System dynamics modelling for electric and hybrid commercial vehicles adoption

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Abstract: - Problems caused by the increasing freight transportation demand in cities call for integrated solutions where all stakeholders' efforts are coordinated, in order to both reduce the negative impacts of freight transportation, such as pollution and congestion, and carry no disadvantages to public and private operators. Among the solutions that can be implemented for these purposes, one of the most studied and applied one is the partial or total substitution of commercial vans with low emission vehicles. Previous studies have been focused mainly on the vehicle-related factors that make such adoption sustainable for the private stakeholders. However, there is a lack of contributions that also take into account the operational aspects of a city logistics system. In order to contribute to this literature, our work develops a System Dynamics model that assesses the adoption of low emission vehicles by analysing the most important operational factors typical of a freight distribution system. Results of the simulation and the sensitivity analyses demonstrate that the adoption of low emission commercial vehicles is feasible within a reasonable time period if some strategies are put in place. For instance, public contribution including both incentives to low emission vehicles and disincentives to traditional ones could effectively increase the adoption process, along with effective advertising campaigns about the operational benefits given by such distribution model.

Key-Words: - **System Dynamics; Diffusion model; Hybrid and electric commercial vehicles; Sustainable City Logistics; sensitivity analysis**

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 fosters the development of integrated logistics systems, where all the stakeholders are coordinated so to reduce negative impacts on citizens. In this sense, 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 [1], [2].

Several policies can be implemented to reduce the negative impacts of CL. For instance, restricting or even banning commercial vehicles from circulating in city centres might improve quality of life of citizens in a considerable way [3]. Other policies include for instance the installation of Intelligent Transportation Systems (ITS) for monitoring road traffic information, the use of reserved lanes for goods vehicles, load factor control and road pricing (e.g. congestion charge) for charging the entrance in restricted areas [4], [5].

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, such as logistics service providers and other freight carriers, it is necessary to deeply understand the main factors for the adoption of these kind of vehicles. In such a context, [6] investigate the case of Amsterdam and notice that the efforts made by the municipality to stimulate the diffusion of electric vehicles, even by ceasing the incentives programme for Euro 6 vehicles, are not necessarily backed up by the private companies that have adopted both the types of vehicles (i.e. Euro 6 and electric). This behaviour is a consequence of the technological gap that exists between Euro 6 vehicles, which by the way have a low environmental impact themselves, and electric vehicles. Moreover, [7] show that investing in electric commercial vehicles turns profitable only under certain operational conditions. In particular, they find that the most profitable strategy would be to purchase the vehicle while renting the batteries; in this case in fact the initial high cost of batteries does not counterweight the advantage of having lower variable costs for operating the vehicle.

In order to contribute to the existing body of literature on the factors for adopting low emission vehicles, we propose a model that assess the diffusion of a CL system based on electric and hybrid vehicles in the city of Torino (Italy), 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 analyse the diffusion of low emission commercial vehicles by focusing on the operational aspects of the associated logistics systems. We compare economic and environmental costs and benefits of the proposed system with the existing CL system, which mostly uses traditional diesel powered vehicles. The results of the simulation and the consequent sensitivity analysis allow us to identify some factors that might drive the adoption and diffusion of this distribution system.

We apply System Dynamics (SD) methodology to develop our model given its proven ability to represent and simulate the behaviour of systems like CL ones. The SD approach was originally introduced in the 1960s at the Massachusetts Institute of Technology to study the evolution over time of complex systems composed by numerous and heterogeneous variables and nonlinear connections between them [8], [9]. 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 a main manufacturer of commercial vehicles.

The paper is structured as follows. In Section 2 we review relevant literature in SD modelling, in order to build significant knowledge on which aspects should be represented in a model of a CL system. In Section 3 we depict the main aspects of the methodology and provide the theoretical background for the selected diffusion model. 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. Then, we propose our interpretation of the results and some policy implications in Section 7. Finally, we draw some conclusions and identify further research opportunities in Section 8.

2 Literature review

We review SD models along two research fields that are relevant for our purpose: i) traffic related issues, such as congestion and pollution, along with mitigating strategies and policies, and ii) adoption factors for low emission vehicles. Our aim is twofold: first of all to highlight the advantages and limitations of the SD methodology to our field of research; second, to identify the main CL variables and relationships among them available in literature, which will form the background for developing our model.

Some authors have focused on traffic congestion and on the consequent problem of polluting emissions. [10] developed a casual loop diagram (see Section 3) for the city of Accra, to investigate the congestion factors and their mutual relationships, along with the associated levels of emission. [11] simulate the behaviour of the parameters influencing pollution levels in Teheran and assess the effectiveness of some environmental policies. Among the policies investigated, the most effective ones are deemed to be technological improvement of vehicles and fuels and construction of public transportation infrastructures. Several SD models have been developed specifically with the aim of evaluating CO_2 mitigating policies and strategies. Some models consider intercity private transport as their study object [12], [13]. In particular, [13] focus on American highways and test different policy scenarios aiming at reducing CO_2 emission levels. Three policy-making strategies are investigated and found to be effective when combined together: increasing fuel efficiency, subsidizing the use of public transportation, and stimulating the adoption of electric vehicles. Strategic choices of private stakeholders are also examined through SD models. [14] qualitatively estimate the effectiveness of incentives to the use of alternative fuels vehicles by considering a timespan equal to the average vehicle lifetime. Besides the strategic decisions of manufacturers, the model also includes consumers' preferences, industry dynamics, and the environmental impacts during the life cycle of a vehicle.

We have found a wide presence in literature of SD models on the diffusion of low emission vehicles.

[15] focus on the adoption of low emission heavy goods vehicles. The authors highlight the importance of having both a potential market and an efficient refuelling network for the adoption of such vehicles. [16] investigate the Colombian market and show that good communication is more effective than fiscal policies to encourage low emission private transportation. [17] study the diffusion and competition between low emission vehicles, in particular electric and hydrogen vehicles. They find that a critical mass should exist for adopting alternatives technologies and that this critical mass is dependent on economic and behavioural factors. Among them the word of mouth appears to be crucial in order to stimulate diffusion.

Some authors have focused specifically on the diffusion of electric and hybrid vehicles. [18] build on the work of [17] to examine the adoption factors for hybrid plug-in vehicels and electric vehicles in the United Kingdom, considering a 40 year time span. The sensitivity analysis reveals that word of mouth, average life of the vehicles and emission rates could influence the adoption of such vehicles more consistently than other aspects such as incentives or specific features of vehicles. Lastly, the model developed by [19] 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.

However, we find a lack of works that investigate the diffusion of low emission vehicles by taking into account the main operational factors of the CL. In fact, SD models in this field usually focus on the impact of policies, operating and acquisition costs of the vehicles and other traditional adoption factors such as word of mouth or advertising. We aim therefore at integrating these factors together with the aspects that define urban freight distribution systems, such as freight demand, daily vehicle routes and distance travelled.

3 Modelling diffusion with System Dynamics

Several diffusion models can serve the purpose of developing a framework for assessing and identifying the socio-economic and cultural drivers that explain the adoption of an innovation, such as the Gompertz model, the logistic model, the Fisher-Pry model and the Bass model [20], [21], [22]. Among them, the Bass model [20] has been applied to various fields, such as retail, industrial and consumer goods, agriculture, education, and pharmaceutical.

Our own model is based on the SD representation of the Bass diffusion model developed by [9], which provides also the theoretical background for other existing models in the CL arena, mainly aimed at studying the adoption of low emission vehicles [17], [23]. Moreover, the Bass model has been chosen because of its qualities, namely simplicity and great capacity of predicting the behaviour of a system [24].

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 the 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 comprehend 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 two stocks or the stock levels.

4 Model development

In the next sections we present in detail the structure of our SD model with its main feedback loops.

It is worth mentioning that 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), we assume that any commercial unit (C.U.), that is any retail store operating in the city of Torino, that 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, we investigated the adoption by the C.Us 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.

For developing the model we used Vensim® DSS by Ventana Systems and we performed simulations over a time period of 120 months, with a time step equal to one month.

4.1 The general structure of the model

Our model presents a general structure subdivided into four parts:

- *Number of vehicles in the system* and associated number of kms travelled, which are estimated on the basis of some operational and demand factors depicted in section 4.2.
- *CO_2 emissions savings*. We consider only CO_2 emissions since the level of PM_{10} emissions is significantly lower. In fact, the PM_{10} emissions for traditional vehicles are on average 0.03 g/km, while the CO_2 emissions are approximately equal to 275 g/km.
- *Total vehicle costs savings*. They include the acquisition cost (amortization), the fuel cost, the maintenance cost (e.g. tire substitution) and the insurance cost. These savings stimulate the adoption of the new distribution system.
- *Charging station costs*. The charging stations are not part of a public infrastructure because we assume that they are located within the premises of the logistics providers or the C.U. suppliers.

The model also takes into account a possible public contribution for purchasing the vehicles and the charging stations. This contribution is dependent on the savings in the level of CO_2 emissions generated by the CL system.

The dynamics of the four parts of the model are represented via three main feedback loops which are detailed in section 4.5. Due to space constraints the present paper only describes the main aspects characterising the developed SD model. The complete model structure as well as the associated equations are available from the authors.

4.2 The sub-models

We developed three sub-models in order to provide a detailed and thorough representation of the general structure of the model. 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:

- Quantity of goods delivered, equal to the average monthly freight demand of each C.U. multiplied by the total number of adopters. The latter is taken from the "C.U. Diffusion Electric/Hybrid" sub-model.
- The carrying capacity of the vehicle.
- The monthly utilization factor of the vehicle, calculated in the model as the reciprocal of the number of monthly routes 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 kilometres they travel increases as well. If we consider a lower operating cost for hybrid and electric vehicles than for traditional vehicles, we can say that for each increase in the total amount of kilometres travelled savings are generated in comparison with the traditional system (from 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 acquisition costs or lower public contributions, the higher 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.

The diffusion sub-model is an elaboration of the SD representation of the Bass model developed by [9]. In our 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 system. 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 kilometres travelled as in the TO BE sub-model. Likewise, we calculated the taxation costs for traditional vehicles by adding a carbon tax and the 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 CO_2 emissions and operating costs, gives rise to interesting feedback loops involving all the sub-models. For example, 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 kilometres travelled increases also the value of *Total CO_2 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 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 CO_2 emissions, *Adoption from Savings in Cost* increases, closing a reinforcing loop.

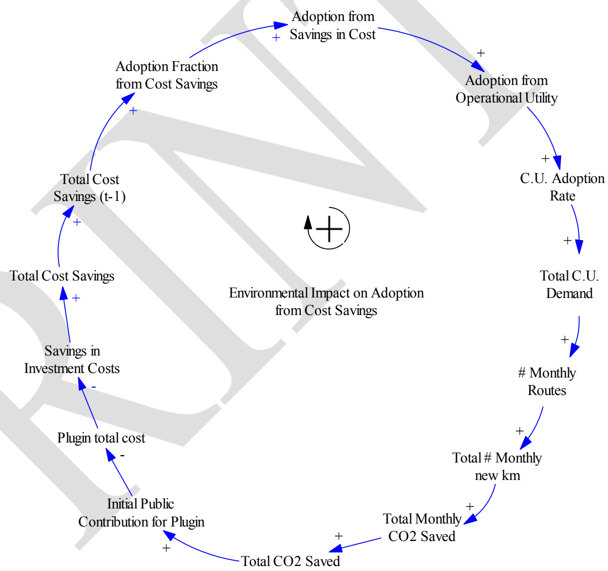


Fig. 1: Effect of CO2 savings on adoption

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 vehicles necessary (*# 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 the total *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 kilometres travelled increases, then savings turn positive, stimulating the adoption process.

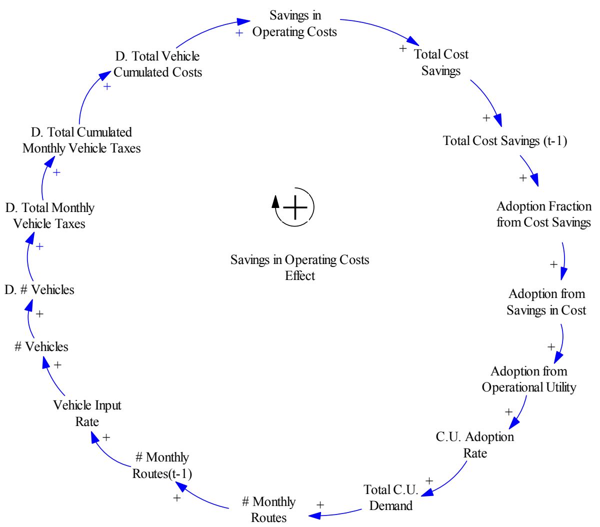


Fig. 2: Effect of savings in operating costs

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 are here presented for each sub-model: we defined d them by crosschecking pertinent literature with data coming from a van manufacturer and other logistics operators. Also, the numerical values in the next sections are related to parcel delivery since this is the product category we will focus on in the subsequent discussion of simulation and sensitivity analysis results.

5.1 Input parameters of the sub-model "Electric/Hybrid Model TO BE"

A first set of parameters is related to the C.Us and the necessary routes to serve them. The value of the variable *Average Distance b/w C.U.* has been estimated higher in case of C.Us located outside the city centre restricted area (ZTL - *Zona a traffico limitato*) than for C.Us located within ZTL because we assume 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 the 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 further from city centres. *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., *C.U. Monthly Delivery Factor* is a dimensionless parameter and is equal to 4 for both type of vehicles.

A second set of parameters relates to the features of the vehicles. *Monthly Vehicle Utilization Factor* is equal to 0.05 for electric vehicles and 0.06 for hybrid vehicles, while the vehicle load is 1.4 t/vehicle for both types. *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 the purchase of low emission vehicles, is equal to € 0.005 for each gram of CO_2 saved.

The third set of parameters considers CO_2 emissions. *CO_2 Emissions per km* is estimated equal to 74.7 g/km for electric vehicles and 180 g/km for hybrid vehicles [25], while *CO_2 Emissions per km AS IS* is set at 356.5 g/km. In our model we included both Well-to-Tank (WTT) and Tank-to-Wheel (TTW) emissions.

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 diffusion model have beenassumed to be the same for both the types of vehicles. For the definition of some standard parameters we refer to the Bass diffusion model representation by [9]. 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* (see [9] for the definition) have been estimated equal to 0.1, 0.04 and 0.08 respectively (unit of measure 1/month). An additional parameter has been introduced: *Emulation Contact Rate* defines how frequently a potential adopter observes the benefits obtained by an adopter, and it is set equal to 0.14.

The potential C.U. adopters are equal to 2,462 for the distribution system with electric vehicles and to 9,538 for the one based on hybrid vehicles. These values are different because in the base case we assume that the distribution with electric vehicles takes place only in the ZTL while the distribution with hybrid vehicles is adopted just by the C.Us located outside the ZTL.

5.3 Input parameters of the sub-model AS IS Model (DIESEL)

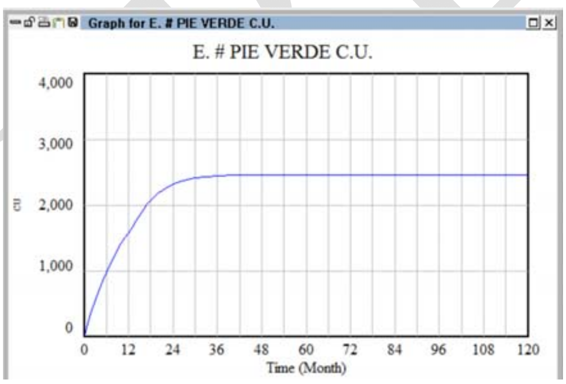
The variable *D.Operating Unit Cost* defines the operating cost for a diesel vehicle and it is estimated equal to 1.6 €/km. *D. Ownership Vehicle tax* and *D. carbon tax* are used to calculate the total taxation costs for a traditional diesel vehicle. The first one is computed on a monthly basis and it is equal to 6.67 €/vehicle; the second one is dependent on emission levels (g/km) and is not associated with the actual use of the vehicle (e.g. kilometre 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 our SD model. In particular, we will focus on the adoption of the new distribution system in terms of C.Us and number of vehicles. Two scenarios are discussed: one scenario considers parcel delivery by electric vehicles within ZTL and the other shows the adoption of hybrid vehicles for delivering parcels to C.Us located outside ZTL.

6.1 ZTL: electric vehicles

The entire stock of C.Us at issue (2,462) adopt the distribution system in a 51 month period, being served by a total number of 40 electric vehicles as shown in Figure 3.



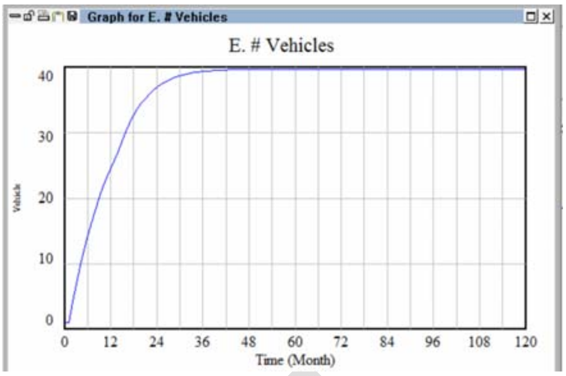


Fig.3: C.Us. and electric vehicles diffusion

Simulation also shows that the total cumulated cost savings in ten years are around € 2 million (Figure 4).

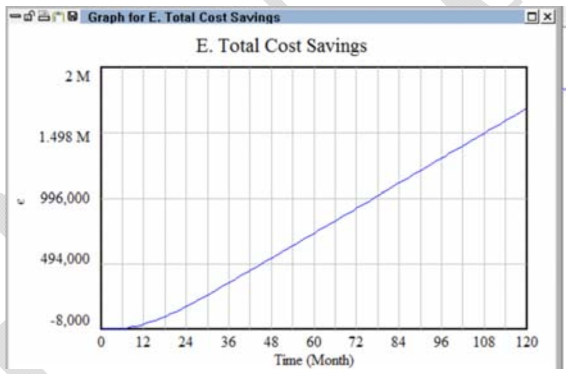


Fig. 4: Total cost savings for electric vehicles distribution

6.2 Outside ZTL: hybrid vehicles

In this scenario market saturation 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.

This scenario achieves total cost savings equal to € 10 million, turning positive from the fourth month of simulation on.

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 [9].

We will discuss how the main elements of our model, namely the number of vehicles, the number of C.Us and the total savings, change as we alter the input parameters. In the following sub-sections we therefore propose the results of the three most significant scenarios, which rely on both univariate and multivariate sensitivity analysis.

The analysis was performed with Vensim DSS, which allowed us to vary 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 blue line represents the base case, while the coloured 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 e Contact Rate

In this scenario we observe how the dynamics of the adoption process changes as the 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 5 presents the total cost savings trend for the new distribution system with electric vehicles. In the first months of the simulation period the advertising and the emulation effect 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 word of mouth action becomes relevant in order to furtherly stimulate the diffusion.

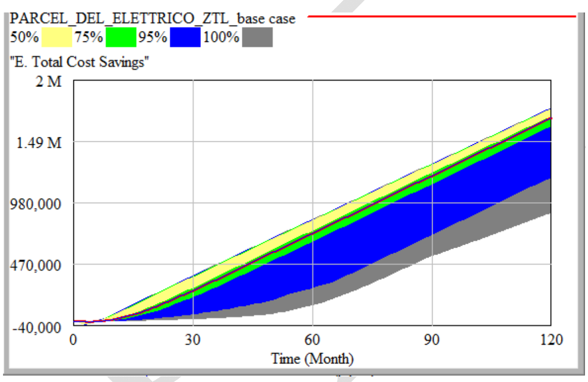


Fig. 5: Sensitivity analysis on Advertising Effectiveness, Emulation Contact Rate and Contact Rate on the total cost savings – electric vehicles

7.2 Univariate sensitivity analysis on Monthly Vehicle Utilization Factor

For this scenario we consider that the parameter *Monthly Vehicle Utilization Factor* follows a uniform distribution varying between 0.015 and 0.06.

This range of values was calibrated so as to obtain a number of routes per day of between 0.76 and 3, plausible values for the product category at issue.

With a Monthly Vehicle Utilization Factor equal to 0.06 a total of 46 electric vehicles is necessary to serve all C.Us. On the contrary, if we consider 3 routes per day (Monthly Vehicle Utilization Factor = 0.015) we reach a total number of around 12 vehicles. For both the output variables analysed, namely the number of vehicles in the system and the total cost savings, we observe significant variation as the values of the selected input parameters change. For instance, total cost savings takes values ranging from around € 500,000 to € 2 million (Figure 6 and Figure 7).

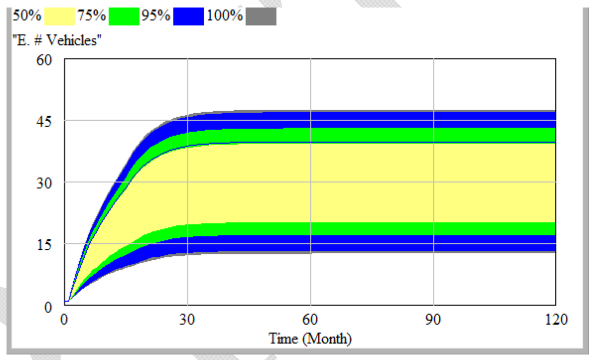


Fig. 6: Sensitivity analysis of Monthly Vehicle Utilization Factor on the number of electric vehicles

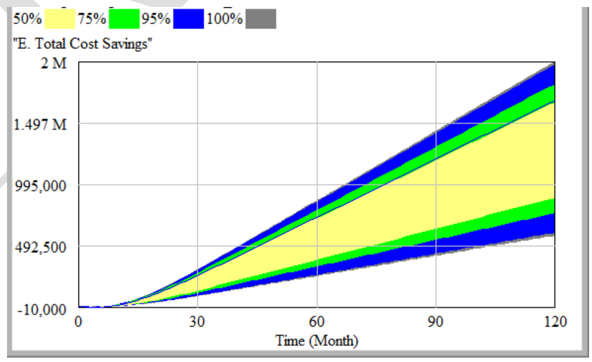


Fig. 7: Sensitivity analysis of Monthly Vehicle Utilization Factor on the total cost savings - electric vehicles

7.3 Multivariate sensitivity analysis on Public Contribution Factor, Public Contribution Factor for Plugin and D. Carbon Tax Factor

Through this sensitivity analysis we investigate the degree to which public contribution can support and influence the adoption of the new distribution system.

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, we observed that the public contribution dependent on the CO_2 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, we noticed 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*. We find out that 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 taxation for traditional vehicles.

8 Discussion of results

With our analysis we demonstrated that a new urban freight distribution system with low emission vehicles is feasible both for the city centre restricted area (ZTL) and for the whole city of Torino.

In fact, by focusing on parcel delivery, in both areas the market saturation is reached within the simulation time horizon, and in particular within 51 months for electric vehicles and 47 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 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 our model, such involvement includes both disincentives to traditional vehicles and incentives to low emission ones. In particular, we calculated the emission gap between the two types of vehicles: 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. To be more precise, *Advertising Effectiveness*, *Public Contribution*, *Initial Public Contribution for Plugin* and *Plugin Unit Cost* are the most influential factors 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 a more eco-friendly freight distribution system.

Therefore, we can state 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.

9 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 behaviour of a complex system and its associated variables. The adoption results to be influenced by the economic savings, the word of mouth and the green image that are related to the proposed sustainable logistics model. The parcel delivery supply chain has been considered. The outcomes show that the market saturation is achieved in about three years and the new CL system leads to a significant reduction in pollutant emissions. The financial sustainability is ensured by the mature vehicle technology and by the public economic contribution. Thus, it can be stated that the actual environmental benefits of the systems that are promoted via advertising campaigns, the involvement of the public authorities, and the adoption of suitable technologies are the main aspects that can stimulate the diffusion. Future research efforts will be directed towards applying the SD model to other product categories.

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