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Sustainability through the Digitalization of Industrial Machines: Complementary Factors of Fuel Consumption and Productivity for Forklifts with Sensors

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Abstract: Increasing the fuel efficiency of industrial machines through digitalization can enable the transport and logistics sector to overcome challenges such as low productivity growth and increasing CO_2 emissions. Modern digitalized machines with embedded sensors that collect and transmit operational data have opened up new avenues for the identification of more efficient machine use. While existing studies of industrial machines have mostly focused on one or a few conditioning factors at a time, this study took a complementary approach, using a large set of known factors that simultaneously conditioned both the fuel consumption and productivity of medium-range forklifts (n = 285) that operated in a natural industrial setting for one full year. The results confirm the importance of a set of factors, including aspects related to the vehicles' travels, drivers, operations, workload spectra, and contextual factors, such as industry and country. As a novel contribution, this study shows that the key conditioning factors interact with each other in a non-linear and non-additive manner. This means that addressing one factor at a time might not provide optimal fuel consumption, and instead all factors need to be addressed simultaneously as a system.

Keywords: digitalization; complementarities; sustainability; fuel consumption; heavy-duty equipment; productivity; sensor data

1. Introduction

In line with the ongoing focus on environmental sustainability in the global economy, the transport and logistics sector is also concerned with the negative environmental impact of using heavy-duty industrial equipment. The depletion of the ozone layer has been a worldwide concern for the last few decades [1], and hazardous materials that affect the ozone layer are emitted through the fuel consumption of various equipment in different industrial sectors. Most heavy-duty industrial equipment, such as forklifts, terminal tractors, cranes, straddle carriers, and reach stackers, are diesel-fueled and have been shown to be a key source for hydrocarbon, NOx, and particulate matter emissions that contribute significantly to the formation of haze/smog [2,3]. Although the number of electric vehicles is increasing [4], reducing fuel consumption from diesel-fueled industrial machines remains one of the key challenges for environmental sustainability [5].

The development of more advanced vehicles has contributed to humans' enhanced capabilities to perform difficult industrial tasks, but this has in turn led to an even stronger response from the environment [6,7]. The growing fuel consumption and carbon emissions from such heavy-duty equipment add to the already existing emissions in the transport and logistics sector [2,8]. For example, without the intervention of governments and clear energy efficiency measures it is predicted that in the European Union greenhouse gas emissions produced by trucks will be around 35% higher in 2030 than the 1990 levels [9]. In comparison to other vehicles, diesel vehicles consume the most fuel [2,10]. At the same time, heavy-duty vehicles are being overloaded in order to reduce operating costs, and this has had significant negative environmental impacts [3]. Thus, because fuel efficiency is directly linked to CO_2 emission [9], vehicle fuel consumption and vehicle productivity [1] should be explicitly considered together in order to reduce these vehicles' environmental impact.

Digitalization and the Internet of Things (IoT) enable us to measure fuel consumption in heavy-duty industrial equipment and to identify factors that influence fuel consumption in a manner that has not previously been possible. The very low transaction costs for operational data collection enabled by digitalization make it possible to collect continuous detailed operational data from a large set of vehicles operating in their actual work contexts. However, in general, the transport and logistics sector is lagging in digitalization, particularly in the European Union [11,12]. Recent concerns include how to transform the massive amounts of data collected from vehicles into useful knowledge [13], and answering this requires more empirical knowledge from longitudinal studies of vehicle use in real-life situations. Given all this, the aim of this study is to identify factors that condition fuel consumption in relation to the productivity of medium-range forklifts that use sensor data.

Studies on road freight transportation and logistics that have analyzed the effect of sensor data on fuel consumption show the importance of factors related to (i) vehicles, (ii) their environments, (iii) their travels, (iii) their drivers, and (iv) their operations [13–16]. However, these studies have focused their attention on only one or a few conditioning factors at a time, while ignoring the complementarity perspective. Previous studies that have summarized fuel consumption factors [17,18] have not demonstrated how these factors interact with each other in an empirical setting, so as to condition the fuel consumption and productivity of forklifts, and this is the first knowledge gap targeted here. While recent studies have focused on truck freight transportation in general, there is a limited number of studies [19–23] that have investigated the factors that condition the fuel consumption and productivity of forklifts, which have different operations from ground transportation, with more starts and stops and shorter travel distances [24]. This is the second knowledge gap addressed in this work. Finally, most studies have focused either on fuel consumption factors or on productivity factors separately, while the present study addresses this knowledge gap by targeting both simultaneously. The work in the present study used empirical data from the actual use of a large set of medium-range forklifts equipped with data sensors and operating in a natural setting over the course of one full year, and this contrasts with other studies looking at small samples of a few machines operating in artificial settings. In order to handle the interactions of the large number of factors (independent variables) studied here, the partial least square regression method was employed for the first time in this context.

Our results demonstrate the importance of a number of conditioning factors, including travel, driver, and operations-related factors related to fuel consumption, such as distance, average speed, and time-related parameters such as production hours, engine hours, hydraulic hours, driving hours, and idling hours. This study shows that operating in certain workload spectra significantly increases fuel consumption. The results also demonstrate the importance of contextual factors and show that specific customer segments and countries realize more efficient fuel consumption than others. One important practical implication of the results provided here is that there is an opportunity to change the behavior of vehicle drivers in order to reduce fuel consumption, which will both increase economic productivity and reduce CO_2 emissions, and thus reduce the negative environmental impact of such vehicles. The results can further be used to monitor driver behavior and to formulate feedback mechanisms and training packages, and can be used to further develop fuel and productivity-related factors. With regards to theory, unlike the partiality of previous studies, this study demonstrates that several factors must be addressed simultaneously and in a complementary manner in order to reduce fuel consumption and thereby increase the productivity and reduce the CO_2 emissions of medium-range forklifts.

The remainder of this paper is organized as follows. The next section presents work related to key drivers affecting fuel consumption. We then present the research methodology, which is followed by a description of the results. Following that, a discussion and conclusion are presented.

2. Related Work

Digitalization has profoundly affected modern nations, organizations, and individuals [12]. The Industrial IoT and new digital environments, such as big data, mobile and service platforms, cloud computing, and social media, enable new combinations of resources, communication channels, products, services, and digital business models [8,25–28]. Numerous sensors, camera images, and barcode scans produce a vast amount of data, and this creates a great opportunity to uncover hidden patterns that might affect fuel consumption and thus CO_2 emissions without reducing equipment productivity in unexpected ways [14,20]. However, making sense of these services and data is a challenge for both manufacturers and customers [11,12], and these advancements in technology, smart services, and large, complex datasets raise many questions regarding the use of digital technologies for environmental sustainability. One such question is how to use and analyze large sets of sensor data in order to reduce the fuel consumption of heavy equipment without reducing productivity.

Over the past few years there has been an increasing number of studies on the factors affecting fuel consumption and CO_2 emissions in the field of road freight transportation and logistics. For example, it was previously found that engine load conditions [29], vehicle speed [30,31], payload [32,33], fleet size and mix [33], driver behavior [34–36], and surface roughness [37] are key factors that affect vehicle fuel consumption. All of these factors were later summarized in the following five key groups of factors (Table 1) that significantly affect the fuel consumption of road freight transport [17,18]: (i) vehicle-related (vehicle weight, shape, engine and transmission models, and fuel and oil type); (ii) environment-related (surface and temperature conditions); (iii) travel-related (speed and acceleration/deceleration); (iv) driver-related (driver behavior, gear selection, and idling); and (v) operations-related (fleet size, mix, payload, and empty kilometers).

Factors affecting fuel consumption have been widely studied in the road freight transportation and logistics fields, but factors affecting the fuel consumption of forklifts have received little attention. Forklift operations differ from ground transportation in that in the former there is a need for more starting and stopping and the distances traveled are much shorter [24]. Most of the studies that have addressed forklift efficiency and fuel consumption have focused on operational features and have developed a number of models that indirectly affect the fuel consumption of forklifts through order sequencing, storage allocation, and path minimization [19–23]. However, these models are criticized for having low flexibility, restricted applicability to the particular operating conditions, and difficulty being adapted to different warehouse layouts. Thus, these models are difficult to apply in more complex real-life settings. Moreover, while driver behavior has a direct influence on fuel consumption and efficiency, it is often neglected in these models. For example, in a recent study [24], it was observed that drivers with similar tasks had different driving behaviors and that average speed was the most significant variable affecting the fuel consumption of forklifts.

A number of studies have also investigated the impact of information and communication technologies (ICT) on fuel consumption and thus on CO_2 emissions. For ICT-based scheduling systems with telematics applications for data communication, it has been shown that positioning and navigation have a rate of return of 40–75% due to savings in fuel consumption [38,39], and the introduction of semi-automated computerized route optimization and scheduling systems and onboard monitoring computers has positively affected fuel efficiency [40]. ICT use at different levels—including vehicle, company, supply chain, and network levels—has also been shown to have a positive effect on reducing mileage, fuel consumption, and CO_2 emissions [41]. Internet-based freight applications that match the consignor's demand and the carrier's supply provide an efficient way to find the right truck and to organize the delivery process in a way that decreases empty travel distances, and thus improves average vehicle load and fuel efficiency while reducing CO_2 emissions [18].

Table 1. Factors affecting fuel consumption.

Categories	Factors
Vehicle-related	Vehicle curb weight Vehicle shape Engine size/type Engine temperature Transmission Fuel type/composition Oil viscosity Other characteristics (maintenance, age, accessories, etc.)
Environment-related	Roadway gradient Wind conditions Ambient temperature Altitude Pavement type Other characteristics (humidity, surfaceconditions, etc.)
Travel-related	Speed Acceleration/deceleration Congestion
Driver-related	Driver aggressiveness Gear selection Idling time
Operations-related	Fleet size and mix Payload Empty kilometers Number of stops

Source: [17,18].

With the advancement of ICT and the proliferation of sensors, companies are now able to capture multivariate time series datasets related to vehicle use. Over the last decade, a number of studies have analyzed large amounts of road freight transportation data in order to identify key parameters and their effects on fuel consumption. For example, data from a global positioning system have been shown to be effective in predicting the driving and idling fuel consumption rates of heavy vehicle fleets [13,15,42]. Among the key parameters collected from the sensor data of heavy-duty vehicles, the most important for fuel consumption are vehicle configuration, speed, payload factors, traffic congestion, and regenerative braking [43]. Differences in the operating environment of long-haul trucks and customer usage also play an important role in fuel efficiency [44], and the analysis of logging data revealed real-world driving behaviors that have a major influence on fuel economy [16]. In addition, big data analysis obtained from digital tachographs demonstrated the importance of driving patterns such as acceleration/deceleration, speed, and revolutions per minute [14] on fuel efficiency. Overall, these studies confirmed previously established factors for efficient fuel consumption.

While recent studies, including sensor-based studies, have already discovered a number of factors that affect vehicle fuel consumption, the majority of them have studied these factors separately, and thus only provide a partial understanding of existing fuel consumption factors. To overcome this, a specific theory of complementarities has been advanced to show that changing only one factor might not come close to achieving the benefits that are available using a system of specific complementarities that are addressed in a purposeful and synchronized manner [45]. In the present study, we apply a methodology that can potentially demonstrate which complementary factors can be studied together in order to improve fuel efficiency. We also focus on fuel consumption as a dependent variable but do not disregard the relationship between fuel consumption and the productivity of a vehicle. Moreover, in the present study we focus on one specific and homogeneous type of heavy-duty vehicle—medium-range forklifts—and thus present a unique and detailed analysis of factors that affect fuel consumption.

3. Method

This study's empirical basis was a particular company that is a leading global provider of heavy industrial vehicles with lifting capabilities, such as forklifts, reach stackers, and terminal tractors. The company's key customer segments include industrial ports, saw mills, and steel mills. The choice of company can be explained by the crucial importance of the transport and logistics sector for economic growth and employment [11,46,47], and current studies demonstrate that this industry has undergone significant development in terms of activities and employment [48]. The demand for road freight transport and logistics services is continuously growing [49], and thus the productivity of this industry has a significant impact on environmental sustainability with regard to CO_2 emission reductions [41]. Although the road freight transport industry is important for the social and economic development of a country, this industry is characterized by environmental, social, and competitive pressures, as well as by demanding customers [50]. Under these conditions, digital technologies are seen as the main enabling tool for effective and efficient operations [18,41], and transport and logistics companies increasingly depend on their ability to use these technologies in analyzing fuel consumption in order to move freight on time with reduced damage to the environment.

The study of the company's vehicles was motivated by several factors. Connectivity of vehicles is a part of the company's strategy, and the number of connected vehicles is constantly increasing. The company is in the transition process with the introduction of sensor data technologies and has a large enough set of vehicles with data sensors sending daily operational data from various countries and customer segments. The sensors on the vehicles send a vast amount of data to the company cloud regarding the usage and performance of the vehicles, e.g., accumulated distance, forward and reverse directions, speed, time, load, temperature, and fuel. The data indicate that diesel fuel consumption varies quite significantly between different customers, and this was the impetus for this study to attempt to identify key determinants of fuel consumption in relation to productivity. Below, the data collection procedures and analytical method are presented in detail.

3.1. Sample and Data Collection

For the purpose of analyzing what factors affect fuel consumption, a homogeneous group of vehicles, i.e., medium-range (9–18 tons) forklifts, which are primarily designed to lift and move materials over short distances, were chosen, and the data were collected daily from 1 January 2017 to 31 December 2017. The main concern from the company under investigation was that the available data indicate that diesel fuel consumption varies quite significantly between different industry segments. The final data sample was represented by 285 forklifts constructed during 2012–2017, including 13 forklift models, 5 engine models, and 3 transmission models. The forklifts operated in 16 countries, primarily in the US (16.5%), Great Britain (13.9%), and Germany (12.5%), and in 15 industry segments (Figure 1), including sawmills (34%), material handling and logistics (26%), brick and concrete industry (9%), and steel mills (6%).

Descriptive statistics are presented in Table A1 (Appendix A). The independent (explanatory) variables used in this study were chosen based on previous studies that identified them as significant for fuel consumption. Among these variables are vehicle distance, speed, number of idles, shock and overload occurrences, engine, driving and idle time, and time spent in different driving modes, time spent and number of lifts in different workload spectra, and variables related to ambient, engine coolant, hydraulic, and transmission oil temperature. For the 285 forklifts, the average forklift drove 29.8 km per day with an average speed of 6.6 km per hour, carrying a total weight of 661 ton and lifting

176 loads. The average time per day that the engine was running while the vehicle was moving or using load handling function was 9.5 h, and the average number of hours a vehicle was idling was 4.1 h. The average time during which a vehicle carried a very heavy load was 0.2 h. On average, the majority of forklifts spent their working time in different workload spectra, but most of them did not spend significant time in heavy load spectra. The average ambient temperature was 16 °C, and the engine coolant temperature, hydraulic fluid temperature, and transmission oil temperature did not exceed their limits. The dependent (output) variables were provided by the company and included average fuel consumption per day, engine hour, load, ton, and ton-meter. On average, one forklift consumed 65 L of diesel fuel per day, 7 L per hour, 1.6 L per load, 0.7 L per ton, and 0.02 L per ton-meter.

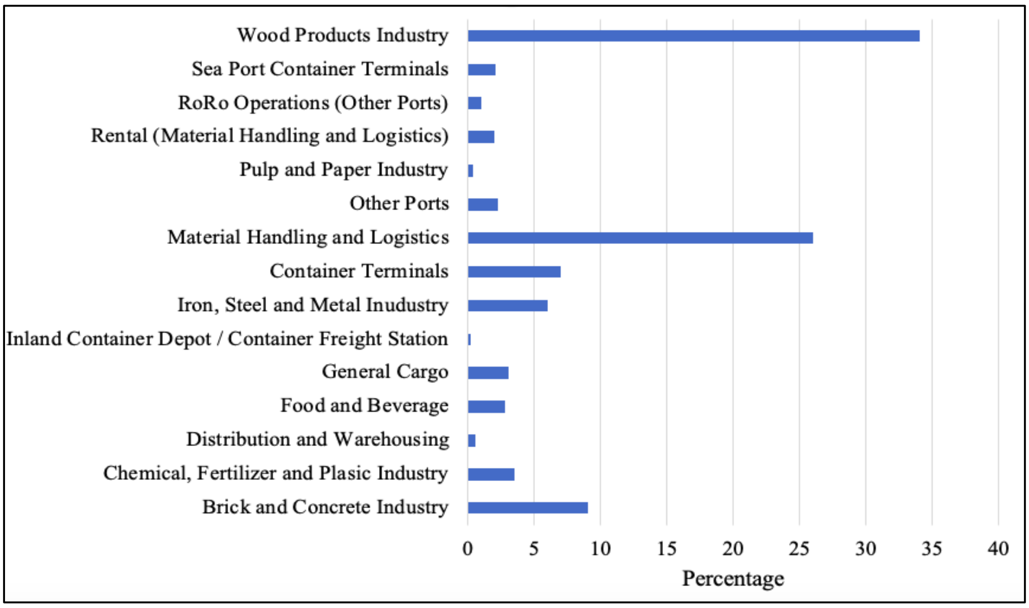


Figure 1. Distribution of vehicles among industry segments.

3.2. Data Preparation and Analysis

The aim of this study was to explore fuel consumption factors using a number of underlying explanatory variables. Partial least-squares regression (PLSR) is a regression method that allows for the identification of latent variables (linear combinations of explanatory variables) and their effects on response variables [51]. Over the last decade, this method has become widely used in various fields of business research, including the Information Systems discipline, marketing, and strategic and operations management [52]. In addition, this method has become popular in the analysis of factors affecting fuel consumption [53,54]. MATLAB software was used for the PLSR analysis.

PLSR is a method that is used for modeling linear regressions between multiple, possibly correlated, explanatory variables and multiple dependent variables. This method combines the basic functions of canonical correlation analysis, principal component analysis, and multiple regressions [55]. The least-squares solution for multiple linear regression [56]:

$$Y = XB + \varepsilon, \tag{1}$$

is given by:

$$B = (X^T X)^{-1} X^T Y. \tag{2}$$

The problem is that $X^T X$ is singular, either because the number of columns (variables) in X exceeds the number of rows (objects) or because of collinearity. PLSR circumvents this by decomposing X to orthogonal scores T and loadings P:

$$X = T\,P. \tag{3}$$

Furthermore, PLSR regresses Y on the first column of the scores, and its aim is to incorporate information on both X and Y in the definition of the loadings and scores. The loadings and scores are chosen in such a way as to describe, as much as possible, the covariate between X and Y.

PLSR overcomes two key challenges of classical regression methods, namely a large number of correlated explanatory variables and a small sample size with a large number of predictors [57]. Another important advantage of PLSR is that it does not have many specific assumptions for the analyzed data. The data only need to be relatively normally distributed (Figure A1, Appendix B) and cleansed of influential outliers prior to analysis [58]. Correlation coefficients between explanatory variables were strong and significant in most cases, demonstrating potential multicollinearity. Therefore, PLSR was an appropriate method for analyzing the available data.

4. Results

The PLSR technique was used to analyze the effect of the explanatory variables on fuel-related dependent variables. First, the prediction ability of key PLSR models with dependent variables, such as liters per day, liters per hour, liters per load, liters per ton, liter per ton-meter, was established by the percentage of variation accounted for by the principal components. Second, key drivers of fuel consumption in relation to productivity were extracted by analyzing the normal probability plots and bar loads of the most important regression variables.

4.1. Prediction Ability

The choice of PLS factors was made by exploring the percentage of the variance explained in the response variables (Figure A2, Appendix C) and the root mean of the dependent variables. Table 2 provides the percentage variation accounted for by the PLS factors.

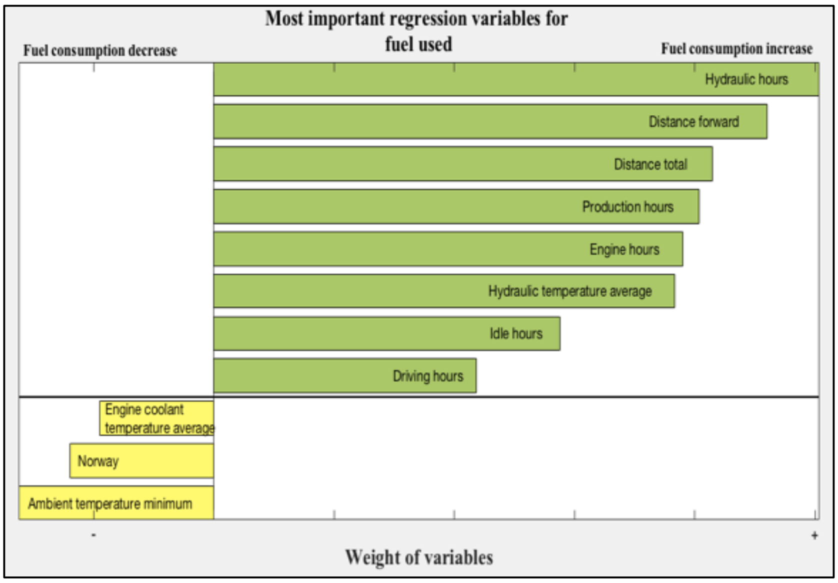
The first nine PLS factors included all of the variance information for X and Y. First, by using 39.063% of the information in potential influencing factors, the first nine PLS factors explained 95.984% of the variance in fuel consumption per day. Second, for 40.722% of the information in potential influencing factors for liters per hour, the first nine PLS factors explained 59.729% of the variance. The percentage of variations accounted for by PLS factors demonstrates that fuel per time unit (day and hour) are promising dependent variables to explain fuel consumption reductions based on the available explanatory variables. Third, for 40.451% of the information in potential influencing factors, the first nine PLS factors explained 38.719% of the variance in liters per load. Fourth, for 40.259% of the information in potential influencing factors, the first nine PLS factors explained 32.045% of the variance in liters per ton. Fifth, for 41.377% of the information in potential influencing factors, the first nine PLS factors explained 28.251% of the variance in liters per ton-meter. The percentage of variation accounted for by PLS factors demonstrates that the models do not have strong predictive ability from the explanatory variables in relation to the constructed variables of fuel consumption per load, per ton, and per ton-meters. Thus, more explanatory variables can improve the predictive ability in relation to fuel consumption per load, per ton, and per ton-meters. These dependent variables can also be subject to further examination of whether they account for relevant activities and measures in the physical world in order to find ways to reduce fuel consumption.

4.2. Key Determinants of Fuel Consumption and Productivity

Normal probability plots and bar loads were used to demonstrate the most important regression variables. Normal probability plots helped us to find cut-off limits in order to select important variables for fuel consumption (Figure A1, Appendix B). We began our analysis by focusing on fuel consumption per day and per hour (Figure 2) and further analyzed what factors affect fuel consumption per load, per ton, and per ton-meter (Figure 3). On the left-hand side of each figure, bar loads demonstrate the weight of the most influential factors of fuel consumption decrease and the right-hand side shows the weight of the most important factors that affect fuel consumption increase.

Table 2. Variation accounted for by partial least-squares factors.

Latent Factor	Percentage of Explained Variance for X	Cumulative Percentage of Explained Variance for X	Percentage of Explained Variance for Y	Cumulative Percentage of Explained Variance for Y	Root Mean Squared Error of Prediction
Liters per day					
1	16.372	16.372	90.645	90.645	12.604
2	5.428	21.800	2.803	93.448	10.548
3	3.245	25.045	1.424	94.872	9.331
4	2.691	27.736	0.542	95.414	8.824
5	2.064	29.800	0.258	95.672	8.573
6	2.168	31.968	0.130	95.802	8.443
7	2.069	34.037	0.091	95.893	8.351
8	2.658	36.695	0.051	95.944	8.299
9	2.368	39.063	0.040	95.984	8.258
Liters per hour					
1	15.079	15.079	24.089	24.089	1.485
2	7.374	22.453	21.527	45.616	1.257
3	4.218	26.671	5.083	50.699	1.197
4	3.687	30.358	3.530	54.229	1.153
5	2.481	32.839	2.325	56.554	1.124
6	1.930	34.769	1.598	58.152	1.103
7	1.530	36.299	1.086	59.238	1.088
8	2.706	39.005	0.258	59.496	1.085
9	1.717	40.722	0.233	59.729	1.082
Liters per load					
1	14.698	14.698	18.262	18.262	1.126
2	8.888	23.586	13.841	32.103	1.026
3	3.801	27.387	2.870	34.973	1.004
4	1.924	29.311	1.789	36.762	0.990
5	2.312	31.623	0.832	37.594	0.984
6	2.810	34.433	0.419	38.013	0.980
7	2.278	36.711	0.343	38.356	0.978
8	2.167	38.878	0.222	38.578	0.976
9	1.573	40.451	0.141	38.719	0.975
Liters per ton					
1	15.628	15.628	14.153	14.153	0.528
2	7.723	23.351	12.18	26.333	0.489
3	3.795	27.146	2.602	28.935	0.481
4	2.159	29.305	1.621	30.556	0.465
5	2.574	31.879	0.654	31.210	0.473
6	2.701	34.580	0.326	31.536	0.472
7	2.179	36.759	0.260	31.796	0.471
8	1.871	38.630	0.151	31.947	0.470
9	1.629	40.259	0.098	32.045	0.470
Liters per ton-meter					
1	11.463	11.463	13.663	13.663	0.017
2	11.89	23.353	7.814	21.477	0.016
3	3.963	27.316	2.839	24.316	0.106
4	2.466	29.782	1.888	26.204	0.015
5	3.012	32.794	0.795	26.999	0.015
6	2.520	35.314	0.508	27.507	0.015
7	2.187	37.501	0.386	27.893	0.015
8	2.018	39.519	0.221	28.114	0.015
9	1.858	41.377	0.137	28.251	0.015



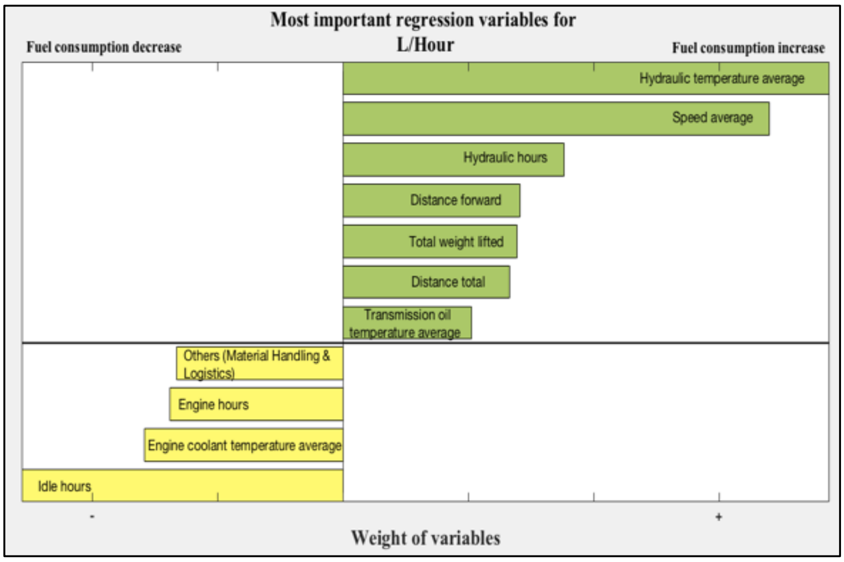


Figure 2. Bar loads of the most relevant variables for fuel consumption per time (liter/day, liter/hour).

The results demonstrated that high fuel consumption per day was mainly caused by distance driven and time-related parameters, such as production, engine, hydraulic driving, and idling hours. Low fuel consumption per day was strongly associated with minimum ambient temperature, and among the different countries, Norway demonstrated the most efficient fuel usage. High fuel consumption per hour depended strongly on distance driven, average speed, and weight lifted. In comparison to other customer segments, the material handling and logistics segment was shown to be the most fuel efficient. Overall, the results demonstrate the importance of travel-related, operations-related, and driver-related factors on fuel consumption per unit of time. Interestingly, the results demonstrated that leaving machines idling for a shorter time period might lead to fuel savings per hour, but in the long run this led to high fuel consumption per day. The results also demonstrated that high hydraulic fluid temperatures can waste fuel, and thus this has to be addressed through maintenance in order to maintain a stable hydraulic system.

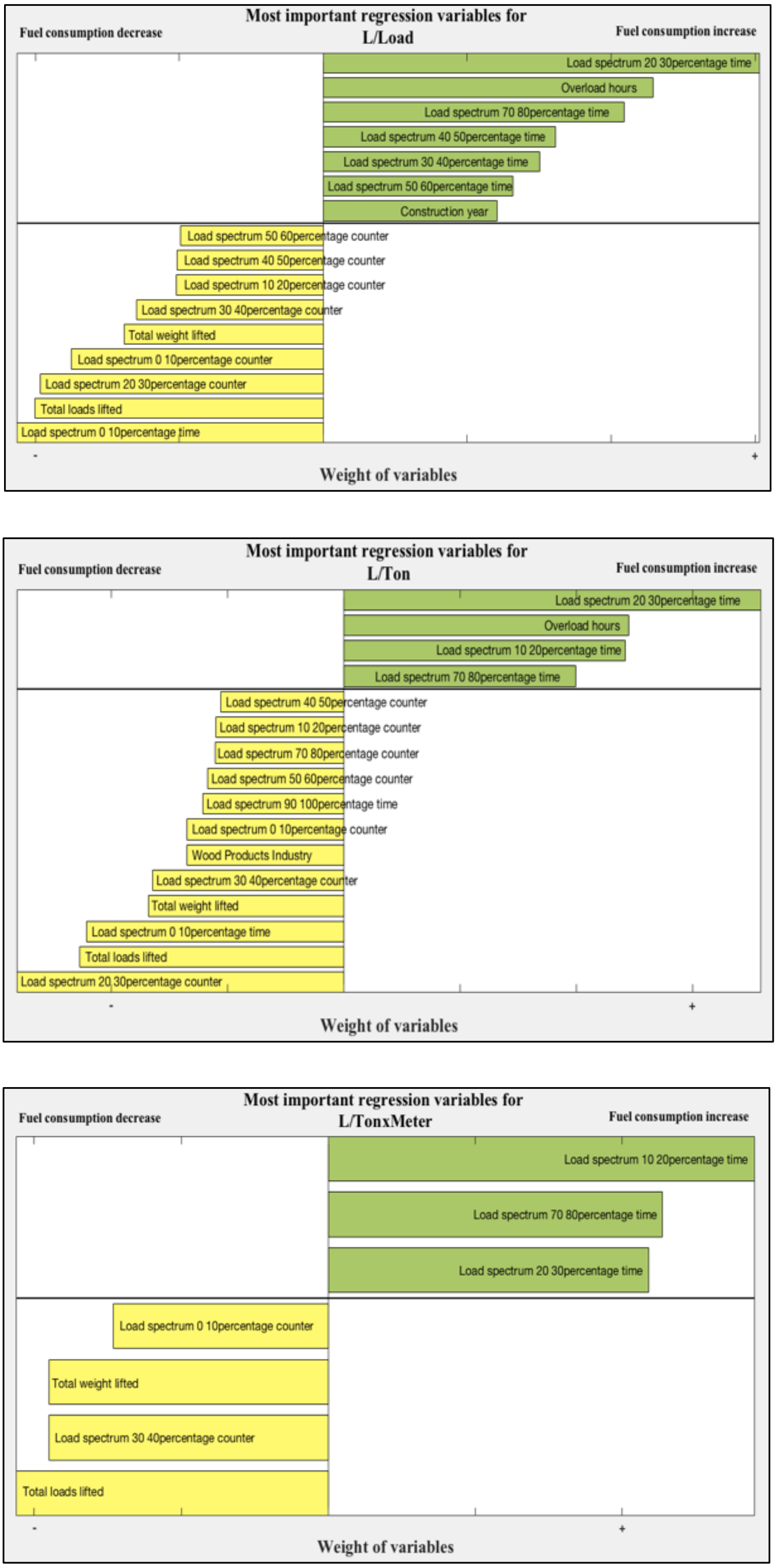


Figure 3. Bar loads of the most relevant variables for fuel consumption and productivity (liter/load, liter/ton, liter/ton-meter).

The results further demonstrated that high fuel consumption per load, per ton, and per ton-meter was associated with time spent in a specific load spectrum. For example, time spent in the load spectrum of 20–30 tons was associated with high fuel consumption per load, per ton, and per ton-meter. Interestingly, a number of lifts in specific load spectra and time spent in these lead spectra in some cases have different effects on fuel consumption. While these factors and their effect as such are interesting, the present study's aim was not to consider one or two factors and their effect on fuel consumption but the whole system of factors together. Overload hours were also associated with high fuel consumption per load and ton. For other segments, the wood products industry was shown to be efficient in terms of fuel consumption and productivity. Although somewhat counterintuitive, total loads lifted and total weight were associated with fuel-saving per load, per ton, and per ton-meter. On the one hand, this can be explained by short distances driven by forklifts, on the other hand, while the less loaded a forklift the less efficient it is, a heavier loaded forklift is more efficient until a certain level and a non-linear behaviour occurs because of the scale effects. This can also be explained by all three dependent variables not having a fixed ratio of driving/lifting/weight for vehicles, and thus to establish how fuel consumption can decrease without losing productivity these variables must be reconsidered.

5. Discussion

While fuel costs are increasing and governments are taking actions towards reducing greenhouse gas emissions, manufacturers and users of heavy-duty equipment are struggling to reduce fuel consumption while improving the productivity of vehicles. Although factors related to fuel consumption are a heavily researched area in road freight transportation and logistics field, the current state of knowledge demonstrates a gap with respect to complementary factors and their interactions, which can reduce fuel consumption and improve the productivity of heavy-duty equipment [1] and, therefore, align with both ecological sustainability and economic productivity. Moreover, making sense of newly collected data via sensors over an extended time period presents another challenge in relation to fuel consumption and productivity. This study attempted to respond to the need for companies to move towards cleaner productivity by finding patterns in a large dataset that are indicative of fuel efficiency and cleaner productivity of heavy-duty equipment, which, in our case, was medium-range forklifts. The present study advances the current literature in the following important ways.

First, our results contribute to the literature that investigates factors of fuel consumption and productivity in the field of road freight transportation and logistics [13,14,16]. In contrast to previous studies, which approached fuel consumption factors in a monolithic manner, studying one or a few factors per study, the present study shows that when several factors are considered at the same time and for a larger set of forklifts that operate in natural settings for a longer time, a more complex situation emerges regarding the factors that affect fuel consumption and thus CO_2 emission. For the first time, this study shows that various factors that have been established as drivers of fuel consumption, when considered jointly, may manifest conflicting contradictors and non-linear behaviour.

Second, our results also contribute to the limited literature that focuses on models that indirectly affect fuel consumption of forklifts through order sequencing, storage allocation, and path minimization [19–23]. These studies are mostly criticized for restricted applicability to the particular operating conditions and difficult application in complex real-life settings. In the present study, we collected and analyzed longitudinal data of forklifts in real-life use. The results from this study reveal that mostly travel-, driver-, and operations-related factors complement each other to increase fuel consumption per unit time, including distance, average speed, and time-related parameters, such as production, engine, hydraulic, driving, and idle hours. The results also demonstrate the importance of the environment- and vehicle-related variables. Additionally, particular industry segments and countries are shown to be more effective in terms of fuel consumption.

Third, besides complementary fuel consumption drivers, the present study supports currently limited evidence on the importance of driver behaviour of forklifts [24]. In contrast to current studies that focus on driver behaviour in freight transportation and logistics in general, there is a limited number of studies that investigate driver behaviour of forklifts in relation to fuel consumption and productivity. The results of the present study demonstrate that driver behavior such as compliance to speed limits and idling can significantly affect the fuel consumption per time unit of a forklift. The impact on fuel efficiency and productivity by this behavior is often highlighted as a promising research direction to identify fuel-saving practices, and the results from this study confirm the importance of driver behaviour as a complementary factor.

The results of the present paper are important for practitioners who focus on drivers of fuel consumption and productivity. In general, the present study demonstrates that several factors available through sensors, of various kinds, should be elaborated in a deliberately synchronized manner in order to improve the fuel consumption and productivity of a vehicle. This study guides practitioners by informing that when considered jointly, various factors that have been established as drivers of fuel consumption may manifest conflicting contradictors.

This study has the following limitations. First, we used only one homogeneous group of vehicles—medium-range forklifts. The analysis can further be applied to a different range of forklifts and adjusted to different types of heavy-duty vehicles, such as reach stackers and tractors. Second, the daily dataset was analyzed for one year and is expandable to include more vehicles and to uncover new patterns in fuel consumption over a longer time. The data from the sensors were sent every second; thus, a more detailed analysis of fine-grained data might also bring new insights into patterns of fuel consumption. Third, the analysis was done on the vehicle level and might further be extended by focusing on the individual driver level. Therefore, future studies over a longer time span and on a larger scale might help to discover new patterns that can be used to adjust fuel consumption and productivity. Finally, while we applied the systems approach of the complementarity theory [59], future experimental studies can explore the nature of the interactions of the various factors identified.

6. Conclusions

In the present paper, an analysis of sensor data aimed at discovering drivers of fuel consumption and productivity was carried out. Most previous studies have focused only on one or a few factors that affect fuel consumption in terms of liters of fuel consumed, and little attention has been paid to complementary relationships among them and their effect on fuel consumption and productivity, which was the target in the present study. An evaluation of the effect of several explanatory variables on fuel consumption revealed the considerable effect of distance, average speed, and time-related variables on overall fuel consumption per unit time. The analysis also demonstrated the importance of activities in different workload spectra and overload hours in relation to fuel consumption per load, per ton, and per ton-meter. In addition, for activity-based parameters, particular industry segments and countries were shown to be more efficient in terms of fuel consumption. In contrast to previous studies, this study demonstrated which combinations of fuel consumption factors can be used to further establish complementary relationships between factors. The results of the study can further be used to conduct controllable experiments to explore the nature of the interactions among particular factors, among which complementary relationships emerge. The results of the study can also be used in a more detailed analysis of forklift activities in different workload spectra and for different dependent variables. The results can also be used to further explore practices in fuel consumption in different countries and industry segments to formulate a list of the best practices. Thus, further analysis can bring new insights into how to reduce fuel consumption and become more cost effective without losing vehicle productivity.

Author Contributions: The individual responsibilities and contributions of the authors are listed as follows: N.P., D.H. and S.C. designed the research; N.P. collected the literature and the data; D.H. guided the research process and revised and edited the manuscript; N.P. and M.K. analyzed the data; N.P., D.H. and M.K. interpreted the results; N.P. wrote the original version of the manuscript; S.C. revised and edited the manuscript.

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Appendix A

Table A1. Descriptive statistics of variables used in the analysis.

Variables	Unit of Measurement	Description	Mean	Standard Deviation
		Counters		
Distance forward	km	Total distance forward covered by a vehicle during a specific time period	24.463	20.707
Distance in reverse	km	Total distance in reverse covered by a vehicle during a specific time period	5.333	6.412
Total distance	km	Total distance covered by a vehicle during a specific time period	29.796	24.230
Idle occurrences	number	Number of times when a vehicle has been idling without performing/producing	8.310	8.867
Shock occurrences	number	Number of shocks (hard braking, crashing into the bumper, crossing a railway, and any other jarring events) experienced by a vehicle	58.240	102.521
Number of overloads	number	Number of times a vehicle lifted more than its rated capacity	15.250	49.380
Total weight	ton	Total number of tons being lifted by a vehicle during a specific time period	660.731	727.788
Total loads lifted	number	Number of loads lifted by a vehicle during a specific time period	175.850	172.781
Speed average	km/h	The average speed a vehicle achieves during a given time period	6.623	3.161
Speed maximum	km/h	The maximum speed of a vehicle within a set time period	20.320	6.763
Diesel level maximum	%	The filling levels of diesel fuel	84.910	22.906
Battery voltage	V	The voltage of the battery	17.188	12.718
		Time		
Driving time	hour	Total number of hours a vehicle is driven (speed greater than 0)	5.273	3.778
Hydraulic time	hour	Total hours of hydraulic function use	2.540	2.004
Idling time	hour	Time the engine is running but the vehicle is not moving or using load handling functions	4.102	3.519
Engine time	hour	Time the engine is running when vehicle is moving or using load handling functions	9.509	6.660
Time in ECO mode	hour	Time the vehicle has been driving in Eco driving mode	0.919	0.925
Time in Normal mode	hour	Time the vehicle has been driving in Normal driving mode	1.814	1.298
Time in Power mode	hour	Time the vehicle has been driving in Power driving mode	2.239	1.560
Production time	hour	Engine time minus idle time	5.408	3.936

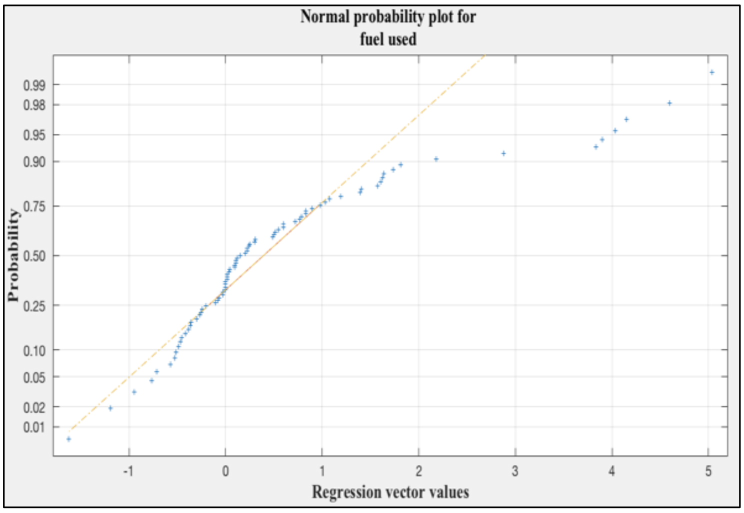
Table A1. *Cont.*

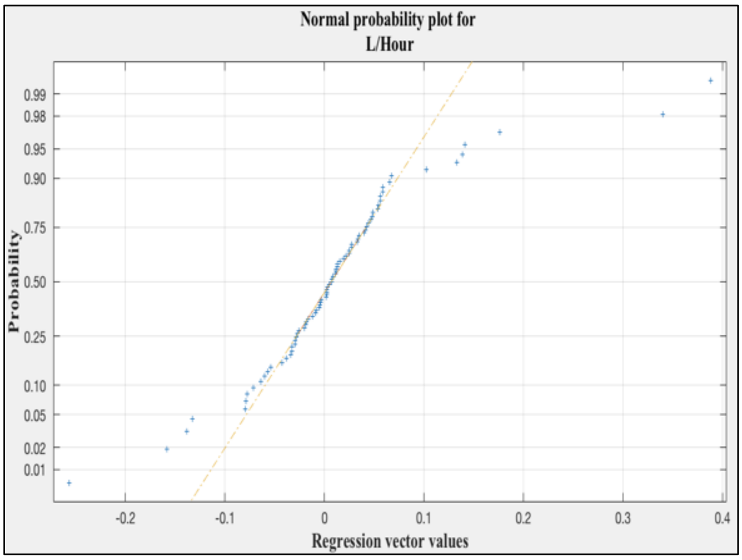
Variables	Unit of Measurement	Description	Mean	Standard Deviation
Time in overload	hour	Time during which a vehicle carried a very heavy load	0.187	0.750
Load spectra (time)				
Load spectrum 0–10percentage time	hour	Time during which a vehicle operated in load spectrum 0–10	2.517	2.418
Load spectrum 11–20percentage time	hour	Time during which a vehicle operated in load spectrum 11–20	0.488	0.582
Load spectrum 21–30percentage time	hour	Time during which a vehicle operated in load spectrum 21–30	0.571	0.814
Load spectrum 31–40percentage time	hour	Time during which a vehicle operated in load spectrum 31–40	0.444	0.687
Load spectrum 41–50percentage time	hour	Time during which a vehicle operated in load spectrum 41–50	0.288	0.383
Load spectrum 51–60percentage time	hour	Time during which a vehicle operated in load spectrum 51–60	0.238	0.369
Load spectrum 71–80percentage time	hour	Time during which a vehicle operated in load spectrum 71–80	0.132	0.264
Load spectrum 81–90percetage time	hour	Time during which a vehicle operated in load spectrum 81–90	0.094	0.271
Load spectrum 91–100percentage time	hour	Time during which a vehicle operated in load spectrum 91–100	0.063	0.193
Load spectrum above 101percentage time	hour	Time during which a vehicle operated in load spectrum above 100	0.255	0.524
Load Spectra (Number of Lifts)				
Load spectrum 0–10percentage counter	number	Number of lifts in load spectrum 0–10	36.670	48.323
Load spectrum 11–20 percentage counter	number	Number of lifts in load spectrum 11–20	31.755	41.679
Load spectrum 21–30percentage counter	number	Number of lifts in load spectrum 21–30	27.693	37.146
Load spectrum 31–40percentage counter	number	Number of lifts in load spectrum 31–40	18.240	25.740

Table A1. *Cont.*

Variables	Unit of Measurement	Description	Mean	Standard Deviation
Load spectrum 41–50percentage counter	number	Number of lifts in load spectrum 41–50	13.190	24.116
Load spectrum 51–60percentage counter	number	Number of lifts in load spectrum 51–60	9.833	17.099
Load spectrum 61–70percentage counter	number	Number of lifts in load spectrum 61–70	7.676	15.649
Load spectrum 71–80percentage counter	number	Number of lifts in load spectrum 71–80	4.699	10.615
Load spectrum 81–90percentage counter	number	Number of lifts in load spectrum 81–90	2.34	7.699
Temperature				
Ambient temperature minimum	°C	Minimum ambient temperature during a given time period	10.940	8.045
Ambient temperature maximum	°C	Maximum ambient temperature during a given time period	20.770	9.290
Ambient temperature average	°C	Average ambient temperature during a given time period	16.190	8.371
Engine coolant temperature average	°C	Average engine coolant temperature during a given time period	78.312	11.117
Hydraulic temperature average	°C	Average hydraulic temperature average during a given time period	44.889	13.079
Transmission oil temperature average	°C	Average transmission oil temperature during a given time period	63.907	12.515
Fuel-related Variables Per Time Unit				
Fuel used	Liter/day	The amount of fuel consumed by a vehicle during a specific time period (per day)	65.409	47.196
Fuel used per hour	Liter/hour	Average fuel consumption per engine hour	7.031	2.391
Fuel used per load	Liter/load	Average fuel consumption per load	1.604	7.398
Fuel used per ton	Liter/ton	Average fuel consumption per ton	0.691	4.925
Fuel used per ton-meter	Liter/ton-meter	Average fuel consumption per ton-meter	0.0216	0.264

Appendix B





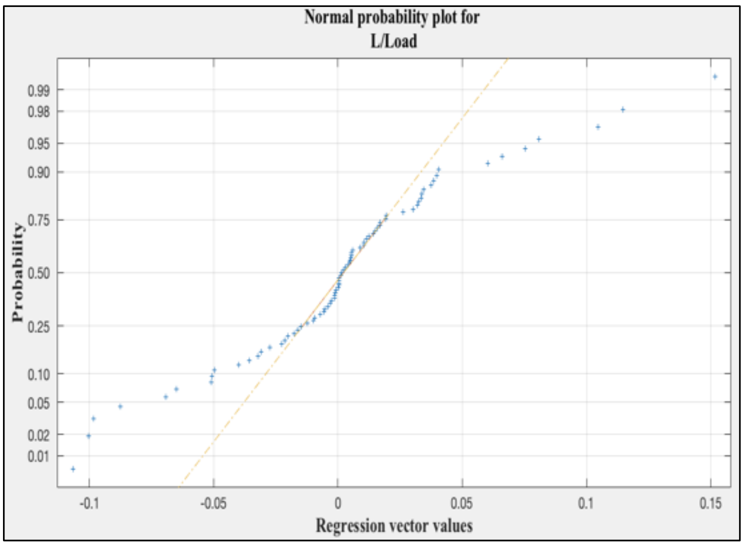
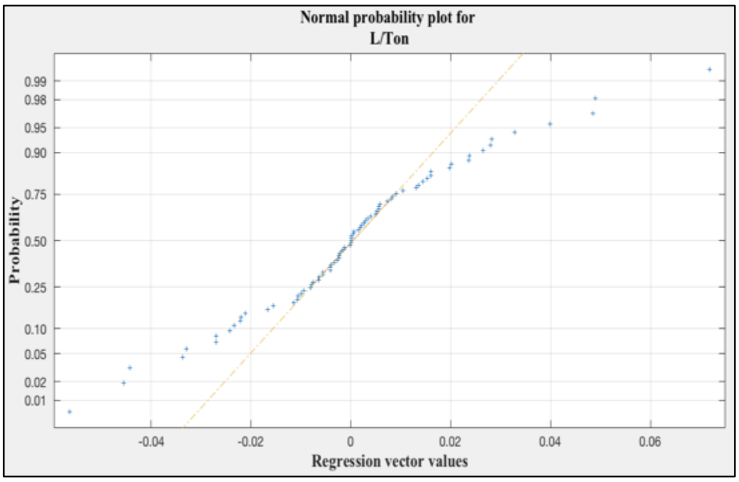


Figure A1. *Cont.*



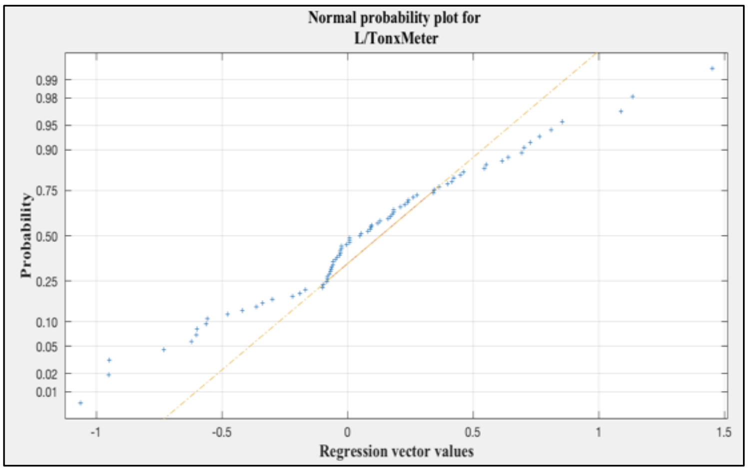


Figure A1. Normal probability plots of the most relevant variables for fuel consumption (liter/day, liter/hour, liter/load, liter/ton, liter/ton-meter). The data that did not follow the straight line were used to find cut-off limits in order to select important variables for fuel consumption.

Appendix C

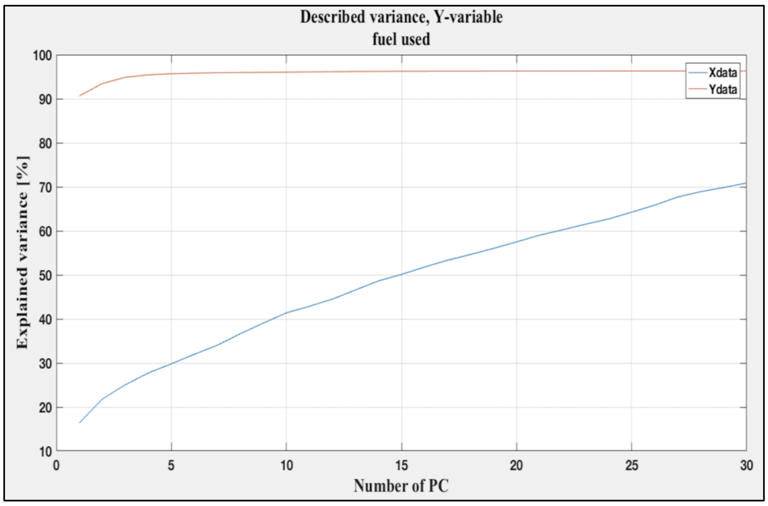
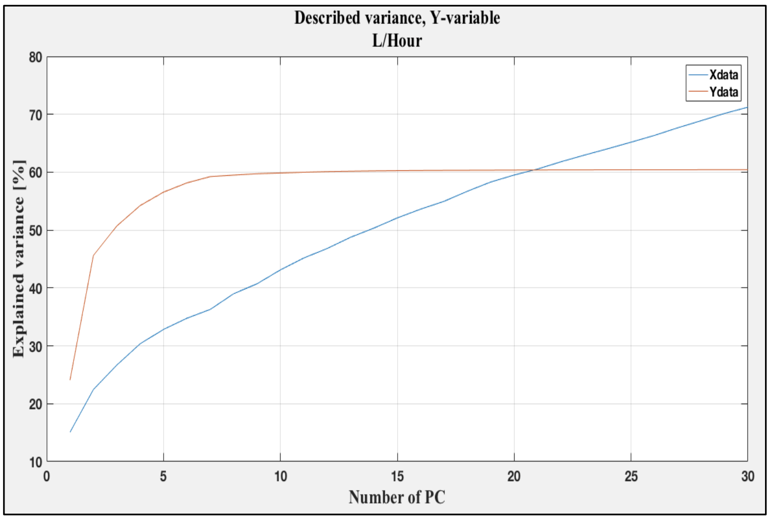


Figure A2. *Cont.*



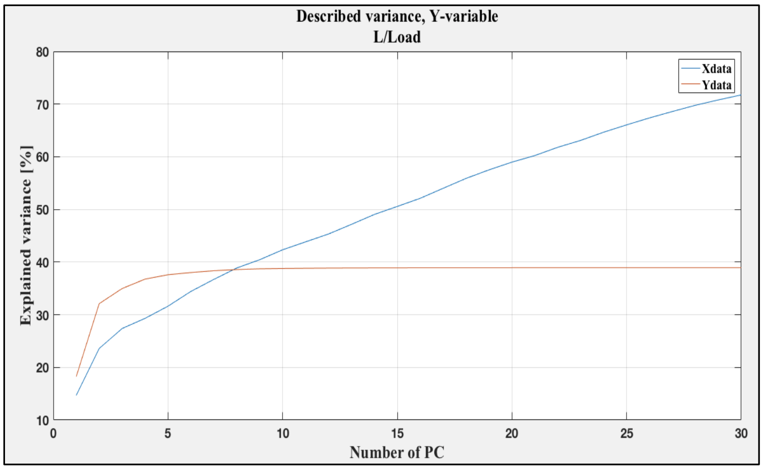


Figure A2. *Cont.*

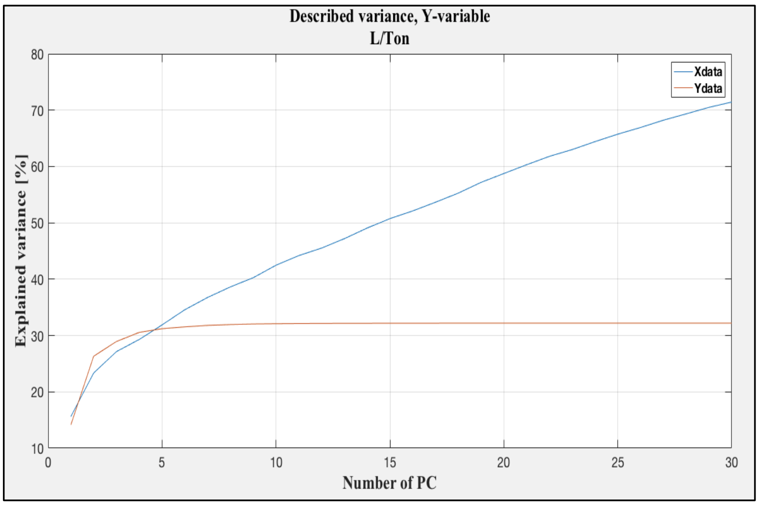


Figure A2. *Cont.*

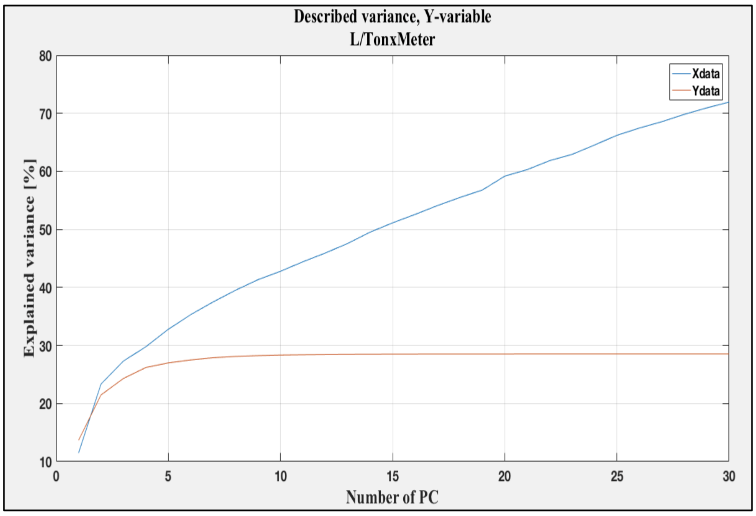


Figure A2. The choice of partial least-squares factors based on explained variance, preserving the essence of the original data (liter/day, liter/hour, liter/load, liter/ton, liter/ton-meter). Those factors that accounted for little variation were excluded from the analysis.

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