Environmental impact of electric cars in the urban area of Palermo.

S. Salerno, P. Zito, M. Migliore & S. Amoroso Department of Aeronautical and Transportation Engineering, Palermo University, Italy.

Abstract

The aim of this research is to analyse the environmental impact that could be determined by the introduction of electric cars in the urban area of Palermo. First of all we've determined the electric car potential demand that has been forecasted using a stated preference (SP) analysis. The survey was carried out at the University of Palermo considering a particular target of consumers: "the hybrid household". A logit demand model has been calibrated using the SP technique to model the choice between electric car and the internal one.

In the second part of the work was determined the pollutant emission decrease due to the introduction of electric cars into the automobile market, comparing the base case scenario, without the introduction of electric cars, and the forecasted one, obtained by the SP analysis data, also considering the higher emissions at electric power plants.

1 Introduction

One of the major source of air pollution is due to road transport, and its share is expected to rise in the future. It has been estimated that the cost for the Community due to disease caused by pollutant emissions (like respiratory or cardiovascular disease) is about 1.7% of GDP (Gross Domestic Product). Road vehicles, and in particular cars, are major contributors to air pollution, expecially in urban areas. The diffusion of electric vehicles could represent one of the possible strategies in order to reduce air pollution caused by road traffic in urban areas, thus realising a more sustainable mobility [1]. Infact over 80% of urban trips are shorter than 50 km per day and electric car seems to be suitable for theese trip's charachteristics.

2 Forecasting electric car demand by an SP analysis

The main point of weakness of electric car is the highness of its purchasing cost; so, such a vehicle, at a first sight, seems to be not competitive. The aim of our study is to evaluate the possible future market share for this ZEV (Zero Emission Vehicle) in spite of electric car's higher price.

In order to calibrate the demand choice model for the electric car, the stated preference tecnique has been adopted carrying out a destination survey at the University of Palermo. To this purpose a questionnaire has been built and submitted to the sample chosen. A part of the questionnaire was dedicated to the decision maker's socio-economic characteristic, useful for his identification, like: sex, age, ownership of two or more cars, ownership of a garage, average number of chilometres travelled per day and household income.

In order to maintain the scenarios' realism, the quantitative attributes able to explain the choice demand model and their values were also identified by a pilot survey. This attributes were: the annual cost for electric (EC) and internal combustion car (ICV), the average time spent to travel by car per day and the average life of the car. In particular the ICV running time from different origins to the University Campus has been estimated elaborating a D.U.E. (Deterministic User Equilibrium) assignment process of the private car O/D matrix (related to rush hour and the average working day) to the urban network [2].

The running time saved by using electric car was calculated considering its possibility of running into reserved lanes and LTA (Limited Traffic Areas). Instead, the annual cost of EC and ICV were calculated considering not only the cost per year related to the average life of the car but also the fuel or electric energy cost, the maintainance costs, the motor vehicle tax, the civil liability and the number of kilometres travelled per year, that we've supposed equal to 10,000 km. All the values were referred to FIAT Seicento Elettra (EC) and to Fiat Seicento SX (ICV). EC annual cost includes the subsidies determined by law in force: no motor vehicle tax for the first five years and the 50% reduction of civil liability's insurance. The subsidies for EC's purchasing price were supposed higher than that determined by law in force. Finally, the average life of EC was considered equal to that of battery and it was estimated considering the number of charging/recharging cycles declared by FIAT. The ICV average life is of seven years [source: Automobile Club of Italy (ACI), 2002]

The identified levels of EC's purchasing cost were 19,446 and 15,831, instead the ICV purchasing cost was of 8,551 euro. This costs were then transformed into annual costs related to car's average life [3]. The identified levels for the ICV's running time were 135 and 105 minutes per day, instead the running time for EC was 75 minutes per day. The average life levels for EC are 6 and 10 years.

Once estabilished all the levels 'n' for each attribute 'a' has been builted the complete factorial plan: $n^a = 2^3 = 8$. The scenarios of the complete factorial plane are 8, so it wasn't necessary to divide them [4]. All the scenarios were presented to each decion-maker which has reported on his questionnaire the choice between the competitive alternatives for each one. 469 questionnaires (3752)

observations) have been carried succesfully on, so we've analysed a sample of 0.11%. Actually the number of household in Palermo is 414,155 [source: ISTAT, 2002].

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The utility functions of the competitive alternatives were:

$$U_{ICV} = \beta_1 * \cos t + \beta_2 * time + \beta_3 * life + \beta_0$$
(1)

 $U_{EC} = \beta 1^* \cos t + \beta 2^* time + \beta 3^* life + \beta 4^* age + \beta 5^* sex + \beta 6^* garage$ (2)

where: U_{ICV} = conventional car utility function; U_{EC} = electric car utility function; cost = cost per year (\in per year); time = average running time (minutes per day); life = average life of the car (years); age = decision-maker'age (years); sex = 1 if the decision-maker is a female, 0 otherwise; garage = 1 if the decisionmaker owns a garage, 0 otherwise; β_0 = constant; β_1 = cost coefficient; β_2 = running time coefficient; β_3 = average life coefficient; β_4 = age coefficient; β_5 = sex coefficient; β_6 = garage ownership coefficient.

The calibration of the binomial logit model has been made using the maximum likelihood tecnique [4] using the Limpdep® 8.0 software.

The results of the calibration process are reported in table 1.

Attribute	Coeff.	Value	Stand. error	t-student	p-value
Cost	βι	-0.00163305	0.000142156	-11.4877	0.00000
Time	β ₂	-0.0122307	0.00239746	-5.10151	0.00000
Life	β3	0.276977	0.019385	14.2882	0.00000
Age	β ₄	-0.0805219	0.0373323	-2.1569	0.0310
Sex	β ₅	0.209702	0.0815229	2.57231	0.0101
Garage	β ₆	0.147276	0.0759454	1.93923	0.0525
ICV	βο	0.411817	0.133113	3.09374	0.0020
$\rho^2 = 0.12565$		V.O.T. = 60* $\beta_1/\beta_2 = 2.07 \ \epsilon/h$			
$\chi^{2}[6] = 649.53437$		Significance $(\chi^2) = 1,00000$			

Table 1 – Binomial logit car-choice model results.

The results of the calibration process show the correctness of the signs and the pvalue shows the significance of each attribute. The constant of garage's ownership has a poor significance, probably because other variables have simulated the a priori preference of the decision-makers for the car. The total significance of the demand model is shown by χ^2 test [4].

According to litterature, it was expected that SP respondents which met criteria such as ownership of two or more cars (85% of the sample), living in Palermo and limited commuting distance (94% of the sample), the so called "hybrid household", should have a greater propensity to purchase and use electric cars. The sample analysed shows this characteristics, but unfortunately it wasn't possible to have reliable data about household income because of the great resistance to answer about it.

The model's predicted probability of chose electric car is of 54.61 %, instead 45.39% will probably chose the conventional one.

Useful information are given by the elasticity of the attributes annual cost and average time. The direct elasticity let us know the effect due to a value's change

of the independent variable on the value of the dependent one. In table 2 are shown the values related to the direct elasticity effect of the analysed attributes of the transport supply on choice's probability between the two alternatives (ICV, EC), averaged over observation.

Alternative	Cost per year [€/y]	Average life [y]	Average running time [min/day]
Conventional car	-2.205	0.885	-0.669
Electric car	-1.960	0.826	-0.348

Table 2 – Direct elasticity split by choice alternative

These data show as an increment of annual cost equal to 1% induce an average reduction of choice's probability equal to 2.21% for the ICV and to 1.96% for EC. It's highlighted an high cost elasticity of demand. The average life shows a perfect elasticity because this value is very near to one for ICV and also for EC. Finally the average running time elasticity demand found for the calibrated model is inelastic, in fact its value is lower than one. Anyway, we have to remember that the average running time variable was expressed by minutes per day.

It's opportune to underline that the value of direct elasticity found for the choice demand model calibrated is also due to the sample distribution among the two transport alternatives. The probability distribution is in fact near to 50%, as before mentioned, and it highlights a great indecision between the alternative presented in the scenarios.

3 Forecasting the emission's reduction and estimation of monetary damage.

As we all know, carbon dioxide is the principal anthropogenic greenhouse gas responsible for most of the global warming. Sulphur dioxide and NO_x are acid species, believed to be responsible for much of the damage to building materials, as well as impacts on forests and aquatic ecosystems, observed in large parts of northern Europe. Climate change impacts are potentially the most important impacts of air pollution, but also the subject of the greatest uncertainty.

All these pollutants are the subject of concern about health and environmental impacts. Many of the pollutants and their secondary product have been identified as potentially injurious to health. Human health impacts are caused by a wide range of air pollutants. Acid gases and the particulate matter PM_{10} are associated with both mortality and morbidity effects. Health impacts have been also estimated through dose-response functions derived from epidemiological studies, which measure the impact of pollutant concentrations on human mortality and morbidity [7]. The major difficulty in quantifying the health impact of air pollution is that a very large number of people are exposed to relatively low levels over long periods of time, resulting in slight or rare health problems that

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The monetary damage have been estimated in this study by a "top-down" approach, through the use of a model, which allows to address transport and environment policy, and also to evaluate the monetary benefits concerning the introduction of electric cars in the urban area of Palermo.

The pollution's decrease determined by the introduction of electric cars in urban mobility is analysed by a comprehensive simulation model, in order to estimate car fleet trend and to forecast the air pollutant emissions. The greater pollutant emissions of the electric power plants, due to the recharge of electric car fleet, have also been considered.

To estimate the car density (number of cars per citizen) it has been used a sigmoid function of time that better fits the dynamic fleet evolution [6]. The population forecast is necessary to obtain car fleet from the estimated car density. Thus, the population trend of Palermo was determined using the past data series since 1991 until 2000. This demographic projections were obtained by a linear regression with correlation coefficient $R^2 = 0.9614$.

The Gompertz's function used to estimate vehicle density is:

$$VD_{i}(t) = \frac{I}{e^{e^{M_{i}+b_{i}t}+k_{i}}}, \qquad k_{i} = -\ln(S_{i})$$
(3)

where: $VD_i(t)$ is the vehicles density of type i (vehicles per 1000 population); t is the time in years (e. g. 0 for 1985, 35 for 2020); S_i is the saturation value: $S_i = \lim_{t \to \infty} VD_i(t)$; M_i , b_i are the parameters of the function. Coefficients M_i , and

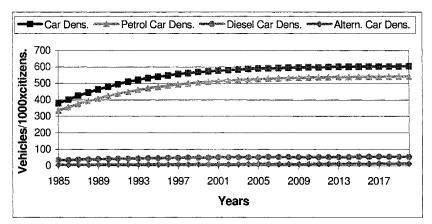
b_i are determined through a least squares error fitting procedure.

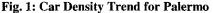
The car density forecasted for different kind of fuel is shown in fig. 1. It should be noted that diesel and alternative fuel (methane and LPG) car fleet together are less than 10% of the entire car fleet density. The internal turnover of car fleet which is the rate at which old cars are scrapped and replaced by new ones, can be calculated using the evolution of the car fleet in Palermo seen before. The estimate of internal turnover is really important, because new cars normally have emission standards stricter than the old ones, making use of new and cleaner technologies. In last years, the emission legislation in force for motor vehicle has become more strictly whether new or old cars. Thus, the replacement rate of car fleet affects directly pollutant emissions.

To calculate the car fleet's turnover for each year up to 2020, considering 1985 as the starting year, it has been used the following equation [6]:

$$C_{i}(t) = C_{i}(t-1) - C_{si}(t) + C_{ri}(t) + C_{ei}(t).$$
(4)

where: $C_i(t)$, $C_i(t-1)$ are the number of cars of type i, during years t and t – 1, respectively; $C_{si}(t)$ is the number of cars of type i, that were scrapped during year t; $C_{ri}(t)$ is the number of new cars of type i, that replaced old ones during year t; $C_{ei}(t)$ is the number of new cars of type i entering in the market during year t without replacing old ones (causing market extension).





The simulation of survival and scrappage rates is carried out with the aid of a modified two-parameter Weibul function with the following reliability function:

$$\varphi_{i}(k) = \exp \left[\left(\frac{k + B_{i}}{T_{i}} \right)^{B_{i}} \right], \qquad \varphi_{i}(0) \equiv 1.$$
(5)

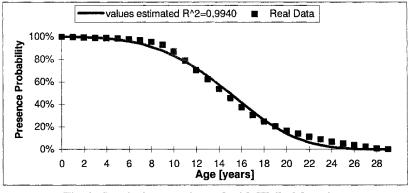
where: k is the age of cars, expressed in years; $\varphi_i(k)$ is the presence probability of cars of type i having age k; B_i is failure rate for car of type i ($B_i > 1$, it increases with age); T_i is the characteristic service life for car type i. These two parameters have been determined by the best fitting analysis with past data series of scrappage cars according to the age (data obtained by ACI, see fig. 2). For the city of Palermo these parameters assume respectively the following values: $B_i =$ 4.5 and $T_i = 21.1$.

For each year the total number of scrapped cars in year t is:

$$C_{si}(t) = \sum_{k=1}^{T_{i}} CC_{si}(t,k) = \sum_{k=1}^{T_{i}} \left[CC_{si}(t-1,k-1) \cdot \left(\frac{\varphi_{i}(k)}{\varphi_{i}(k-1)} \right) \right].$$
(6)

The higher emissions of particulates from heat engines, coupled with impact assessments based on recent studies, identify the fine particles as responsible of chronic bronchitis and the major cause of air pollution related mortality and morbidity.

The goal of the survey was to determine the monetary benefits produced by the pollution reduction, caused by the substitution rate of heat engine cars with electric ones in the urban area of Palermo. The substitution rate was calculated through the stated preference survey and the successive calibration of a logit choice model demand, that we've just presented in the first part of this w ork. The year 2004 has been assumed as the starting year in which the electric car market's penetration begins and also as the year in which the Euro IV technology will be available. So, the technology evolution of internal combustion engine has been also considered.





The study has taken into account car fleet's growth rate, the replacement of old cars with new ones, the technology substitution and the scrappage rate in order to analyse two different car's market scenarios: base scenario characterised by the absence of electric car's market penetration (fig. 3); and a reference scenario characterised by an electric car's market penetration rate equal to 54.6% of new registered cars, as indicated by the calibrated choice model demand (fig. 4).

In the analysis the following pollutants have been considered: hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO₂), nitrogen oxide (NO_x), sulphurous dioxide (SO₂), particulate matter (PM_{10}). Emission factors, to estimate pollutant emission levels, have been obtained taking into account mainly standard emission car's technologies that are already available. The emission factor levels for the internal combustion car are taken from the data base CORINAIR and from the emission model COPERT III.

Once obtained emission factors for all the pollutant considered, a simulation has been carried out, where the car fleet has been divided according to the engine technology evolution; the trend has been calculated considering the substitution rate; and finally the analysis has been built up imagining that the oldest technology will be replaced from a new cleaner one. Data obtained have been used to estimate pollutant emission levels.

The base scenario takes into account the car fleet's trend for the actual technology (without electric car introduction) and 10000 kilometres travelled per year for each vehicle.

In the evaluation of the environmental benefit produced by electric car introduction in urban mobility, the power plant emissions has been estimated, considering also that in general transport and electrical energy supply sector emissions occur at different locations and are characterised from following differences: 1) electricity sector emissions are mainly from high stacks, whereas road transport emissions are close to ground level; 2) electricity emissions are concentrated at a few locations, largely in rural areas far from cities, whereas exhaust emissions occur in a range of environments from the open countryside to the centres of major conurbations.

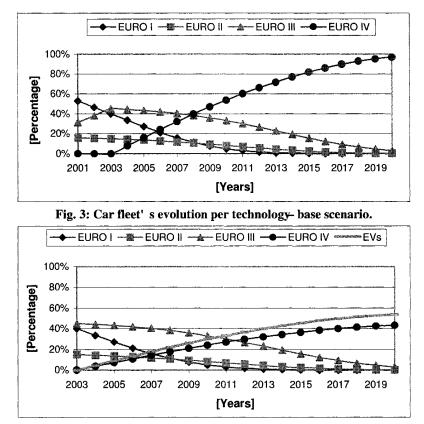


Fig. 4: Car fleet' s evolution per technology- reference scenario.

In order to estimate power plant emissions, various important factors should be considered: weather parameters, type of fuel, technology, age, topography and so on. It's very difficult to asses which kind of power plant (heating or hydroelectric plant) supplies necessary electrical energy to recharge the batteries of electric car fleet, considering also the lack of a recharging infrastructure. Then it has been taken into account the conservative assumption to consider that, the whole electrical energy is supplied by oil fuel heating electric power plants (whose emission factors have been obtained from the report: ENEL 2001). A car range of 100 kilometres with a single recharge of electrical batteries, an average annual car mileage of 10.000 kilometres per year and a stored electrical energy of 13 kWh per100 kilometres have been supposed.

In table 3 the pollutant emission rate found for the year 2020 has been compared with that of 2004 for the base case, and the reference scenarios. The power plant emissions and the reference scenario have been also considered together and shown in the last row.

Year	SO ₂	NOx	CO ₂	СО	HC	PM ₁₀	Scenario		
2004-2020	-2.83%	-95.10%	-7.78%	-63.19%	-74.66%	-46.58%	Base		
2004-2020	-55.04%	-97.58%	-57.33%	-82.20%	-87.82%	-74.70%	Reference		
2004-2020	116.43%	-92.98%	-39.89%	-79.01%	118.19%	-61.54%	Power Plants		

Table 3 - Pollutant emission rate.

The pollutant change emission rate values, expressed by percentage, were determined considering: the base scenario, without electric vehicle's market penetration (fig. 3); the reference scenario, with an electric vehicle's market penetration rate equal to 54.6% of new registered cars (fig. 4). The reference scenario analysed is characterized by a decreasing rate of all pollutants (see table 3). In particular, in this scenario it could be noted a relevant decrease for SO₂, PM_{10} and CO₂. Whilst considering the power plant emissions, the levels of single pollutions change drastically. In particular the pollutant levels of CO, PM_{10} , and CO₂ decrease respect to the base scenario, while the other pollutions increase drastically. However it should be noticed that, to consider only heating power plant is largely conservative. Moreover if we suppose that the recharging is only during nights, it allows to smooth the minimum peak's electrical energy demand in the load diagram supplied by hydroelectric plants.

Various attempts have been made to quantify the economic value of the human health damage. Many of these used exposure response functions derived from epidemiological studies to estimate the proportion of health endpoints, such as hospital admissions, attributable to air pollution. In particular the study made from Eyre [7] estimates the exposure of the population in the urban area of London specifically to road transport emissions and quantifies the external costs (ϵ /km per vehicle, for kind of fuel, and for urban or rural area) due to the damage produced on human health and buildings. Moreover, in most urban areas, concentrations of vehicle exhaust are significantly enhanced by the fact that many road have buildings alongside (canyon effect).

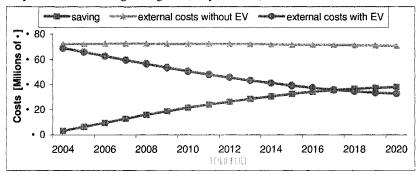


Fig. 5: External cost related road transport emissions in Palermo.

Finally, a simulation has been carried out, whose results are shown in fig. 5, once known the car fleet evolution in both base and reference scenarios and the environmental costs related to the different impacts caused by road transport

emissions. This picture highlights the external costs and the saving due to the introduction of electric cars in the urban mobility of Palermo. In monetary terms the charge which the population of Palermo should bear in the next years.

4 Conclusions

Since now the high purchase price of EC and the poor attention to the environmental problems have produced as direct results no market share for EC. Anyway as shown by the choice model demand, if a careful policy with the aim of saving for e.g. more time for EC will be followed up, it will be chosen by many people. The choice probability given by the calibrated model reflects in fact the willingness to pay of the citizen, in terms of time and cost, and their sensitivity concerning health and environmental themes.

However, the cost benefit analysis has shown that monetary benefits produced by pollution reduction due to EC's in troduction are actually lower than the costs supported by society for EC's subsidies. We've to underline that the cost for environmental damages used in the analysis probably does not include all the damages produced by road emissions in Palermo's CBD (cen tral broad district). Thus market penetration of electric car could depend mainly on pricing of environmental benefits. New fiscal, regulatory, planning and policy instruments which reflect the environmental benefits, such as vehicle purchase taxes, fuel taxes and especially road pricing in CBD, should be addressed.

As further work, other survey will be carried on and the sensitivity and reaction to road pricing in CBD will be analysed.

References

- [1] Pederiva G. et al.: L'auto elettrica a noleggio: esperienze e riflessioni. *Trasporti Europei*, 8/9, pp. 5-9, 1998.
- [2] Comune di Palermo: Piano Urbano del Traffico della città di Palermo. Palermo, 1997.
- [3] Cascetta E.: Teoria e Metodi dell'Ingegneria dei Sistemi di Trasporto. UTET, 1998.
- [4] Ortùzar J. De Dios and Willumsen G.: Modelling Transport. Ed. J. Wiley & Sons, 1996.
- [5] Amoroso S. et al.: Environmental impact of electric vehicles: analysis and comparison. Proc. of the Conf. On Networks for Mobility, Stuttgart -September 18-20, 2002.
- [6] Samaras Z. et al.: A methodology and a database for forecasting anthropogenic atmospheric emission in Europe. *Atmospheric Environment*, 33, pp. 3389-3404, 1999.
- [7] N. J. Eyre, D. W. Pearce et al.: Fuel and location effects on the damage costs of transport emissions. *Journal of Transport Economics and Policy*, January pp 5-24, 1997.