Available online at www.sciencedirect.com

ScienceDirect

Procedia - Social and Behavioral Sciences 111 (2014) 890 – 898

Procedia
Social and Behavioral Sciences

EWGT2013 – 16th Meeting of the EURO Working Group on Transportation

Impact of dynamic characteristics of supply chain on own-account fleet size in the optimal transport sourcing mix

Đurđica Stojanović[a]*, Emilija Nikolić-Đorić[b]

[a]University of Novi Sad, Faculty of Technical Sciences, Trg D. Obradovica 6, 21000 Novi Sad, Serbia
[b]University of Novi Sad, Faculty of Agriculture, Trg D. Obradovica 8, 21000 Novi Sad, Serbia

Abstract

In this paper, we explored the impact of time demand characteristics in supply chain on role of own-account fleet in the optimal transport sourcing mix. For that purpose, we used the multiple regression analysis to evaluate the simulation and optimization results, and the historical database of a real trade company. The regression analysis reveals that the certain indicators of demand variability and uncertainty directly impact on the optimal number of vehicles in own-account fleet. Further, the intercept in regression equation for the dependent variable number of own-account vehicles can be expressed as the function of daily demands and fleet characteristics.

Selection and/or peer-review under responsibility of Scientific Committee

Keywords: Outsourcing; make or buy decision-making; fleet sizing; demand variability; multiple linear regression analysis.

1. Introduction

Transport fleet size and structure in logistics systems strongly depend on demand characteristics, and especially on time demand characteristics in supply chain. The fleet used for transport operations may involve own-account vehicles, hired carriers, or vehicles from both sources.

In the literature, dynamic characteristics of supply chain, i.e. variability and, particularly, amplification, are analysed primarily from the production, storage or customer service quality perspective (Potter, 2005). However, the dynamic characteristics of supply chain strongly impact on transport system characteristics, too. This aspect is partly neglected in the literature. Some authors (e.g. Lee *et al*., 1997, Potter, 2005) argue that amplification may cause decreased fleet utilization, vehicle filling and increased transport costs. Yet, the impact of demand variability and amplification on transport outsourcing decision is even less explored. One of the reasons may be

* Corresponding author. Tel.: +381 21 485-2490; fax: +381 21 458-133.
E-mail address: djurdja@uns.ac.rs

1877-0428 © 2013 The Authors. Published by Elsevier Ltd.
Selection and/or peer-review under responsibility of Scientific Committee
doi:10.1016/j.sbspro.2014.01.123

that outsourcing is often considered as a tool to push the demand uncertainty and variability to carriers and so externalize the whole problem (e.g. see Potter & Lalwani, 2008).

Mixed solutions, discussed in some sources (e.g. Chopra & Meindl, 2004) assume tailored transportation options based on spatial and time demand characteristics, but operationalization and concrete solutions which can support transport sourcing decision-making are rare in the literature. In this paper, the research focus is shifted toward the first steps of outsourcing problem — the role of own-account fleet in an optimal mix of transport sources, regarding time demand characteristics in supply chain. More precisely, we tried to find a regularity which can support transport sourcing decision-making, by focusing on sizing of own-account fleet, whereby in-house fleet reaches economies of scale and acceptable level of utilization. According to the literature, in stationary systems with relatively stable demand, there should be a rationale to partly cover demand with own-account fleet. A portion of "demand surplus" strongly depends on demand time characteristics. Although there are variations between industry and countries, such description is appropriate for firms on many markets. Further, the size of own-account fleet should depend on supply chain dynamic characteristics, i.e. demand variability, amplification and uncertainty. This is our starting hypothesis. Using the results of simulation model, which is based on a real-life example for three variants, a linear regression analysis is applied to explore the impact of time demand characteristics on own-account fleet sizing and, consequently, on make-or-buy decision making in transport system.

The paper is organized as follows. In the second Section the theoretical background is given. In the third Section, the applied simulation model, the explored alternatives and application of linear regression analysis are briefly described. The variables in linear regression analysis are selected from model input/output sets. In the fourth Section, main results of regression analysis are given, while the fourth and last Sections present discussion and main conclusions respectively.

2. Theoretical background

Traditionally, transport has been one of the most suitable logistics activities for outsourcing. According to some sources, today almost 80% of companies worldwide outsource transport service (Langley *et al*., 2012). The "renaissance" of own-account road transport is not expected, but it still has its own niche in many firms (Croucher, 1998). The logistics outsourcing decision may cause opportunistic behaviour, increased costs, decreased quality and control (Lonsdale, 1999). Therefore, the right demand assignment between own-account fleet and external carriers, e.g. making the most appropriate boundaries between transport fleet subsystems is very important.

The choice between own-account and hired vehicles traditionally belong to the "make or buy", or transport outsourcing decision-making, while the Transaction Cost Economics (TCE) is often used as the theoretical background. However, nowadays many authors conceptually support the idea that outsourcing in logistics should not be treated as an "all or nothing" kind of decision and that mixed solutions may often give the best results (Wilding & Juriado, 2004;Gajić*et al.,* 2004;Stojanović *et al*., 2011 etc.).

Though, the problem of dual or even triple sourcing, which includes own-account transport is rarely considered in outsourcing literature. The experts are mostly focused on dual suppliers/vendors inventory problem (Sajadieh & Eshghi, 2009), although some authors explore the problem of assignment transport tasks between common and private carriage systems (e.g. Hall & Racer, 1995). Also, carrier selection problem, as the last step in transport outsourcing decision-making, is widely explored. Still, such kind of research rarely include the possibilities for development of long-term contracts, i.e. middle solutions between private and common carriers (see, e.g. Alp *et al*., 2003).

Make-or-buy decisions are dynamic and, therefore, related decision-making have to be incorporated into the management mechanisms (Moschuris, 2007). Transport outsourcing decision-making procedure should consider the impact of time demand characteristics, including some of less explored aspects such as amplification and uncertainty. However, a body of literature which explores their impact on outsourcing decision and methods and techniques which gives practical directions is surprisingly scarce (Cakić, 2009). The normative research focus is mainly on fleet sizing and scheduling problems, or carriers' selection on market.

3. Methodology

3.1. Problem formulation

The impact of time demand characteristics on transport sourcing is explored by using the model developed on a real example. For that purpose, we used the historical database of a trade oil company that operates on Serbian market, which covers six years. The company has developed its own distribution network, with its own facilities and in-house transport fleet. The observed supply chain includes flows from factories to central warehouses and from warehouses to petrol stations. In observed time period, the company has met transport demands with both own-account vehicle and external carriers. However, the own fleet was oversized, so they could meet most of demands. This starting point allows the choice between own vehicles and external carriers in assignment transport tasks on available capacities without capital investments. Moreover, for the research purpose, it is assumed that three instead two types of transport capacity sources are available - own-account fleet (N_{own}), contract carrier (N_{cc}) and common carriers on transport market (N_{tm}).

The own-account vehicles are dedicated to the transport of selected liquid derivatives — gasoline and diesel fuels — and have special equipment. The enterprise is oriented toward a very specialized transport market niche, i.e., high transport asset specificity. According to TCE, it is reasonable to develop vertical integration in such conditions, i.e. own-account fleet. Similar like in (Redmer *et al.,* 2012), a list of key restrictions is adopted, regarding the commodity and distribution system characteristics. Further, to keep the focus on the main idea, we adopted some additional specific conditions and constraints in simulation, as follows:

- The number of daily transport demand $z^d(t)$ is a sequence of independent and identically distributed random variables with normal distribution $N(\mu, \sigma)$;
- Transport demands have to be satisfied on the same day as they arrive;
- The vehicles from real case are classified into the classes, so a homogenous fleet, average transport distance, and shipment size are used in the calculation, as well as average in-house fixed and variable costs. Here is presented the calculation for the class of vehicles with average load 22.7 tons;
- Unit transport costs of own-account fleet should be less than contract carrier's unit costs, while both have to be less than unit transport costs on market. All carriers on transport market use the same average freight rate for given (average) transport distance.
- The number of own-account and contract carrier's vehicles is limited, but the number of vehicles available on transport market, and, consequently, the total number of vehicles is unlimited;
- Using own trucks is preferred to hired carriers in an operative (daily) planning period, while using contract carrier is preferred than carriers from transport market;
- In-house trucks have to achieve at least a margin of profitability in the planning horizon. Contract carrier has to achieve minimum of fleet utilization to be engaged in the planning period.

Thus, it is supposed that transport demands series are stochastic and stationary. The objective function is to minimize the long-run overall transportation costs T by distribution of transport tasks between the in-house fleet and hired carriers, while keeping an acceptable level of service quality. T is the function of own-account costs T_{own}, hired carriers cost T_{cc} and costs of carriers on transport market T_{tm}. An arrangement with external carriers assumes some opportunities and obligations for both sides. In that sense, two main constraints were assumed, concerned with own-account unit price t_{own}, unit prices of contract carrier $\boldsymbol{t}_{cc}$ and transport market t_{tm},as well as the utilization of own fleet α_{town} and hired carriers' fleet α_{tcc} in planning period. The carrier's price is lower than transport market price, while his capacities are constrained as well as the own-account ones.

The problem is considered for three different situations - variants:

- Variant V1 – stationary demand model and single-stage tariff model for contract carrier
- Variant V2 - stationary demand model and two-stages tariff model for contract carrier
- Variant V3 – seasonal time series forecast model and two-stages tariff model of contract carrier

V1 includes constraints for minimum fleet utilization of own-account and contract carrier's fleets. V1 assumed the predefined minimum fleet utilization for both own-account fleet and contract carrier in planning horizon. V2 assumes more sophisticated contract. Fleet utilization is not constraint, but if the fleet is less utilized than it is determined by contract, oil company pays penalty, that is higher service price than in case of good fleet utilization. More precisely, it is assumed that if carrier's fleet utilization is less than 50%, his price is 85% of market price. Otherwise, it is 70% of market service price, like in case V1. Thus, both sides take opportunities and responsibility for planning and assignment transport capacities in given planning horizon. Also, in V1 it is assumed that the fleet utilization rate due to technical characteristics is 1 (all vehicles are technically available every day, with no time for repair or maintenance); in V2 and V3 it is 0.7.Constraints in V2 and V3 are also related with daily dispatched vehicles N^d from denoted sources, as well as with a maximum daily engaged own-account vehicles N^d *max*.

Stationary time series are often used in theoretical models, while seasonal time series are rather applied in describing real systems so we wanted to analyse both of them. V1 model includes stationary input demand series and constraint related with fleet utilization. V2 includes additionally constraints related with contract carrier's price, while V3 considers constraint related with the relationship between market carriers' price and related own-account unit costs. By using checking data, it was confirmed that simulated time series describe well real system.

The objective cost function *T* for all variants is the same (Eq. 1.), but the constraints are different (Tab. 1.):

$$min\ T(T_{own}, T_{cc}, T_{tm}) \tag{1}$$

Subject to:

Table 1. Constraints for the same objective function *T* and different variants

Constraints in V1	Constraints in V2	Constraints in V3
$N^d_{own}+N^d_{cc}+N^d_{tm}>=N^d max$	$N^d_{own}+N^d_{cc}+N^d_{tm}>=N^d max$	$N^d_{own}+N^d_{cc}+N^d_{tm}>=N^d max$
$t_{own}<t_{cc}$	$t_{own}<=t_{cc}$	$t1_{own}<=t_{cc}$
$\alpha_{tcc}>=0.65$	$N_{own}>= N^d_{own}max$	$N_{own}>= N^d_{own}max$
$\alpha_{town}>=0.8$	if $\alpha_{tcc}<=0.5$ then $t_{cc}=t_{tm}*0.85$, else	if $\alpha_{tcc}<=0.5$ then $t_{cc}=t_{tm}*0.85$, else
$0<=N_{own}<=30$	$t_{cc}=t_{tm}*0.7$	$t_{cc}=t_m*0.7$
$0<=N_{cc}<=20$	$0<=N_{own}<=30$	$0<=N_{own}<=35$
	$0<=N_{cc}<=20$	$0<=N_{cc}<=35$

3.2. Simulation model for measuring impact of time demand characteristics on transport sourcing

We developed a relatively simple two-echelon predictive and normative simulation model based on a real case, by using the academic version of the package GoldSimPro 9.60, the tool Optimizer and MS Office Excell 2007 for systematization input and output variables into the spreadsheets. It is a dynamic model, where the attributes of system is changing during the time, depending on input, output and state of the system. Model simulates the daily time and spatial demand characteristics, and includes the demand amplification. In the broader sense, it belongs to the group of generic simulation models for inventory and transport management. In the narrower sense, it belongs to the control systems for inventory, order and transport resource management (Disney &Towill, 2005). Model can be used for measuring an overall impact of time demand characteristics on transport performances and indicators. Yet, the research focus is only on their impact on own-account fleet size.

Time demands nature is analysed by techniques such as time series decomposition and exponential smoothing. The tool GoldsimPro Optimizer, which is a part of the package GoldSim9.60, is used to calculate the optimal number of vehicles in each fleet, according to constraints given in Tab. 1. It uses the heuristic "complex" method for maximization or minimization the objective function, based on Box's "complex" method (GoldSim, 2007: *User's Guide*, Vol. 1, 365). By varying input parameters standard deviation of daily demands σ_d and exponential smoothing α_a, we have got 44 combinations of input parameters values. For each combination, 100 repeats have been realized to obtain Monte Carlo probability distribution of output variables, which gave 4400 repeats per variant or 13200 repeats in total.

3.3. The variables in linear regression analysis

The developed model is used to explore the impact of dynamic characteristics of distribution system on the share of own-account vehicles in the optimal transport sourcing mix. For that purpose, the package Statistica 8.0 is used for multiple linear regression analysis, to find out possible interrelationship between independent and dependent variables and evaluate the accuracy of obtained general equations. Dependent and independent variables used in regression analysis are shown in Tab. 2. Independent variables are indicators of variability - i.e. parameters of normal distribution for supply and sell uncertainty, respectively $N_1(\mu_1, \sigma_1)$, $N_2(\mu_2, \sigma_2)$ and related coefficients of variations CV_1 and CV_2, uncertainty - i.e. parameters of normal distribution of average error forecast ε: $N(\varepsilon_\mu, \varepsilon_\sigma)$ and amplification, which is changing variability within the system $A=CV_2/CV_1$, as well as annual total transport volume Q.

Table 2. Dependent and independent variables used in regression analysis

Independent variables		Dependent variable
σ_d, α_a, σ_1, μ_1, CV_1, σ_2, μ_2, CV_2, A, ε_μ, ε_σ, Q	$\rightarrow$	N_{own}

4. Results

The main model outputs are an optimal demand assignment to the different transport sources, the number of vehicles necessary to perform the task in the most cost-effective way, fleet utilization, and some other main transport indicators. The set of the suitable solutions allows the using of own-account fleet, carriers or their mix. The share of own-account vehicles depends on input parameters, but in all variants and runs, all three sources made the optimal sourcing mix. The Tabs. 3 and 4 contain the main results of stepwise regression analysis for each variant.

In V1 and V2 independent variables have statistically very significant partial correlation with dependent variable (p<0,01) and significant beta coefficients. In V3, own-account vehicle fleet has the same number in all runs.

Table 3. Main results of linear regression analysis for each variant

Variant	Dependent variable	Multiple linear regression equation	Intercept
V1	N_{own}	$=16,45393-4,55397*\varepsilon_{\sigma}$	15,795
V2	N_{own}	$=93,610-3,041*A+3,753*\alpha_a-241,418*CV_1-0,03*\mu_2+6,085*\varepsilon_{\sigma}$	22,860
V3	N_{own}	=const	28 (const)

Table 4. Regression summary for dependent variable N_{own} for each variant

Variant	Dependent variable	Significant Beta		R	R^2	F	p
		Direct dependence	Inverse dependence				
V1	N_{own}	-	ε_{σ}	0,83423	0,69593	$F(1,42)=96,12471$	<0,000000
V2	N_{own}	α_a, ε_{σ}	A, CV_1, μ_2	0,96486	0,930957	$F(5,38)=102,4768$	<0,00000
V3	N_{own}	–	–				

Considering that in both cases (V1 and V2) $R^2>0,5$, it can be concluded that both regression lines represent well the empirical data (Žižić *et al.*, 2001, 296). In V3 N_{own} and N_{cc} were constant for all values of selected parameters. Varying model parameters impacts on N_{tm} and daily engaged number of vehicles - the maximum (N^d_{max}) and the average ones (N^d_{sr}).

N_{own} depends on supply chain dynamic indicators, but their impact depends on model characteristics and regression model in V2 explains 93% of total variations N_{own}, which is much better than in V1 ($R^2=0,69593$). Again, all variants include own-account transport fleet in the optimal transport mix, which is consistent with some previous research (Wilding & Juirado, 2004; Stojanović *et al.*, 2011, etc.). The constraints given in particular variants impact only on the number of N_{own} and, consequently, on its share in the optimal transport capacities mix. Surprisingly, in seasonal model (V3) daily oscillations and exponential smoothing do not have impact on N_{own}.

It can be concluded that, if the decision-making is based on economic principles, in systems with relatively stable demands own-account fleet has a rationale. Additionally, a common characteristic of intercepts in all regression equations is that it can be expressed by Eq. 2:

$$N0_{own} = \frac{\mu_{dl}}{q_t * z_l^d * \alpha_t * C} \tag{2}$$

Whereby

$N0_{own}$– the value of the intercept in regression equations
μ_{dl} - the average weight of daily demands (in tons)
q_t – the load factor of the vehicle type
z_l^d – the average daily number of deliveries per vehicle
α_t– the average rate of fleet utilization due to its technical characteristics (vehicle availability, not on the repair or maintenance)
C – constant($0\leq C \leq 1$).

The constant $N0_{own}$ expresses the optimal own-account fleet size in case that dependent variables in regression equations in Tab. 2 do not exist. For example, if error forecast would be constant ($\varepsilon_{\sigma}=0$) in V1, N_{own} could directly depend on average value of daily demand in tones and number of daily tours per vehicle. The absolute values for C are given in Tab. 5. In V3, instead of intercept, we used calculated N_{own} and its value is between the ones in V1 and V2. This equation can be used in seasonal models (V3) even when standard deviation of demands is 25% of mean.

Table 5. The obtained values of C in Eq. 2

	V1	V2	V3
C	1,070938	0,211528	0,707109

5. The role and significance of own-account fleet in transport sourcing

Transport sourcing is a strategic decision which has to respect supply chain dynamic characteristics. The enterprises have globally shifted from own-account toward outsourcing transport activities. The reasons are different, but among the most important are costs and flexibility. The later includes an easier adaptation on market changes, including changes on supply and, particularly, demand market, which cause supply chain dynamics.

The indicators of demand uncertainty in given conditions and constraints have a significant linear impact on chosen transport capacities. However, this impact in most of cases is not as it was expected. The indicator ε_σ has somewhat stronger impact than ε_μ. Also, more sophisticated variant regarding the carrier contract and fleet utilization (V2) is more sensitive on supply chain dynamics. Surprisingly, in the seasonal model, the size of own-account fleet was constant for all parameters' values.

Further, although it has not been an expected research result, it was interesting to find out a mathematical expression of the intercept in linear regression equations which describe the interdependence of optimal size of own-account fleet and internal and external factors, i.e. own fleet characteristics, organization and daily demands (Eq. 2). That means, the most obvious impact on own-account fleet size has the average number and load of daily demands, while the impact of uncertainty and supply chain dynamics (i.e. bullwhip effect) is more complex and less obvious.

It is confirmed that optimal own-account fleet size depends on dynamic characteristics of supply chain in stationary models, but not in the seasonal model within the given constraints. However, the intercept in regression analysis, as well as the optimal number of vehicles in seasonal model (V3) can be mathematically expressed as the function of the average value of daily demands (in tons) and fleet characteristics, i.e. the load factor of the vehicle type, the average daily number of deliveries per vehicle, and the average rate of fleet utilization due to technical characteristics.

According to obtained results, C in Eq. 2 has the values near 1. Actually, C>1 in case when the average rate of fleet utilization due to technical characteristics (vehicle availability, not on the repair or maintenance) α_t=1 (V1), which is impossible in real systems. Therefore, it can be expected that in real systems 0<C<1.

Our research results support the literature body which argue that the mixed sourcing solutions give the best results. The research implication is that the scholars and transport managers should consider to shift their focus from the "*make or buy*" toward "*make and bu*y" decision-making models and procedures in the future. This approach could help the practitioners to decrease overall transport costs and increase the utilization of involved vehicles. At least, more attention should be given to the mixed solutions, or suitable sourcing mix of transport capacities in the praxis. In all observed cases, there was a suitable niche for own-account transport. Still, the system conditions (constraints) strongly impact on share of different resources and transport performance on a whole. Spreading company on new markets, or economic crisis are beyond the scope of research.

In developing simulation model, it is necessary to make balance between time spent in model and its validation. Therefore, the developed model has a number of serious limitations and constraints, as follows:

- Limitations regarding to the field of applicability (characteristics of supply chain, market, industry);
- Limitations related with applied methods and techniques, which can be further developed on:
  - Limitations related with the applicability of the simulation results in real environment (results applicability, existing own-account fleet with no investments);
  - Limitations related with the applied method (multiple regression analysis and statistical techniques)

The main limitation of all regression techniques is that they can find the relationships, but they cannot explain the causality between the regression variables (Statsoft, 2008). Besides, in case where the linear relationship between own-account fleet size and independent variables does not exist, it is possible that there is a kind of more complex dependence. It is necessary to explore more in-depth the relationship between N_{own} and μ_{dl}; this could contribute to better knowledge of the nature of constant *C*.

It should be also pointed out that the case study is rather singular. Further research on the nature of constant *C*, or other aspects of demand variability impact on own-account fleet in an optimal transport sourcing mix, assumes the model modification. The included commodities, e.g. consolidated shipments, perishable goods, etc. strongly impact on the demand time nature in supply chain and, consequently on the best sourcing mix and the nature of constant C.

6. Conclusion

Our goal was to find possible regularity in impact of time demand characteristics on own-account fleet sizing and so support the optimal transport sourcing mix design. In supply chains with relatively stable market, where the company has historical database, there could be identified a room with high demand frequency and low uncertainty and supply chain dynamics. In this paper, we argue that this room is economically suitable for performing transport tasks with own-account fleet. If annual time-demand series has the zone covered in the most of time, this should be the room where own-account transport is more rationale than external carriers. In that case "or-or" decision-making represents a simplified solution, while the optimal solution lays in an appropriate "sourcing mix".

By using the simulation model which describes well the real distribution system and the linear regression analysis, it is confirmed that in a dynamic environment mixed solutions ("make *and* buy") give better results than classical approach ("make *or* buy"). Logically, the next question is concerned with criteria for own-account fleet sizing. The multiple regression analysis shows that indicators of demand variability and uncertainty directly impact on the optimal number of vehicles in own-account fleet. Further, the intercept in regression equation for the dependent variable number of own-account vehicles can be expressed as the function of daily demands characteristics and selected techno-economic transport fleet indicators, influenced by operative transport planning and scheduling. This was a surprising result and further research is necessary to explore more in-depth this interdependence. These results may encourage further research toward the normative models used in transport outsourcing decision-making.

Acknowledgements

This paper was realized as a part of the projects (36030) and (43007) financed by the Ministry of Education and Science of the Republic of Serbia for the period 2011-2014.

References

Alp, O., Erkip, N.K., & Gullu, R. (2003). Outsourcing Logistics: Designing Transportation Contracts Between a Manufacturer and a Transporter. *Transportation Science,* 37(1), 23-39.

Cakić, Đ. (2009). *Oblikovanje transportnih resursa u lancima snabdevanja*. PhD dissertation, Faculty of Technical Sciences at University of Novi Sad, Novi Sad, Serbia.

Chopra, S., & Meindl, P. (2004). *Supply Chain Management, Strategy, Planning and Operations* (2nd edition). Pearson Prentice Hall.

Croucher, P. (1998). Insourcing. *Logistics Focus,* March 1998, 3-8.

Disney, S.M., &Towill, D.R. (2005). Eliminating drift in inventory and order based production control systems. *International Journal of Production Economics,*93/94, 331-344.

Gajić, V., Cakić, Đ., & Mandić, G. (2004). Making the transport outsourcing strategy by transport costs mapping*, EUROSIM 04, 5th EUROSIM Congress on Modelling and Simulation,* September 06-10, 2004, Paris.

Goldsim Technology Group (2007). *Goldsim User's Guide, Probabilistic Simulation Environment*, Vol. 1 and 2, pp. 1-767.

Hall, R.W., &Racer, M. (1995). Transportation with common carrier and private fleets: System assignment and shipment frequency optimization**,** *IIE Transactions;* Apr 1995; 27, 2; ABI/INFORM Global, pp. 217-225.

Langley, C.J., Albright, D., Fletcher, B., Wereldsma, D., Alf, M., Hoemmken, S., Leuthardt, T., Wyss, N., Gueth, P., Kuehner, L., Collins, N., Deming, Z. Saynor, C., & O'Reilly, K. (2012). *The state of logistics outsourcing*, *2012 third-party logistics - results and findings of the 15th Annual study*. Capgemini, PennState, Georgia Institute of Technology, Heidrick & Struggles and EyeforTransport.

Lee, H.L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The Bullwhip effect. *Management Science,* 43(4), 546-558.

Lonsdale, C. (1999). Effectively managing vertical supply relationships: a risk management model for outsourcing. *Supply Chain Management: An International Journal,* 4(4), 176-183.

Moschuris, S. (2007). Triggering Mechanisms in make-or-buy decisions: an empirical analysis. *The Journal of Supply Chain Management: A Global Review of Purchasing and Supply*, 40-49.

Potter, A., & Lalwani C.S. (2008). Investigating the impact of demand amplification on freight transport.*Transportation Research*,Part E 44 835–846.

Potter, A.T. (2005). *The Impact of Supply Chain Dynamics on Transport*, PhD Thesis, Cardiff University, UK.

Redmer, A. Żak, J., Sawicki, P., & Maciejewski, M. (2012). Heuristic approach to fleet composition problem, *EWGT 2012 15th meeting of the EURO Working Group on Transportation, Procedia - Social and Behavioral Sciences* 54, pp. 414 – 427.

Sajadieh, M.S., & Eshghi, K. (2009).Sole versus dual sourcing under order dependent lead times and prices. *Computers & Operations Research,* 36, 3272 – 3280.

Statsoft (2008). *Elementary Concepts in Statistics*, http://www.statsoft.com/textbook/stathome.html

Stojanović, Đ., Nikoličić, S., & Miličić, M. (2011). Transport Fleet Sizing by Using Make and Buy Decision-Making. *Economic Annals*, 16(190), 25-50.

Wilding, R., & Juriado, R. (2004). Customer perceptions on logistics outsourcing in the European consumer goods industry. *International Journal of Physical Distribution & Logistics Management* 34(7/8), 628-644.

Žižić, M., Lovrić, M., & Pavličić, D. (2001). *Metodi statističke analize (11th Edition*), Ekonomski fakultet, Beograd.