, its determinants and practical constraints (Mohamed *et al.*, 2018; Bertoli *et al.*, 2018). The diversity of research applications prompts the analysis of multiple variants of problems with different characteristics. Models are typically refined in three directions: considering more relevant performance goals and metrics, integrating vehicle routing assessments with other tactical decisions, and considering detailed but relevant aspects of modern supply chains (Vida *et al.*, 2020).

Most work considers the problem of routing with inventory and optimizing the logistics ratio, defined as the ratio of routing costs to the quantity of product delivered over the planning horizon (Song and Savelsbergh 2007; Benoist *et al.*, 2011, Archetti *et al.*, 2017b) or measuring the average cost of delivering a unit of product (Matl 2019).

Another modelling objective is to maximize profits while considering distance (Baldacci *et al.*, 2018) and time constraints (Aksen *et al.*, 2012). A publication (Ceschia *et al.*, 2011) considers a cost function with coefficients depending not only on distance and load, but also on geographical aspects related to the furthest customer along the route.

Stenger *et al.* (2013b) solve a variant with multiple bases, while Stenger *et al.* (2013a), Gahm *et al.* (2017) and Dabia *et al.* (2019) consider non-linear cost functions resulting from volume discounts. Finally, Goeke *et al.* (2019a) design a state-of-the-art branch-and-price algorithm. Route planning can specify a cumulative target (*Cumulative VRP*) expressed as the sum of individual arrival times to customers (Silva *et al.*, 2012; Golden *et al.*, 2014).

The fulfilment of general cargo orders is often undertaken by logistics operators who, to guarantee a certain level of service, define a minimum on-time delivery rate. In this type of VRP problem, deliveries are divided into groups with service level constraints (Bulh˜oes *et al.*, 2018a; Orlis *et al.*, 2019). Using metaheuristics for time constraints, solutions based on route dependencies are created (Goeke *et al.*, 2019b) or self-overlapping time windows are proposed for each customer (Jabali *et al.*, 2015, Spliet and Gabor 2015).

In route planning, the research also aims to balance workload allocation to ensure that vehicle reliability is maintained and that constraints related to service times, total demand or number of customers are met (Matl, 2018; Kalcsics, 2015). The problem of available time windows is also highlighted in the route planning problem (Hoogeboom and Dullaert, 2019; Soriano *et al.*, 2019) or maintaining geographical consistency that divides deliveries into specific regions (Rossit *et al.*, 2019). Finding reliable route planning solutions that remain effective in practice in the presence of uncertainty has become a major issue (Gendreau *et al.*, 2014; 2016).

Models of heterogeneous VRP problems require a common definition of vehicle types and routes. Each vehicle type may have distinct characteristics such as payload, fixed and variable costs, customer service constraints. Typically, two canonical problems are distinguished: VRP on fleet size and composition FMVRP (*Fixed Multiple Vehicle Routing Problem*) and VRP with *heterogeneous* fixed fleet HFVRP (*Heterogeneous Fleet Vehicle Routing Problem*).

FMVRP that there is a fixed number of vehicles available for assignment to specific routes. In this case, optimization typically involves minimizing cost, time or other metrics related to delivery efficiency. For HFVRP, fleet diversity refers to the different types of vehicles that are available to service routes. The objective is to efficiently assign tasks to the appropriate vehicles considering various constraints such as vehicle availability, time windows and cost minimization (Vidal, Laporte, and Matl, 2020).

A model based on the split delivery vehicle routing problem is also the subject of much research. This issue is referred to as the *Split Delivery Vehicle Routing Problem (*SDVRP) and is a flexibilization of the classical VRP vehicle routing problem (Karkula, 2018). A proposal for solving the integrated loading and routing problem with split delivery and incomplete demand information was also presented by Burcu *et al.* (2014). A metaheuristic approach was also applied by Mahomed *et al.* (2018) building an efficient model based on customer demand coverage with targeted route generation schemes.

The rationalization of transport processes characterized by dynamic variables is a complex discrete optimization issue. Most research into the process of fulfilling general cargo orders focuses on route design. In complex real systems, the efficiency of LTL process execution is influenced by many external conditions that cannot be described and systematized.

In practice, freight dynamics mainly indicate unplanned stops, the addition or subtraction of points during order fulfilment or constraints defined by individual customer requirements. The transport process is complicated by the additional dynamic element of external conditions determining the reliability and quality of the service provided. These aspects confirm that assessing and modelling the LTL freight process is difficult. At the same time, this situation forces haulers to look for effective methods and quick tools to calculate in most effective way the order price.

The literature review presented here confirms that the modelling of LTL freight in relation to cost-effectiveness mainly sets cost minimization or profit maximization as the objective. In this paper, the authors have developed a mathematical model that provides a practical tool for determining the value of an LTL order.

The model takes into account the intensity of vehicle uses and the number of loading and unloading points. In the literature cited, no proposal was found aimed at transporters of N1 category vehicles that considers securing financial continuity by assessing the value of an LTL order.

3. Modelling the Assessment of LTL Order Fulfilment Value

Correlation and regression theory, provides a basis for accurately determining the degree and direction of association between variables. Regression analysis is used to model the relationship between a random variable Y (dependent, explanatory) and one or more explanatory variables (called predictors, independent, explanatory): X_1 , X_2 , . . . X_n , where for n = 1 we have a simple regression, while for n > 1 we have a multivariate regression. Given the nature or type of variables acting as predictors, between-group systems containing only qualitative (categorized) predictors may be called ANOVA (analysis of variance) systems, while between-group systems containing only quantitative predictors may be called regression systems.

Given *n* observations of the variables $x_1, x_2, x_3, \dots x_k$ influencing variable *y*, the linear multivariate regression model takes the following form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon, \tag{1}$$

Where:
β_j - model parameters (regression coefficients);
ε - random component.

Coefficients β_j are theoretical values, the determination of which would require the measurement of an infinite number of observations. It is therefore necessary to use sample-based estimates of these coefficients. The estimation of a multivariate regression equation takes the form:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k. \tag{2}$$

In practice, it is not possible to obtain complete information on the whole population. The regression function determined by the method of least squares on the basis of a sample drawn from the general population is an approximation of the regression in the whole population. With the determination of the regression function comes the problem of assessing the differences describing the discrepancy between the values of the dependent variable and the values calculated from the model.

As a measure of this discrepancy, the standard deviation of the residuals can be used. In statistics, the accuracy of an estimator is measured by its variance. The standard error of the estimation informs about the average magnitude of the empirical deviations of the values of the dependent variable from the values determined by the model and is defined by the formula:

$$S_e = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n-2}} \tag{3}$$

Where:
y_i - empirical values;
$\hat{y}_i$ - theoretical values;
n - number of elements.

In regression modelling, it is necessary to determine the coefficient of determination. The basis for determining the coefficient of determination is the sum of squares of deviations of individual observations from their mean, which can be described by the following relation:

$$\sum_{i=1}^{n}(y_i - \bar{y})^2 = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

Where:
$\sum_{i=1}^{n}(y_i - \bar{y})^2$- total sum of squares;
$\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$- the explained sum of squares describing the variation explained by the model;
$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$- the residual sum of squares describing the variability unexplained by the model.

The coefficient of determination represents the ratio of explained variation to total variation and is defined by the following equation:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \tag{5}$$

Introducing further (additional) variables into the model increases the R^2 coefficient, while the aim of the research is to indicate the relationship between the variables and to reliably assess the parameters, not to maximize the fit coefficient. Caution should be exercised when $n=k+1$ (in which case $R^2 =1$), when the model is not linear or when there is collinearity between the independent variables.

When the independent variables are correlated, then they deprive each other of explanatory power. In such a situation it is justified to use the corrected (adjusted) R^2. The value of the adjusted R^2 decreases when variables that do not cause a significant increase in the sum of squares of deviations are introduced into the model.

Partial correlations are correlations between a given independent variable taking into account its correlation with all other variables and the dependent variable taking into account its correlation with all other variables. These coefficients explain the effect in the sense of co-variance rather than in the context of a causal relationship.

The complexity of LTL order fulfilment results in multiple characteristics being observed and their interaction with the dependent variable being analyzed, hence the reason for selecting such a tool for process modelling.

The study was conducted based on data on the fulfilment of transport orders, collected from among 7 companies providing LTL groupage transport services in the country. The companies carry out deliveries of one type of goods on the order of the same customer, who specifies the demand for the number of loading and unloading places.

Analysis of the orders carried out and the intensity of use of the vehicles made it possible to develop a set of technical and operational parameters, which includes:

R_p – year of production [year];
P_u – vehicle mileage [km];
M_u – cargo weight [t];
C_u – vehicle operating time [h];
J_u – vehicle driving time [h];
T_u – vehicle standstill time [h];
T_r – travelling speed [km/h];
K_r – LTL order execution cost [PLN/t];
L_u – the sum of the loading and unloading points;
Z_u – gross LTL order value [PLN];
D_u – gross income [PLN].

Over a period of 2 years, each vehicle forming the fleet of an individual company carried out daily transport orders, which formed the basis for the development of a set of indicators. Analysis of the indicators made it possible to assess the intensity of vehicle use and to evaluate the efficiency of the transports carried out.

1. **Order value indicator E_1:**

$$E_1 = \frac{Z_u}{P_u \cdot M_u} \text{ [PLN/tkm]} \tag{1}$$

Where:
Z_u - LTL order value [PLN];
P_u - vehicle mileage [km];
M_u - cargo weight [t];

2. **Cost value index E_2:**

$$E_2 = \frac{T_r}{P_u} \text{ [PLN/tkm]} \tag{2}$$

Where:
K_r - LTL order execution cost [PLN/t];
P_u - vehicle mileage [km];

3. **Income value indicator E_3:**

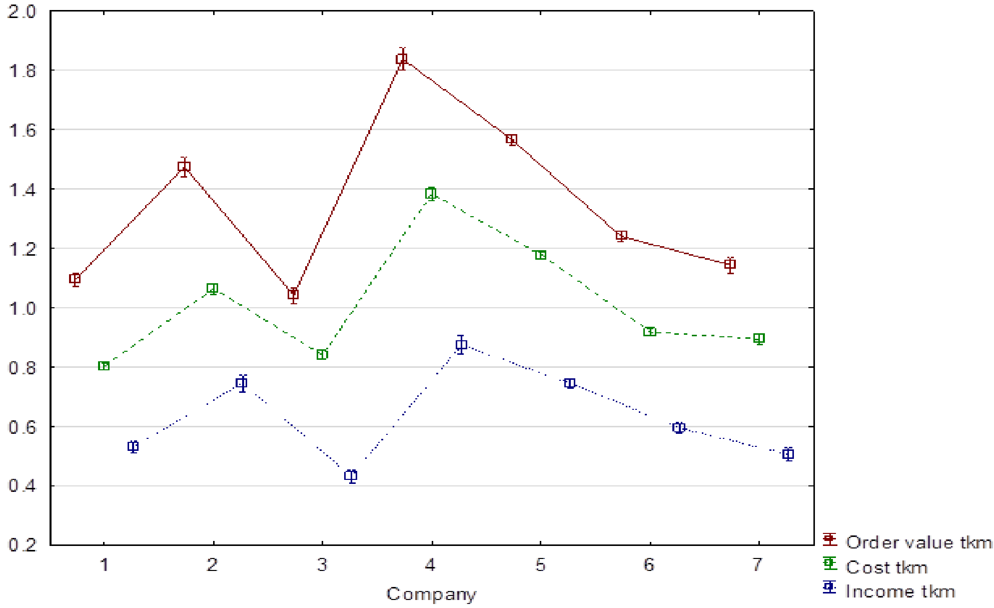
$$E_3 = \frac{D_u}{P_u \cdot M_u} \text{ [PLN/tkm]} \tag{3}$$

Where:
D_u - income [PLN].

The results of the ratio analysis shown in Figure 1 showed that each company has a different strategy for determining order value. The highest revenue/tkm is obtained by company 4, which simultaneously determines the highest LTL/tkm order fulfilment value and has the highest cost per tkm ratio. The lowest value of the order value/tkm indicator is obtained by company 3, which thus obtains the lowest revenue/tkm.

The analysis carried out leads to the search for reasons that determine the value of income/tkm and leads to the assumption that company 1, 3, 6 and 7 could analyze the intensity of vehicle use and verify the correctness and efficiency of the order value assessment.

Figure 1. *Indicator analysis chart*



Source: *Own study.*

This was followed by an analysis of the jobs carried out in terms of the assessed value of the order, the costs incurred, and the income generated. The basic parameters of the jobs carried out were also examined in relation to the weight of the load carried, the mileage, the number of loading and unloading points, working time or stoppage time, as well as driving style parameters, such as average driving speed. In a first step, basic statistical values were calculated for the above-mentioned variables.

The dataset showing the parameter values in Table 1. provides a basis for analyzing and comparing vehicle use intensity and economic efficiency for each company.

Table. 1. *Analysis of the average values of the parameters describing the execution of LTL orders*

	Companies						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Daily mileage [km]	445,55	437,48	454,87	415,45	431,39	457,41	456,76
Cargo weight [kg]	1304,27	1329,30	1428,31	1300,70	1234,84	1441,05	1279,60
Driving time [h]	0,37	0,34	0,38	0,33	0,34	0,30	0,30
Operating time [h]	0,43	0,41	0,44	0,38	0,40	0,34	0,35
Standstill time [h]	0,06	0,07	0,06	0,04	0,06	0,05	0,05
Driving speed [km/h]	50,35	49,68	50,13	49,67	49,35	49,84	49,72
Sum of loading and unloading points	4,08	4,83	3,91	5,77	5,20	4,30	4,55
LTL order value [PLN]	783,61	723,63	769,34	708,17	714,01	764,55	735,53
Income [PLN]	315,23	287,28	236,09	264,57	269,73	291,45	262,37

Source: *Own work.*

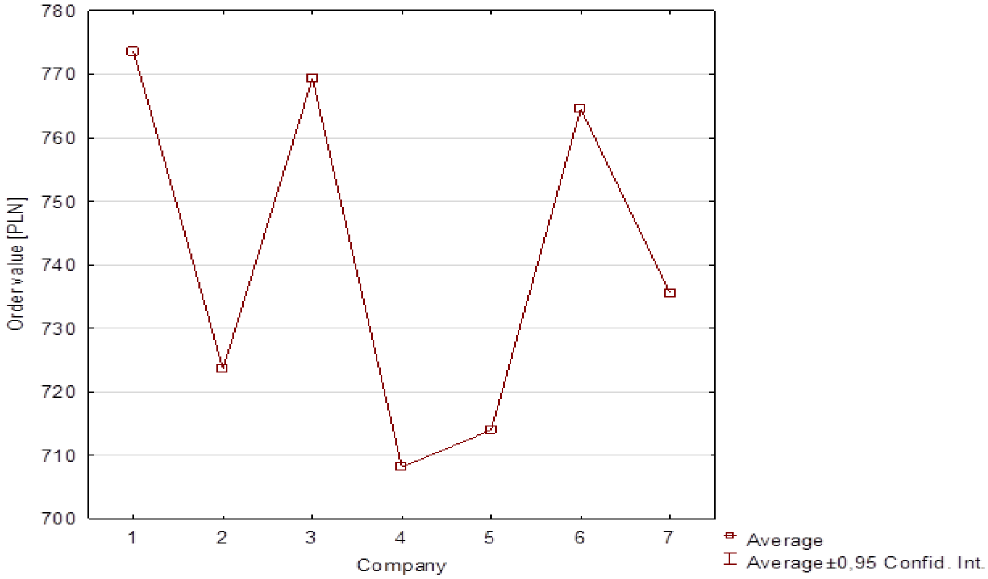
The average mileage during transport assignments in the individual companies is in the range of 400-450 km, while the weight of the cargo carried is also in the range of 1200-1400 kg. It should be noted that the driving, working and stopping times are similar in the individual companies, as is the average speed. The average number of points served during a single order in the individual companies varies from approx. 4 to approx. 6.

Subsequently, an analysis of the value of the orders carried out (valuation is done individually for each company) (Figure 2), as well as an analysis of the income generated (Figure 3) was carried out.

Differences can be observed between the values of the orders in the different companies, as well as between the income achieved. This is also confirmed by the Kruskal-Wallis test (carried out due to the absence of a normal distribution of the values tested), for which the null hypothesis states that all observations come from one population, i.e. there are no significant differences between them. This test was carried out for the variables income and order value for individual companies.

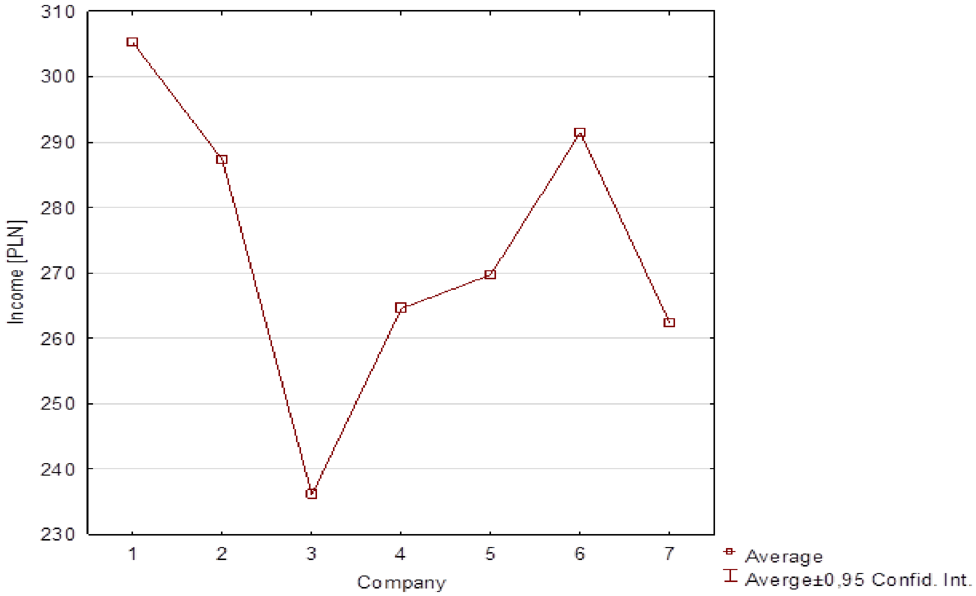
With an assumed significance level of $\alpha=0.05$, the calculated value of the test statistic for the order value is $H=1058.19$ and the corresponding p-value=0.00, indicating that the null hypothesis against the alternative hypothesis should be rejected, and therefore there are statistically significant differences between the order value of the individual companies. A similar situation exists with regard to income. The value of the test statistic $H=283.23$, with p-value=0.00, which also indicates statistically significant differences.

Figure 2. *Graph of average LTL order values*



Source: *Own study.*

Figure 3. *Graph of average income values*



Source: *Own study.*

In the next step, a detailed analysis was made of the orders carried out. A comparison was made between them in relation to the weight of the freight carried and the daily mileage. Again, the Kuskal-Wallis test was carried out, with the following results: for freight weight, the calculated p-value was p=0.13 and for mileage p=0.18. This indicates that, with the assumed level of significance, there are no statistically significant differences between mileage and freight weight in the orders carried out.

Preliminary data analyses and a literature review have shown that there are a number of studies dealing with order scheduling, but no analyses of its value assessment. Furthermore, it should be noted that a company's revenue is determined by the appropriate valuation of the order. The above data indicate that the valuation of orders in individual companies is not correct.

For example, in company No. 3, with similar parameters of the executed orders, the achieved income is the lowest. All this leads one to conclude that there are no tools that can be universally used to assess the value of LTL orders. This has become the scientific objective of the following study. The analyses carried out are carried out for companies from the group of small and medium-sized enterprises, i.e., a group of entities that cannot afford to invest in advanced IT systems for data analysis, so it is necessary to provide them with tools that are both analytically uncomplicated and do not require high expenditures during implementation.

The above leads the paper to propose a multivariate regression model for forecasting and assessing the value of LTL orders. Due to the small amount of data available (which is provided by customers at the time of the enquiry), only three independent variables were selected to build the model, i.e. daily mileage, cargo weight and number of loading and unloading points.

As a first step, an assessment was made as to whether the selected variables have an impact on the phenomenon under study. Due to the quantitative nature of the variables, a correlation analysis was carried out.

Table 2. *Result of correlation analysis*

	Gross value of transport order [PLN]
Daily mileage [km]	0,310474
Cargo weight [kg]	0,370175
Total points	-0,147958

Source: *Own work.*

All the variables selected have a significant impact on the value of a transport order. The above indicates that as the distance and weight of the cargo transported increases, the value of the order should increase, while it should decrease as the number of loading and unloading points increases.

The construction of the model then proceeded. Estimation of the regression parameter values was carried out based on the least squares method. All calculated parameters of the model are statistically significant (evidenced by the calculated p-value=0.00). The model's coefficient of determination is 62%, i.e., that the selected parameters represent 62% of the estimated valuation of the transport order. The model equation takes the following form:

$$value = 458.79 - 5.82 \cdot number\ of\ points + 0.13 \cdot cargo\ weight + 0.38 \cdot daily\ milage$$

In the next step a validation of the model was carried out, by analyzing its residuals. In the first step, the conformity of the distribution of the residual component to a normal distribution was checked. For this purpose, the statistical Kologomorov-Smirnov test was carried out, for which the null hypothesis is that the distribution of the factor under study is consistent with a normal distribution. The resulting value of the test statistic is d=0.06 and the corresponding p-value is p=0.00. This means that there is no basis for accepting the null hypothesis and therefore the distribution of the residuals is not random.

There are, therefore, other factors that can affect the value of a transport order that are not included in the model. These include parameters related to the driver's driving style or the technical parameters of the vehicle, which are difficult to estimate at the valuation stage and were therefore omitted when building the model.

In addition, the White test was conducted for homogeneity of the residuals, for which the calculated p-value is 0.15, which does not give grounds to reject the null hypothesis of the test, stating that the variance of the residuals (random component) is homoscedastic, and therefore the explanatory variables are not correlated with them. This is also confirmed by the Durbin Watson test carried out, for which the calculated value of the test statistic is 1.925 (parameter value dg=1.92, for a model with k=3 and n=13 000).

It should be noted that an increase in the value of mileage during the execution of a transport order by 1 km results in an increase in the value of the order by PLN 0.38, in the case of an increase in the weight of the cargo by 1 kg, the increase in the value of the order is PLN 0.13, while each additional loading and unloading point results in a decrease in the value of the order by PLN 5.82.

4. Conclusive Remarks

Calculating rates for the provision of an LTL service can be a complex process that requires many factors to be considered. It is necessary to identify all costs associated with the execution of the service, determine minimum routes, optimize cargo space or additional requirements of customers.

Deciding whether to carry out transport requires an analysis of the profitability of the orders undertaken. It is therefore necessary to take an integrated approach to the factors determining the value of an order.

Based on a set of technical and operational parameters describing the fulfilment of LTL orders, an analysis of the intensity of vehicle use was carried out and a set of indicators was developed, providing a basis for assessing the effectiveness of the transport carried out.

The results confirmed that each company adopts a different strategy to determine the value of an order, for which rates vary from 1.1 PLN/tkm to 1.8 PLN/tkm. An analysis of the average values of parameters describing the execution of LTL orders for each company confirmed that the intensity of vehicle use for daily mileage assumes a range of 415-457 km, cargo weight of 1279-1441 kg, working time of 20-26 min and average speed of 50 km/h.

The average number of loading and unloading points per order oscillates between 4-6 for each company. The analysis confirmed that for similar values of the parameters for general cargo orders, company 3 has the lowest revenue value, even though the company's order value was the second highest in relation to all other companies.

Given the lack of precision in determining the value of a LTL groupage order and the lack of standards defining the profitability of the services provided by haulers, a model was developed to assess the value of LTL order fulfilment. The model makes it possible to secure the financial continuity of transport companies by analyzing the intensity of vehicle use on an ongoing basis and determining the value of an order. The model considers the mileage performed, the weight of the cargo transported and the total number of loading and unloading points.

The developed model can serve as a tool to support haulers in analyzing the efficiency of the execution of a given order. The tool can form part of a strategy that will support haulers in building financial stability, creating healthy competition and industry standards.

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