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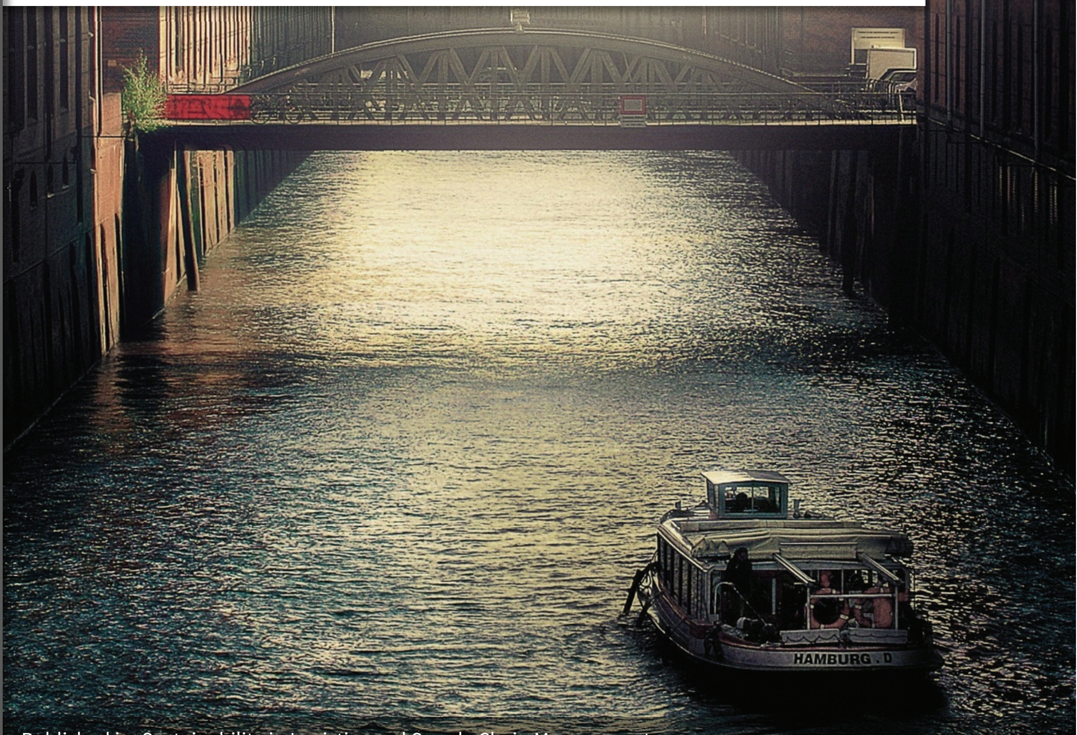

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City logistics (CL) has recently emerged as a comprehensive and coordinated approach to reduce the negative impacts of last mile logistics, making urban freight distribution more sustainable from both an economic and an environmental point of view. Assessing the viability of CL initiatives is necessary to comprehend the relevant aspects that can support their adoption by private stakeholders. This work focuses on a new CL system relying on low emission vans for a large city in Northern Italy. A System Dynamics simulation model has been developed in order to assess the potential diffusion of the system at issue and understand the main factors that either stimulate or hinder it. Behavioral, economic, and environmental issues that characterize urban freight distribution are taken into account. A sensitivity analysis has been performed to test the robustness of the model and to predict the CL system behavior when its underlying parameters change. The outcomes show that the new system is feasible and allow suggesting some policies to encourage its adoption.

Keywords: System Dynamics, Diffusion Model, Low Emission Vehicles, Sustainable City Logistics

1 Introduction

In recent years problems caused by the increasing freight transportation demand within cities, such as pollution and congestion, have led both researchers and public authorities to concentrate their efforts on City Logistics (CL) initiatives. CL has been defined as "the process of totally optimizing urban logistics activities by considering the social, environmental, economic, financial and energy impacts of urban freight movement" (Taniguchi et al., 2001). CL fosters the development of integrated logistics systems where all the stakeholders are coordinated to reduce negative effects on citizens. Thus, a CL model should be planned and managed with the aim of improving the quality of life of communities, while at the same time carrying no disadvantages to both public and private operators. In literature, there is a substantial amount of works focusing on the positive and negative impacts of urban freight distribution from an operational and economic point of view, taking into account the effects on both public and private stakeholders (Figliozzi, 2010; Browne and Gomez, 2011).
Several policies can be implemented to reduce the negative impacts of CL, such as restricting or even banning commercial vehicles from circulating in city centers, using reserved lanes for goods vehicles, load factor control, and road pricing (e.g. congestion charge) for charging the entrance in restricted areas (Visser, Van Binsbergen and Nemoto, 1999; Witkowski and Kiba-Janiak, 2012).
CL initiatives often include also the partial or total substitution of existing commercial vehicles with low emission ones, mainly electric or hybrid vehicles. However, in order to make these initiatives sustainable for private

stakeholders it is necessary to understand the main factors for the adoption of such kind of vehicles. In fact, private companies do not always follow up on the efforts made by municipalities to stimulate the diffusion of low emission vehicles (Trip and Konings, 2014). In addition, investing in electric commercial vehicles turns profitable only under certain operational conditions (Gries, et al., 2014).

In order to contribute to the existing body of literature on the factors for adopting low emission vehicles, a model assessing the diffusion of a CL system based on electric and hybrid vehicles in the city of Torino (Italy) is here proposed, by taking into account all the typical operational factors of a freight distribution system. As a matter of fact, current literature on CL lacks studies that analyze the diffusion of low emission commercial vehicles by focusing on the operational aspects of the associated logistics systems. Economic and environmental costs and benefits of the proposed system are compared with the existing CL system, which mostly uses traditional diesel powered vehicles. The results of the simulation and the consequent sensitivity analysis allow to identify some factors that might drive the adoption and diffusion of this distribution system.

System Dynamics (SD) methodology is applied for the development of the model. The SD approach was originally introduced in the 1960s at Massachusetts Institute of Technology to study the evolution over time of complex systems composed by numerous and heterogeneous variables and nonlinear connections between them (Forrester, 1961). The variables and parameters of the model are based on reviews of similar case studies, interviews with the main stakeholders in the CL system at issue, as well as

detailed data on the characteristics of the vehicles that were provided by the main manufacturer of commercial vehicles involved in the research.
The paper is structured as follows. In Section 2 the relevant literature on SD modelling is reviewed, in order to understand which aspects should be represented in a model of a CL system and to provide the theoretical background for the selected diffusion model. In Section 3 the main aspects of the methodology are explained. The development of the model is presented in Section 4 and its calibration is proposed in Section 5. The results of the simulations and of the sensitivity analysis are discussed in Section 6 and 7. Finally, the authors propose some interpretations of the results along with policy implications and concluding remarks in Section 8.

2 Modelling the Diffusion of Low Emission Vehicles with SD

The literature review aims to identify the main variables that should constitute a sustainable urban freight distribution system and their relationships. Thus, the variables retrieved literature will form the background for developing the model.
Seitz and Terzidis (2014) focus on the adoption of low emission heavy goods vehicles. The authors highlight the importance of having both a potential market and an efficient refueling network for the diffusion of such vehicles. Ardila and Franco (2013) investigate the Colombian market and show that good communication is more effective than fiscal policies to encourage low emission private transportation. Struben and Sterman (2008)

study the diffusion and competition between low emission vehicles, in particular electric and hydrogen ones. They find that a critical mass dependent on economic and behavioral factors should exist in order to adopt alternatives technologies. In particular, the word of mouth appears to be crucial for stimulating diffusion.

Some authors have focused specifically on the diffusion of electric and hybrid vehicles. Shepherd, Bonsall and Harrison (2012) build on the work of Struben and Sterman to examine the adoption factors for hybrid plug-in and electric vehicles in the United Kingdom considering a 40-year time span. The sensitivity analysis reveals that word of mouth, average vehicle lifetime, and emission rates might influence adoption more than other aspects such as incentives or specific technical features. Lastly, the model developed by Gorbea, Lindemann, and de Weck, (2011) takes into account fuel prices fluctuation, incentives, network effects (e.g. word of mouth), operational costs, and ownership costs in order to model the adoption of light hybrid and electric vehicles.

The model developed in the present work is based on the SD representation of the Bass diffusion model (Bass, 1969) developed by Sterman (2000), which provides also the theoretical background for other existing models in the CL arena, mainly aimed at studying the adoption of low emission vehicles (Struben and Sterman, 2008; Park, Kim, and Lee, 2011). However, there is a lack of works investigating the diffusion of these vehicles by taking into account the main operational CL aspects. In fact, SD models in this field usually focus on the impact of policies, operating and acquisition costs of vehicles, and other traditional adoption factors such as word of mouth or advertising. Therefore, the aim of this work is to integrate such factors together with the aspects that define urban freight distribution systems, such as freight demand, daily vehicle routes, and distance travelled.

3 SD Methodology

This section presents the SD methodology as discussed by Forrester (1961) and Sterman (2000). From a methodological point of view, three main elements compose a SD model: Causal Loop Diagrams, Stock and Flow Diagrams, and equations representing the relationships between variables. The Causal Loop Diagram (CLD) is a qualitative and graphical representation of variables and their mutual connections. These connections are depicted through feedback loops, both negative (balancing) and positive (reinforcing) ones. Feedback loops, or causal loop, are best defined as closed sequences generated by causes and effects triggered between variables. In particular, reinforcing loops connect variables that are positively linked: for each increase in one variable within the loop, the growth generated in the linked variables originates an additional increase in the first variable. The opposite process happens for balancing loops: the increase in the value of one variable causes changes in the values of the linked variables that then result in a decrease in the value of the first variable. It is worth noting that CLDs do not include equations. Stock and Flow Diagrams (SFD) are made up of four funding elements: stocks, flows, auxiliary variables, and connectors. Stocks are cumulated quantities given by the difference between the inflow and the outflow of a process. They can represent accumulations of goods, money, customer orders, etc. over time. Flows can be physical, economical or informational quantities that either increase (inflows) or decrease (outflows) the value of a stock. Auxiliary variables can be either constant or variable over time. In the second case they are functions of stocks, flows or other auxiliary variables. Connectors represent the relationships between the previous mentioned three elements. Finally, the equations of a SD model can be either algebraic or differential in nature, they are independent from one another, and are functions of the state of the system in the previous time steps. They can define for instance the values of flows connecting stocks or the stock levels.

4 Model Development

In the next sections, the detailed structure of the SD model together with its main feedback loops is presented.

Since the SD approach does not allow flows of different elements (e.g. different kinds of adopters) to be easily modelled and simulated as flowing together out of the same stock (e.g. the total number of potential adopters), it is assumed that any retail store operating in the city of Torino, also named commercial unit (C.U.), which adopts the new distribution system makes an exclusive choice on the type of vehicle. For this reason, two configurations of the model have been developed: the first one for the adoption of electric vehicles (variables marked with the prefix E) and the second one for the adoption of hybrid vehicles (variables marked with the prefix H). A second assumption has been made on the type of adopters. In fact, the adoption by the C.Us is considered as a direct consequence of the adoption by logistics providers. Hence, the population stock of the diffusion model is composed by the potential C.Us that could be served by the new CL system.

The software Vensim® DSS by Ventana Systems is used to develop the model; simulations cover a time period of 120 months with a time step equal to one month.

4.1 The General Structure of the Model

The model presents a general structure divided into four conceptual parts developed according to pertinent literature and agreed with the van manufacturer:

— Number of vehicles in the system and associated number of kilometers travelled (Figliozzi, 2010; Egilmez and Tatari, 2012; Trip and Konings, 2014), which are estimated based on some operational and demand factors depicted in Section 4.2.

— Savings in CO2 emissions (Egilmez and Tatari, 2012; Trip and Konings, 2014). Only CO2 emissions are included in the model since the level of PM10 emissions is significantly lower. In fact, according to the van manufacturer estimates, the PM10 emissions for traditional vehicles are on average 0.03 g/km, while the CO2 emissions are approximately equal to 275 g/km.

— Total vehicle cost savings (Armenia, et al., 2010; Gorbea, Lindemann, and de Weck, 2011; Shepherd, 2014). They include the acquisition cost (amortization), the fuel cost, the maintenance cost (e.g. tire replacement), and the insurance cost. These savings stimulate the adoption of the new distribution system.

— Charging station costs (Clement-Nyns and Haesen, 2010). The charging stations are not part of a public infrastructure but they are located within the premises of the logistics providers or the C.U. suppliers.

The model also takes into account possible public contributions for purchasing the vehicles and the charging stations. These contributions are dependent on the savings in the level of CO2 emissions generated by the CL system.

The dynamics of the four parts of the model are represented via some feedback loops detailed in Section 4.3. Due to space constraints the paper only describes the main aspects characterizing the developed SD model. The complete model structure as well as the associated equations are available from the authors.

4.2 The Sub-Models

Three sub-models compose the SD model providing a detailed and thorough representation of its general structure. The first one is named “Electric/Hybrid TO BE” sub-model and assesses the vehicles diffusion by comparing the new system with the traditional one, whose operating variables are in turn estimated in the “AS IS Model (DIESEL)” sub-model. Then, the “C.U. adoption Electric/Hybrid” sub-model studies the adoption process of the C.Us and is directly linked to the first one.

4.2.1 "Electric/Hybrid Model TO BE"

As mentioned above, this sub-model aims at representing causes and effects that lie behind the diffusion of electric and hybrid vehicles within the new distribution system.

The number of vehicles depends on a variety of factors such as:

— The quantity of goods delivered, equal to the average monthly freight demand of each C.U. multiplied by the number of adopters. The latter is taken from the "C.U. Diffusion Electric/Hybrid" sub-model.

— The monthly utilization factor of the vehicle, calculated in the model as the reciprocal of the number of monthly routes necessary to serve the C.Us.

— The increase in the number of vehicles generates both a reinforcing and a balancing loop.

As the number of vehicles in the new distribution system increases, the total number of kilometers they travel increases as well. If the operating costs for hybrid and electric vehicles are lower than for traditional vehicles, one can say that for each increase in the total amount of kilometers travelled savings are generated in comparison with the traditional system (simulated in the AS IS sub-model). Consequently, such savings generate more adoptions of electric and hybrid vehicles, closing a reinforcing loop.

On the contrary, the more the vehicles the more the total investment in charging stations leading to increased investment costs, which negatively affect the adoption (balancing loop). The higher the initial investment costs, for instance because of higher purchasing costs or lower public contributions, the grater the effect of the balancing loop and the disincentive to the adoption of the new distribution system.

4.2.2 "C.U. Adoption Electric/Hybrid"

This sub-model studies the dynamics of the adoption process of the C.Us. In the developed model, the adoption process takes place as a consequence of different factors:

- The advertising performed by the vehicles themselves, which will carry a sign stating that they are part of an eco-friendly distribution system.
- Formal advertising campaigns.
- Word of mouth actions between adopters and non-adopters.
- Observation of the cost savings generated by the new distribution system.

As a matter of fact, non-adopters are stimulated to adopt in order to take advantage of the lower operating costs comparing with the traditional distribution system. In this way, they are able to offer lower distribution fares to their customers, avoiding the possibility of decreasing their market share because of customers turning to the adopters of the new CL model.

4.2.3 "AS IS Model (DIESEL)"

The present sub-model was developed to make comparisons between the new and the traditional logistics systems. It is indeed the simplest part of the SD model.

In each time step the operating costs of a traditional system are calculated for the same number of vehicles and kilometers travelled as in the new system. Taxation costs are calculated for traditional vehicles by adding a carbon tax and an ownership tax. Operating costs and taxation costs makes up for the total costs of the AS IS system.

4.3 Analysis of the Main Feedback Loops

The adoption of the new distribution system through the obtained savings, in terms of both CO2 emissions and operating costs, gives rise to interesting

Figure 1 Effect of CO2 savings on adoption

feedback loops involving all the sub-models. Figure 1 shows the positive impact of the savings in polluting emissions on the adoption. As Adoption from Savings in Cost increases, the number of adopting C.Us increases (C.U. Adoption Rate) generating more freight and transportation demand in the distribution system (Total C.U. Demand; Total # Monthly New km). Consequently, when the number of kilometers travelled increases also the value of Total CO2 Saved grows in comparison with a traditional distribution system, increasing in turn the value of the variable Initial Public Contribution for Plugin. The higher this contribution the lower the cost carried by private

Figure 2: Effect of savings in operating costs

operators to buy charging stations (Plugin Total Cost) and the higher the savings (Savings in Investment Costs and Total Cost Savings). As a consequence of these economic benefits generated by the positive impact of the CO2 emissions, Adoption from Savings in Cost increases, closing a reinforcing loop.

Figure 2 depicts the effect on the adoption of the variable Savings in Operating Costs. If this variable increases, the variables Total Cost Savings as well as Adoption from Savings in Cost increase. As mentioned above, the total transportation demand grows, together with the number of necessary vehicles (# Vehicles). If logistics providers and C.U. suppliers used the same number of traditional vehicles to fulfil the C.U. demand (D. # Vehicles), they would bear the costs related to the taxation of the vehicles, which include ownership taxation and carbon tax (D. Total Monthly Vehicle Taxes). Since these types of taxation are not due for electric and hybrid vehicles, the associated savings increase the value of Savings in Operating Costs, closing another reinforcing loop.

During the first months of the simulation savings in operating costs are lower than investment costs, hence the sum is negative and the adoption is lagging. As the number of C.Us and kilometers travelled increases, then savings turn positive stimulating the adoption process.

5 Model calibration

In order to carry out the simulation runs, it is necessary to provide the input values for the parameters that contribute to define the base case for the sensitivity analysis (Section 7). The values here presented for each sub-model are retrieved from the data provided by the van manufacturer and the logistics operators involved in the research as results of their investigations of the Torino area as well as previous similar studies. Also, the numerical values in the next sections are related to parcel delivery and frozen food since these are the product categories investigated in the present work.

5.1 Input Parameters of the Sub-Model "Electric/Hybrid Model TO BE"

The first set of parameters is related to the C.Us and the necessary routes to serve them. The variable Average Distance b/w C.U. has been estimated assuming a higher value in case of C.Us located outside the city center restricted area (ZTL - Zona a traffico limitato) than for C.Us located within ZTL because there is a lower density of commercial establishments outside ZTL. In particular, this parameter is equal to 0.04 km/C.U. in ZTL and 0.9 km/C.U. outside ZTL. On the contrary, the value of the parameter Setup Distance (average distance travelled by a vehicle from the depot to the first visited C.U. and from the last C.U. back to the depot) is higher in case of ZTL than for the outside areas since warehouses are usually located far from city centers. Setup Distance is equal to 9.5 km when talking about ZTL C.Us and equal to 5.5 km for C.Us located outside ZTL. C.U. Monthly Demand is equal to 0.44 t/C.U. for parcel delivery and to 24.2 ton/CU for frozen food. C.U. Monthly Delivery Factor is a dimensionless parameter and is equal to 4 for both the types of vehicles.

The second set of parameters deals with the features of the vehicles. Monthly Vehicle Utilization Factor is equal to 0.05 for electric vehicles and

0.06 for hybrid vehicles for parcel delivery. The vehicles associated with frozen food have a Monthly Vehicle Utilization Factor equal to 0.024 for electric onesand to 0.025 for hybrid ones. The carrying capacity is 1.4 t/vehicle for both the types of vehicles. Operating Unit Cost is equal to 1.7 €/km for electric vehicles and 1.6 €/km for hybrid vehicles and represents the operating cost of the vehicle before public contribution. Public Contribution Factor, meaning the contribution for purchasing low emission vehicles, is equal to € 0.005 for each gram of CO2 saved.

The third set of parameters considers CO2 emissions. CO2 Emissions per km is estimated equal to 74.7 g/km for electric vehicles and 180 g/km for hybrid vehicles (Element Energy Limited, 2012), while CO2 Emissions per km AS IS is set at 356.5 g/km. Both Well-to-Tank (WTT) and Tank-to-Wheel (TTW) emissions are included in the model.

The fourth and last set of parameters of this sub-model is related to the plugin units:

- Plugin Unit Cost: 7,000 €/unit
- # Vehicle per Plugin Unit: 4 vehicles/unit (electric) and 8 vehicles/unit (hybrid)
- Public Contribution Factor for Plugin: 0.001 €/(g*unit).

5.2 Input Parameters of the Sub-Model "C.U. Adoption Electric/Hybrid"

The input values for the adoption sub-model have been assumed to be the same for both the types of vehicles. These values are set intentionally low in order not to overestimate the impact of the parameters on the adoption process, which would lead to unfeasible outcomes.

The parameters Contact Rate, Adoption Fraction and Advertising Effectiveness have been estimated equal to 0.1, 0.04 and 0.08 respectively (unit of measure 1/month). Emulation Contact Rate, which defines how frequently a potential adopter observes the benefits obtained by an adopter, is set equal to 0.14.

The potential C.U. adopters are equal to 2,462 and 120 for the parcel delivery and frozen items distribution system with electric vehicles, and to 9,538 and 1,380 for the same distribution systems based on hybrid vehicles. These values are different because the distribution with electric vehicles is supposed to take place only in ZTL while the distribution with hybrid vehicles is adopted just by the C.Us located outside ZTL.

5.3 Input Parameters of the Sub-Model AS IS Model (DIESEL)

The variable D.Operating Unit Cost defines the operating cost for a diesel vehicle and it is estimated equal to 1.6 €/km. D. Ownership Vehicle Tax and D. Carbon Tax are used to calculate the total taxation costs for a traditional diesel vehicle. The first one is computed on a monthly basis and it is equal to 6.67 €/vehicle; the second one is dependent on the emission levels (g/km) characterizing a specific kind of vehicle and is not associated with the actual use of the vehicle (e.g. kilometer travelled), it is also computed on a monthly basis and it is equal to 1.0 (€*km)/(Vehicle*g).

6 Simulation

This section shows the results of the simulation runs of the SD model. Simulations are based on the database resulting from the study carried out in the Torino area by the van manufacturer and the other research partners. In particular, the adoption of the new distribution system is assessed in terms of C.Us and number of vehicles. Two scenarios are discussed: one scenario considers electric vehicles within ZTL and the other shows the adoption of hybrid vehicles for deliveries to C.Us located outside ZTL.

6.1 Inside ZTL: Electric Vehicles

The entire stock of parcel delivery C.Us at issue adopt the distribution system in a 51 month period, being served by a total number of 40 electric vehicles as shown in "Figure 3" and "Figure 4".

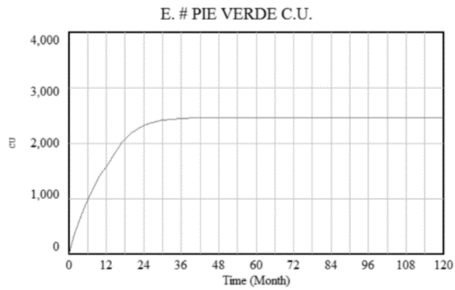

Figure 3: C.Us. diffusion for parcel delivery

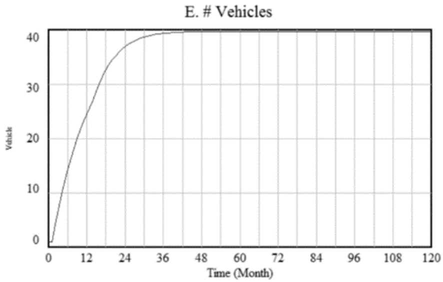

Figure 4: Electric vehicles diffusion for parcel delivery

Also the simulations show that the 120 CUs related to frozen items join the new configuration within 3 years and they are served by 26 vans ("Figure 5" and "Figure 6").

Finally, simulations prove that in the case of parcel delivery the total cumulated cost savings in ten years are around € 2 million. In the frozen food case, starting from the ninth month the savings become positive up to 1 Million €.

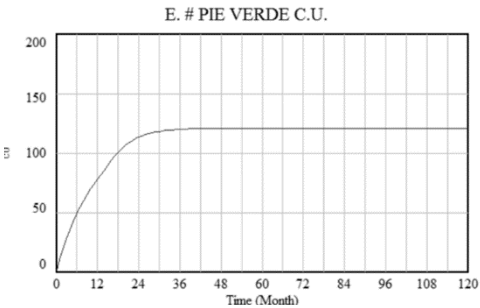

Figure 5: C.Us. diffusion for frozen food

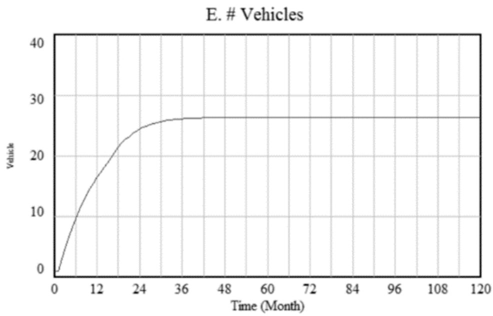

Figure 6: Electric vehicles diffusion for frozen food

6.2 Outside ZTL: Hybrid Vehicles

In this scenario, market saturation in the parcel delivery sector is reached in 47 months. The 9,538 C.Us are served by 181 hybrid vehicles, each of them performing on average 16 monthly routes. The saturation for the 1,380 CUs in the frozen food market is got in 48 months. Overall, 279 vehicles are necessary.

This configuration achieves total cost savings equal to € 10 million, turning positive from the fourth month of simulation on for both the product categories under study.

7 Sensitivity Analysis

The aim of the sensitivity analysis is to reveal how the outcomes of the model vary when the main input parameters change. This objective is instrumental not only to understand the dynamics of the diffusion process and highlight the most important stimulating factors, but also to validate the robustness of the SD model at issue (Sterman,2000).

In this section the sensitivity of the main elements of the model, namely the number of vehicles, the number of adopting C.Us, and the total savings, to changes in the input parameters is investigated. In the following sub-sections the results of the three most significant scenarios, which rely on both univariate and multivariate sensitivity analysis, are proposed.

The analysis was performed with Vensim DSS, which allows varying the input parameters according to a selected probability distribution. The software executes a fixed number of simulations, usually 200, calculating the output variables for each value of the input parameter. In the next figures the thin black line represents the base case, while the grayscale bands are the confidence bands where the output values can be found with probabilities equal to 50%, 75%, 95%, and 100%.

7.1 Multivariate Sensitivity Analysis on Advertising Effectiveness, Emulation Contact Rate and Contact Rate

In this scenario the dynamics of the adoption process changes as three parameters, Advertising Effectiveness, Emulation Contact Rate, and Contact Rate, vary between 0 and 0.4 [1/month] according to a standard normal distribution. "Figure 7" presents the total cost savings trend for the new distribution system with electric vehicles in the parcel delivery market. In the first months of the simulation period, the advertising and the emulation effects drive the adoption and the associated savings. When a considerable number of C.Us has already started being served by the new CL system the

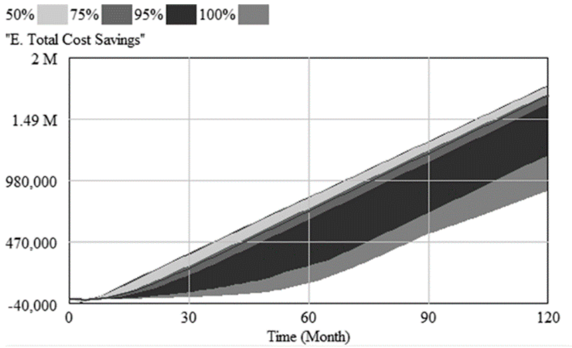

Figure 7: Sensitivity analysis on Advertising Effectiveness, Emulation Contact Rate and Contact Rate on the total cost savings – electric vehicles for parcel delivery

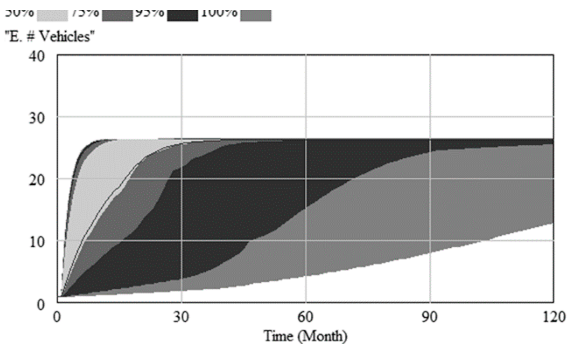

Figure 8: Sensitivity analysis on Advertising Effectiveness, Emulation Contact Rate and Contact Rate on the total cost savings – electric vehicles for frozen food

word of mouth action becomes relevant in order to furtherly stimulate the diffusion.

For the frozen food market, 120 months of simulation are not enough to reach the saturation when the values of all the three parameters are low ("Figure 8").

7.2 Univariate Sensitivity Analysis on Monthly Vehicle Utilization Factor

In this scenario, the parameter Monthly Vehicle Utilization Factor changes according to a uniform distribution varying between 0.015 and 0.06.

This range of values was calibrated to obtain a number of routes per day ranging from 0.76 to 3, feasible values for the product categories at issue.

For parcel delivery, with a Monthly Vehicle Utilization Factor equal to 0.06, a total of 46 electric vehicles are necessary to serve all the C.Us. On the contrary, with 3 routes per day (Monthly Vehicle Utilization Factor = 0.015) a total number of around 12 vehicles is required ("Figure 9"). For both the output variables analyzed, namely the number of vehicles in the system and the total cost savings, significant variations as the values of the selected input parameters change are observed. For instance, the variable Total Cost Savings takes maximum values ranging from around € 500,000 to € 2 million in case of parcel delivery ("Figure 10").

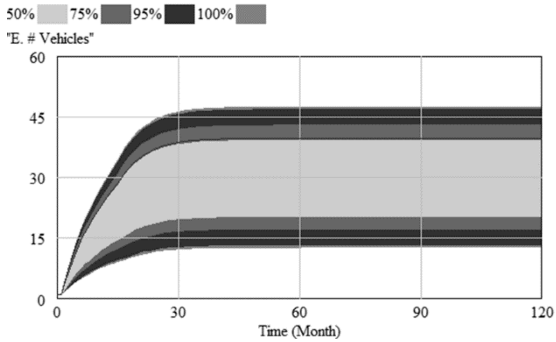

Figure 9: Sensitivity analysis of Monthly Vehicle Utilization Factor on the number of electric vehicles for parcel delivery

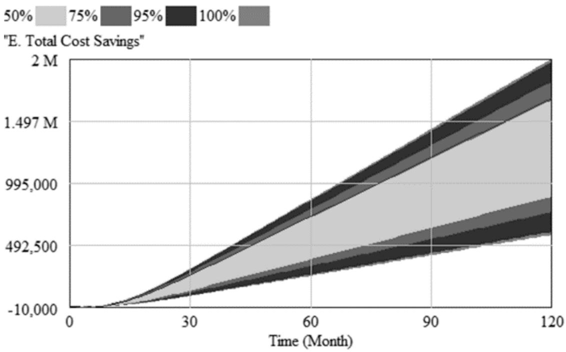

Figure 10 Sensitivity analysis of Monthly Vehicle Utilization Factor on the total cost savings - electric vehicles for parcel delivery

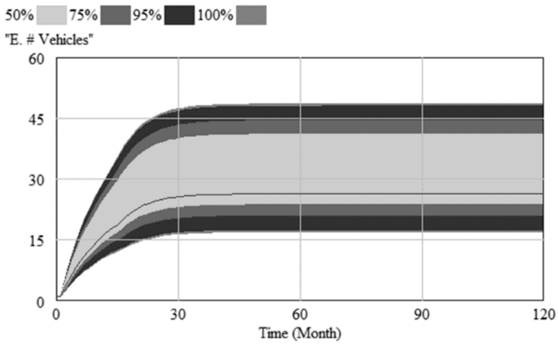

Figure 11 Sensitivity analysis of Monthly Vehicle Utilization Factor on the number of electric vehicles for frozen food

Similarly, for the frozen food market a Monthly Vehicle Utilization Factor equal to 0.045 requires 50 vehicles to serve all the C.Us ("Figure 11"). On the contrary, a Monthly Vehicle Utilization Factor equal to 0.015 leads to around 15 vehicles.

7.3 Multivariate Sensitivity Analysis on Public Contribution Factor, Public Contribution Factor for Plugin and D. Carbon Tax Factor

The degree to which public contribution can support and influence the adoption of the new distribution system is here assessed.

All the three input parameters follow a standard normal distribution. Public Contribution Factor ranges from € 0 and € 0,009; Public Contribution Factor for Plugin ranges from € 0 and € 0.003, while D. Carbon Tax Factor can take values from € 0.1 to € 2.

As expected, the public contribution dependent on the CO2 emission reduction is able to lead to a significant increase in the total cost savings of

the distribution system because this contribution has a direct impact on the adoption from savings. Moreover, the analysis shows moderate indirect effects of the public contribution on word of mouth actions.
The same sensitivity analysis was performed excluding the parameter D. Carbon Tax Factor. In this case, the positive effects mentioned above are weakened, meaning that public intervention is more effective on the adoption if it comprises both incentives for low emission vehicles and taxes for traditional vehicles.

8 Discussion and Conclusion

This work studies the dynamics of the adoption of electric and hybrid commercial vehicles to perform freight distribution activities in the city of Torino (Italy). The analysis has been conducted through the SD approach since it appears to be very useful to describe the behavior of a complex system and its associated variables. The simulations and sensitivity analyses show that a new urban freight distribution system with low emission vehicles is feasible both for the city center restricted area (ZTL) and for the whole city.

In fact, by focusing on two different fields of application, namely parcel delivery and frozen food , in both the areas the market saturation is reached within the simulation time horizon, and in particular within 51 and 36 months for electric vehicles and 47 and 48 months for hybrid vehicles. Moreover, the model simulation reveals that the new distribution system could bring significant savings over ten years, equal to around € 2 and 1 Mln for electric and € 10 Mln for hybrid vehicles

Such results are due to two main factors. First, the involved technology can be considered mature, in terms of costs (the difference in operating costs between low emission and traditional vehicles is less than 10 cents per km) and in terms of operating time of the batteries that now allow for a whole trip to be completed without being recharged. Second, the involvement of the public sector could significantly support the diffusion of low emission freight distribution systems. In the model, such involvement includes both disincentives to traditional vehicles and incentives to low emission ones. In particular, the CO_2 emission gap between the two types of vehicles is calculated: the higher this gap, the higher the public contribution. This leads private operators to adopt the new system.

The sensitivity analyses performed show that the most determinant aspects for the diffusion process are the same for electric and hybrid vehicles and for both the product categories. Advertising Effectiveness, Public Contribution, Initial Public Contribution for Plugin and Plugin Unit Cost are the most influential variables for stimulating the diffusion process. As a matter of fact, the total cost savings deriving from the distribution with low emission vehicles are moderate, because of the low gap in operating costs and the necessary investment in charging stations. This means that the economic aspect is less relevant to the diffusion process than the awareness of adopting an eco-friendly freight distribution system.

Therefore, results of the simulations and sensitivity analyses imply that this new freight distribution system should be implemented based on structured advertising campaigns aiming at delivering the real environmental and operational benefits of such a CL model, on a public intervention and on consolidated and mature technologies. Only with these pillars it is in fact possible to reach a complete diffusion in reasonable times. Future research efforts will be directed towards further validation of the model and to its application to other cities.

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